1. Introduction

Successive UK government policies have aimed for and introduced a number of health care reforms to improve both health care service delivery and generate saving through increased efficiency and productivity. To implement and to assess efficiency, the UK National Health Service (NHS) has produced a number of efficiency tools, such as efficiency indices, performance indicators, and cost and performance league tables, to ensure that scarce resources have been used effectively and efficiently (Bevan, 2010, 2011; NHS Group, 2014). While these reforms are made at the national level, the efficiency and saving issues are addressed at hospital levels where most resources are used.

Health services in Scotland are funded almost entirely out of taxation and access is universal with almost all hospital care free at the point of consumption. The share of private patients in Scotttish hospitals is less than 0.1% (Harker 2012). As shown in Table 1, public expenditure on health grew in real terms during the period being studied. The majority of these funds are allocated to fourteen geographically defined NHS Boards, responsible for planning and delivery of health care services. 'Operating divisions' within each Board are responsible for the provision of care and the hospitals therein are publicly owned. Following a period of large reductions in the number of hospital bed numbers in the previous two decades, acute hospital beds were reduced by only 2.2 per cent between 2002 and 2006 (PESA 2008).

--Table 1 here --

Since 2004, the NHS in Scotland has pursued a series of policies aimed at improving the patient's experience of health care. Targets have been used to monitor, enhance and encourage progress using measurable key variables (Hollingsworth and Parkin 2003; Propper et al. 2010). Improvements in target areas such as waiting times and day case surgery rates can be achieved through technological change, better management of resources and/or more resources. However, given limited resources, pressures of costs, and uncertainty around technological developments, there is an imperative to increase productivity via efficiency and technological improvements in order to meet planned improvements in performance.

Lean, a technique that can increase efficiency by improving processes, has been applied on a limited basis in Scotland (Antony and Kumar 2012).The most frequent benefit from the application of this technique has been the reduction of a) costs, b) patient waiting times and c) waste within processes (Antony and Kumar 2012; Radnor et al 2006)). While the studies of application of Lean are helpful in identifying germane issues facing Scottish NHS hospitals, we add to this by examining the underlying productive performance that can further provide information to address these concerns**.**

Unlike the rest of the UK, Scotland has not utilized the explicit financial incentives (e.g., prospective case-mix based funding and rewards for meeting targets) employed elsewhere in the UK (Farrar et al. 2009, Propper et al. 2010) nor has it matched the English NHS progress in a range of single dimension output measures and in particular rates of hospital activity per member of staff. In fact, unlike the English NHS that is more -public-private, the Scottish NHS has been more closely aligned with the original social contract between citizens and the provision of health care/hospital services (The Future of the NHS in Scotland, 2008). The Scottish Parliament also has the law making powers over running the NHS in Scotland and allocates decision making to the 14 local health boards in both the areas of funding and provision of services. Interestingly, this lack of efficiency assessment in Scottish hospitals comes despite higher levels of per capita expenditure (Connolly et al. 2010).

Per capita expenditures for Scotland were the highest of the UK nations -- £1,766 as compared to £1,515 in England, £1,688 in Wales and £1,700 in Northern Ireland (Harker 2012). Therefore,a study of the NHS in Scotland can provide information about how hospital productivity and efficiency have changed during the 2000s. Because of this social rather than a more market oriented approach, measuring efficiency and productivity changes over time has relevance especially as the debate continues on the role of government in the provision of these hospital services.

While the studies of health care efficiency and productivity have been increasing since the early 1980s, most hospital efficiency studies are from the US (see, e.g., Hollingsworth 2008). Only a few efficiency studies in the UK on the English health care system (Ferrari 2006; Hollingsworth and Parkin 2003; Gerard and Roderick 2003; Street 2003) or on Scottish hospitals (Hollingsworth and Parkin 1995, 2001; Jacobs & Street 2006; Maniadakis et al 1999; Maniadakis and Thanassoulis 2000) have been published. None of the Scottish hospital studies used data more recent than 1996.

In this study, we apply a Malmquist approach to assess levels and changes of efficiency and technology in Scottish hospitals using more recent data. Hospitals in England have targets and performance approaches but Scotland does not. Given the availability of recent data, we can add important information regarding improvements in productivity of Scottish hospitals. In other words, our work examines an interesting situation in which there is explicit pressure for improvements in the patient service experience, but no explicit incentives for efficiency improvement. In what follows we measure the productivity change through the Malmquist index. This index was introduced into DEA literature by Caves et al. (1982) and has a number of desirable features. Unlike the other indices –

Laspeyres, Paasche, Fisher and Törqnqvist -- the Malmquist does not require input prices or output prices in its construction. This makes it particularly useful in situations for the analysis of the productivity change in the public sector, where output prices are not in general available (Coelli, Rao and Battese, 1998). A further advantage of the Malmquist approach is that, once the production technology is estimated, one can decompose total factor productivity (TFP) change into its component parts: efficiency change and technical change. Finally, the Malmquist index can be calculated using either parametric methods or linear-programming DEA-type methods.

As compared to the seminal work by Färe et al.(1994) using this Malmquist approach in studying hospitals, we go one step further in applying a time-series assessment of changes in efficiency and technical change as a function of production performance.

In Section 2 we describe the methodology used to estimate efficiency and productivity changes. We report the results in Section 3 and conclude with a discussion in Section 4.

2. Methodology

As stated above, the Scottish NHS is more socially driven as compared to the more public- private orientation as in the English NHS. Because of this social framework, typical economic specifications such as cost minimization or profit maximization are not appropriate. Rather, we opt for the non-parametric Malmquist approach as popularized by Färe, Grosskopf, Lingren, and Roos (1992;1994) and expand on this approach by applying a time-series analysis to determine time trends. To derive the Malmquist measure and its decomposition, we begin by representing hospital technology with the input requirement set, which includes all sets of inputs that can be used to obtain a specific set of outputs given the available technology. We begin by defining the technology as input quantities $x = (x_1, \dots, x_N) \in \mathbb{N}_+^N$ and outputs are given by $y = (y_1, \dots, y_M) \in \mathbb{N}_+^M$. The technology consisting of all feasible (x, y) is defined by:

$$T = \{(x, y): x \; can \; produce \; y\} \tag{1}$$

A piece-wise linear version of the input requirement set is given by

$$L(y) = \{x: z \cdot M \geq y, z \cdot K \leq x, z \in \mathbb{N}_+^N\} \tag{2}$$

where and $z = (z_1, \dots, z_N)$ is a vector of non-negative weights that are applied to the observed input and output vectors ensuring a convex combinations of the vectors that envelop the data, forming the frontier. The lower bound of the input requirement set determines the best-practice frontier.

Over time, hospital productivity can increase or decrease via changes in the production technology (i.e., technical change) and changes in the efficiency with which technology is applied (i.e., efficiency change). To gauge how hospitals' total factor productivity has changed over time, we calculate the input-oriented Malmquist index of productivity change and its components (see Färe et al. 1994).

In a deterministic setting the Malmquist index for each hospital, or decision making unit (DMU), is obtained by solving four data envelopment analysis (DEA) problems -- see Thanassoulis et al. (2008) and Simar and Wilson (2008) for more details. The DEA basic model, which assumes constant returns to scale everywhere, measures the Shepard (1970) input distance $D_i^t = (x_i^t, y_i^t)$ for a DMU *i (1=1,2,…,n)* at time *t (t=1,2,…,T)*, relative to the technology existing at the same period and it is always less than one.. Computing the Malmquist index requires an additional input distance function to be defined: $D_i^{t+1} = (x_i^t, y_i^t)$ is the input distance function of the same DMU at time *t*, relative to technology at the period *t+1*. Grifell-Tatjéa and Lovell (1995) argued that when using the Malmquist approach to measuring total factor productivity, the constant returns to scale constraint must be employed. Using the variable returns to scale constraint would lead to biased findings.

More formally, in a DEA setting the input based Malmquist index $(M_{\downarrow}i^{\uparrow}(t, t+1))$ and its decomposition into efficiency and technological change indices between periods *t* and *t+1*, can be defined as (Färe et al., 1992, 1995):

$$x_{\square\downarrow}$$

$$= EC_i^{t,t+1} \cdot TC_i^{t,t+1} \quad (i=1,2,\ldots,n;\ t=1,2,\ldots,T\text{-}1) \qquad (3)$$

where $EC_i^{t,t+1}$ and $\cdot\, TC_i^{t,t+1}$ represent the efficiency change and technological change, respectively. We define efficiency change as the movements towards the frontier whereas technological change measures the shift of the frontier. This is the consistent definition of the decomposition of the Malmquist measure. Specifically, values of $M_i^{t,t+1}$, $EC_i^{t,t+1}$ or $\cdot\, TC_i^{t,t+1}$ less than one indicate a positive change for a DMU *i (i=1,2,…,n)* between period *t* and *t+1*. The shift in the frontier measures "true" technical change, while the changes in efficiency are measures of how well an observation is "catching up" with best-practice (Nishimizu and Page, 1982).

As noted by Semenick and Sickles (2000), the Malmquist approach along with its decomposition into efficiency and technological change captures how firms, in our case, hospitals, converge practices with each other. Two phenomena might be detected. The first, coined as cointegration (the tracking of efficiency scores) demonstrates that the scores are moving in the same direction. The second is called convergence of technologies (the catching up of technology) and it indicates that the frontiers are moving closer together. Both aspects are directly measured in the derivation of the Malmquist index, efficiency change, and technological change. As defined by Semenick and Sickles (2000) link this convergence to the competitive effects of deregulation of markets. Although not subject to such deregulation, the Scottish health care sector has consistently faced budgetary constraints and efficiency targets during the 2000s (Scottish Executive Health Department, 2001, Scottish Executive, 2004) and these may have similar convergence and cointegration effects to competition, .

To expand on the existing literature applying the Malmquist approach to hospital productivity, efficiency, and technological change, we apply the work of Simar and Wilson (1998, 1999), and analyze the productivity evolution of hospitals in an inferential setting. In fact, as noted by the two authors, the traditional DEA estimator is biased by construction (downward for output orientation) and is affected by the uncertainty resulting from sample variation.

Efficiency change identifies the DMUs' movements toward the frontier, whereas technological change measures the shift of the frontier. Values of $M_i^{t,t+1}$, $EC_i^{t,t+1}$ and $TC_i^{t,t+1}$ less than one indicate an improvement for the DMU i $(i=1,2,\ldots,n)$ between period t and $t+1$. Given the nature of the derivation of the Malmquist measures and their decomposition, we cannot determine whether changes in productivity, efficiency or technology are real or merely artifacts since we do not know the true production frontiers and must estimate them from a finite sample (Simar and Wilson 1999). We address this issue by employing a consistent bootstrap estimation procedure for correcting and obtaining confidence intervals for the Malmquist index and its two components. The idea underlying the bootstrap is to approximate the sampling distribution of the Malmquist index by simulating the data generating process (DGP). In other terms, given the estimates $\widehat{M}_i^{t,t+1}$ of the unknown true values of $M_i^{t,t+1}$ we generate through the DGP process a series of pseudo datasets to obtain bootstrap estimate $\widehat{M}_{i,b^*}^{t,t+1}$. Simar and Wilson (1998) discussed the problems that arise for bootstrapping in DEA models and they suggested the use of a smooth bootstrap procedure. In addition, the Malmquist index uses panel data, with the possibility of temporal correlation. For this reason, Simar and Wilson (1999) modified the bootstrap algorithm for efficiency scores to preserve any temporal correlation present in the data by applying a bivariate smoothing procedure. The procedure can be summarized as follows:

1. Compute the Malmquist productivity index $\widehat{M}_i^{t,t+1}$, for each hospital $i=1,2,\ldots,n$, by solving the DEA models as described in Färe et al. (1992, 1995).
2. Calculate the pseudo dataset $\{(x_{i,b^*}^t, y_{i,b^*}^t): i = 1,2,\ldots,n; t = 1,2\}$ to obtain the reference bootstrap technology by using bivariate kernel density where the bandwidth was selected following the normal reference rule.
3. Compute the bootstrap estimate of the Malmquist index $\widehat{M}_{i,b^*}^{t,t+1}$ for each hospital through the pseudo sample obtained in step 2.
4. Repeat steps 2 and 3, *B* times (number of bootstrap replications) in order to obtain the bootstrap sample $\{\widehat{M}_{i,1^*}^{t,t+1},\ldots,\widehat{M}_{i,b^*}^{t,t+1},\ldots,\widehat{M}_{i,B^*}^{t,t+1}\}$.
5. From the bootstrap sample, compute bias-corrected estimates and confidence intervals for the Malmquist index by selecting the appropriate percentiles. Where, *b* is the bootstrapped value for the individual observation or DMU and *B* is the total sample of bootstrapped values.

The bias-corrected estimates of the Malmquist index, are obtained from:

$$\widetilde{M}_i^{t,t+1} = \widehat{M}_{i,b^*}^{t,t+1} - \widehat{bias}_i = 2 \cdot \widehat{M}_i^{t,t+1} - B^{-1} \sum_{b=1}^{n} \widehat{M}_{i,b^*}^{t,t+1} \qquad i=1,\ldots,n \qquad (4)$$

However, the correction of the bias introduces additional noise, which increases the variance of the estimator. Thus, as rule of thumb, Simar and Wilson (1999) recommended that one not correct for the bias unless $|\widehat{(bias)}_i| > \sqrt{3} \cdot std(\widehat{M}_{i,b^*}^{t,t+1})$, where $std\left(\widehat{M}_{i,b^*}^{t,t+1}\right)$ is the sample standard deviation of the bootstrap values. The construction of the confidence intervals is obtained sorting the values $\left\{\widehat{M}_{i,b^*}^{t,t+1} - \widehat{M}_i^{t,t+1}\right\}_{b=1}^{B}$ in increasing order and deletes the $(\alpha/2 \cdot 100)$ -percent of the elements at either end of the sorted list. We define the endpoints as $-\hat{a}_\alpha^*$ and $-\hat{b}_\alpha^*$ (with $\hat{a}_\alpha^* < \hat{b}_\alpha^*$), coupled with the estimated $(1-\alpha)$-percent confidence interval for the productivity index leading us to:

$$\widehat{M}_i^{t,t+1} + \hat{a}_\alpha^* < M_i^{t,t+1} \leq \widehat{M}_i^{t,t+1} + \hat{b}_\alpha^* \qquad (5)$$

Relations 4 and 5 are similarly computed for the two components of the Malmquist index: efficiency change and technological change. With the obtained confidence interval for Malmquist index and its components, it is possible to determine whether productivity improvement (or decline) is significant at the established confidence level. The smooth bootstrap procedure for productivity was implemented using the FEAR package Version 1.15 (Wilson 2008).

Once we have boot-strapped our Malmquist, efficiency, and technological change indices, what we are primarily interested in is whether we can detect statistically significant trends in Scottish hospitals' movement over time. As such, we wish to use a trend analysis via time-series to address any obfuscation that may arise because of noise. Because the Malmquist measure is not truncated or censored as is the case of the DEA input-based measure that cannot exceed the value of one, we can use the OLS time-series approach for trend analysis. Even though the Malmquist approach and its component parts has been applied to the hospital and health care sector, rather than tracing the changes over time, we add to the literature by performing a formal trend analysis using time series ordinary least squares (OLS) using the SAS autoreg command to measure any bias from autocorrelation. This approach to assessing specific time trends using the Malmquist and decomposed measures is an addition to the literature gauging hospital productivity.

2.1 Data

To measure hospital performance we used data from 43 general acute care Scottish hospitals that supplied complete data for the period 2003-2007. These hospitals include those that were defined by the Scottish Government Health Directorate as teaching, large general, general or community hospitals. In 2007, this amounted to 61 hospitals. The small community hospitals with less than 16 beds which focused on either nursing home or hospice care and those hospitals with incompelet data were deleted. Using these data, we define inputs as: 1) DOCTORS (physicians and dentists)[1], 2) NURSES (nurses in all categories including nurse trainees), 3) OTHER LABOR (all other labor inputs) and 4) STAFFED BEDS, a proxy for capital. All labor categories are expressed in fulltime equivalents (FTEs). Outputs included: 1) INPATIENT CASES (inpatient elective cases and inpatient emergency cases) and 2) OUTPATIENT and SHORT STAY PATIENTS (inpatient

[1] A benefit of using these data to study Scottish hospitals, as compared to the usual data employed in studies of U. S. hospitals, is the availability of physicians in the former but due to contractual arrangements missing in the latter.

day cases, clinic attendances and emergency ward attendances). Descriptive statistics for the inputs and outputs are shown in Table 2.

--Table 2 here --

Inpatient cases were adjusted for case-mix using relative resource consumption in Healthcare Resource Group (HRG) categories. Separate case mix indices were calculated for inpatient admissions categories as: 1) elective, 2) emergency and 3) daycase. The following general formula was used:

$$CM_i^t = \frac{\sum_i^n \sum_j^J w_j^t \cdot p_{i,j}^t}{\frac{1}{n}\sum_i^n \sum_j^J w_j^t \cdot p_{i,j}^t} \qquad (6)$$

where, CM_i^t represents the case mix index for the *ith* hospital in year *t*; w_j^t represents the weighting factor for the jth HRG at time *t*, $p_{i,j}^t$ represents the proportion of cases in the *jth* HRG in hospital *i* during time *t*. This is the first DEA study of Scottish hospitals to use Health Resource Groups (HRGs) for case-mix adjustment of hospital outputs.

Critiques have been raised about using the CRS technology for assessing hospital productive performance. Since the derivation of the Malmquist measures require CRS to avoid biases, some argue that this mixes small and large hospitals together. In response to this argument, it should be noted that by including the case-mix index, we are explicitly designing peer groups that provide comparable resource intensity care. Hence, since assessing changes in productivity (Malmqusit, Efficiency, and Technical) in providing hospital care is the focus of this paper; we are less concerned about size and more concerned about resource use given patient outputs.

3. Results

From the descriptive measures presented in Table 3, the biased corrected Malmquist index, the efficiency index, and the technology change index all appear to go up and down over the four time intervals with the overall indices (2003-2007) demonstrating a decline in the Malmquist index but an improvement (albeit slight – 0.99) in efficiency. Similar to the Malmquist index, there appeared to be an overall decrease in technological change. (Full results can be requested from the authors.)

--Table 3 here --

The descriptive statistics suggest a lack of trend which could be related to "noise" masking the trend. In order to address this noise issue, we use a trend analysis via time-series.

--Table 4 here --

In Table 4, we show the results for the last Malmquist, efficiency, and technology change indices regressed on the previous three time interval sub-groups. (Recall we use the unbiased, corrected indices derived using bootstrap methods.) We focus on the last time interval as the dependent variable to first identify whether the three previous time intervals has an effect on the final Malmquist, efficiency, and technology change findings.

The first regression we assess is the time-series regression on the Malmquist. Using the three time intervals as lagged independent variables, we find that only the base time period, 2003-2004 had a positive and statistically significant finding demonstrating that the last time period's Malmquist was positively affected by the base year Malmquist. The findings from time series on the sub-group pairings exhibit a negative t effect between 2004-2005 regressed on 2003-2004 and between the effect of 2005-2006 regressed on 2006-2007. The only statistically significant effect that

2004-2005 had on the 2005-2006 Malmquist index. We note that there does not appear to be any strong evidence of autocorrelation (Durbin-Watson between 1.5 and 2.3) but via the R^2 findings, there appears to be between 7% and 20% of the variability explained.

Moving next to the efficiency results, similar to the overall Malmquist regression, the overall efficiency regression demonstrated only a statistically significant and positive effect on the last time period's efficiency by the base year's efficiency. From the results presented in Table 3, the efficiency analysis by sub-group demonstrated the same pattern as the Malmquist sub-group analysis of negative and statistically significant effects of the previous time period's performance on the later time period performance. We also did not note strong evidence of autocorrelation but we did find low R^2's in the efficiency analysis (0.05-0.19) indicating the less than 20% of the variation in the dependent variable(s) was explained by the independent lagged time period variable(s).

For our last set of regression models, we assess whether any statistically significant trends were detected for the technological change index. Contrary to the findings in the Malmquist or efficiency analysis, there was a negative and statistically significant effect on technological change (2006-2007) by technological change in the preceding time interval rather than the base time interval. There was also a strong trend demonstrated by the sub-group regression analyses illustrating that there was a consistent improvement over time in technological change. However, unlike the findings in the Malmquist and efficiency change regression models, there was no statistically significant effect of the first technical change measure on the final technical change measure. Similar to the Malmquist and efficiency analyses we did not find strong evidence of autocorrelation via the Durbin-Watson tests; but unlike the previous analyses, we found much higher R^2's ranging from a low of 0.25 to a high of 0.89 with the remaining two R^2's of 0.56. From these results we find some evidence of a trend toward improvement in all three indices from 2003-2004 to 2006-2007 for the Malmquist and efficiency change that would not have been identified if the analyses rested only on the descriptive statistics results. The negative effect of the preceding technical change measure on subsequent technical change demonstrates that there is a continual slowdown in technical change.

4. Discussion

The basic question we ask in this paper is whether the Scottish hospitals improved their productivity and efficiency over time in an environment where they were required to improve their services. Using data from 2003 through 2007, we applied a bootstrapped Malmquist, efficiency change, and technological change in order to assess if the Scottish hospitals met this objective.

Our sample was not large enough to stratify by size, which may be an issue since the Malmquist approach and its component parts are derived using the CRS technology. However, by adjusting the outputs for case mix, we are also able to set apart those hospitals treating more seriously ill patients naturally requiring more inputs from hospitals treating less resource intensive patients. Even though our results indicated some time trends in among hospitals Malmquist, efficiency and technology change over the years in our sample, we admit that this is too short of a time period to make any long term predictive policy changes and once we have longer time periods of study, more stratification may be possible to gain insights into not only these generalized trends, but whether different types of hospitals have different productivity changes over time.

Tracing the hospitals over time we did not find a consistent direction of either improvement or devolution; however, when we applied a trend analysis using time-series OLS, we found varying changes that lead to different conclusions. Using the parlance of Semenick and Sickles (2000, when cointegration arises, the movement of hospitals is in the same direction rather than convergence in that the frontiers are moving closer together.

Even though the Scottish hospitals operate under a government run NHS and not a price driven competitive market, these hospitals are required to produce services efficiently or else, because of the fixed budget, they cannot provide as much care. The Malmquist and efficiency changes are not as strong (demonstrated by the lower R^2s) as the technological change findings providing us with evidence of convergence – meaning that hospitals are improving and moving their "frontiers" farther out in each time interval. This was demonstrated most clearly by comparing the first period(s) Malmquist and efficiency change affecting the last period(s) Malmquist and efficiency change. Inter-temporal changes within these two time periods were not conclusive, at a statistically significant level.

The most striking finding in the time-series study is the consistent devolution in technical change. We note that in each case, each previous technical change variable had a negative effect on the later time technical change. This finding indicates that high changes in one period lead to negative changes in the next. This result may imply that it may take time for hospitals to absorb the new technology in treating patients. In light of budgetary constraints, this finding may also imply that increases in any kind of input is slowed in subsequent periods of time so as not to exacerbate increasing health care costs. From these findings, we surmise that the frontiers were not converging in a positive direction.

We also cannot claim definitively that cointegration is continuous since the scores in the time period immediately before the time period for which the scores are under evaluation have a negative influence. This somewhat unexpected result may be an artifact of the short term fluctuations of technology diffusion, i.e., the new technology has not been fully in place. Again, a longer time period would be necessary in order to make any type of conclusion of whether changes in how these hospitals produce patient care is improving in terms of total factor productivity and its component parts.

As far as methodological advances to the literature, we have gone beyond the initial Malmquist study of hospitals (Färe et al., 1994) by applying a bootstrapped Malmquist approach to the hospital sector as well as employed a time series trend analysis to gauge changes without the obfuscation by white noise. If only the means of the indices were traced over time there would be no consistent discernible trend in the hospitals either improving or worsening their performance. By using regression, we found a definite and statistically significant trend of improvement, lending encouragement to the Scottish hospital management that they are doing more with less – which is particularly relevant in times of more austerity in government spending but without a decrease in demand. However, our work does not directly analyze how costs have changed. It would be interesting to examine changes in costs or cost-inefficiency in the Scottish context.

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Table 1. Public expenditure in Scotland (2007/6 prices)

Category	2002/3	2003/4	2004/5	2005/6	2006/7
Total public expenditure	37,565	39,344	39,753	42,279	43,718
Total health expenditure	6,029	6,824	7,341	8,335	9,064
Health expenditure per head of population	1,193	1,349	1,445	1,636	1,776
Average available acute care staffed beds	17,903	17,710	17,559	17,537	17,505

Source: Public Expenditure Statistical Analysis (PESA) 2008, HM Treasury/Office for National Statistics, April 2008.

Table 2 Descriptive Statistics of Output and Input Variables

		2003	2004	2005	2006	2007
OUTPUTS						
INPATIENT	Median	17,403.7	17,918.2	16,695.5	17,454.7	18,665.4
	Mean	18,305.7	18,843.4	19,020.7	19,275.8	19,814.8
	S.D.	17,906.8	18,414.3	18,854.3	19,546.4	20,175.5
	Min.	183.2	179.3	175.9	143.8	109.5
	Max	64,992.0	65,224.4	72,039.8	78,740.5	82,359.7
OUTPATIENT	Median	227,523.0	248,839.9	268,369.2	264,370.4	
	Mean	198,064.9	201,492.2	214,571.9	214,935.0	221,189.9
	S.D.	174,904.0	178,132.8	191,193.8	186,704.2	194,286.1
	Min.	0.0	75.0	185.0	13.0	9.0
	Max	712,536.4	724,844.1	766,397.2	706,857.1	761,675.4
INPUTS						
BEDS	Median	351.0	339.0	351.0	341.0	341.0
	Mean	339.0	338.9	354.1	350.2	353.4
	S.D.	292.7	297.4	302.8	305.0	310.0
	Min.	16.0	16.0	16.0	16.0	16.0
	Max	931.0	947.0	962.0	920.0	970.0
DOCTORS	Median	112.6	141.1	132.9	139.1	141.9
	Mean	137.6	147.1	150.5	159.7	167.8
	S.D.	150.5	161.4	160.9	170.8	181.4
	Min.	0.3	0.2	0.3	0.3	0.3
	Max	611.9	611.9	580.9	589.4	684.1
NURSES	Median	594.7	552.3	672.9	637.9	707.2
	Mean	600.2	628.1	670.7	694.3	705.9
	S.D.	559.6	586.1	631.8	659.5	666.0
	Min.	15.3	15.9	16.2	17.8	16.4
	Max	2,157.0	2,157.0	2,183.1	2,288.5	2,350.5
OTHER	Median	470.8	435.0	427.0	473.9	489.9
LABOR	Mean	429.1	449.2	480.2	510.5	517.2
	S.D.	397.2	421.3	449.2	475.9	481.8
	Min.	5.9	7.0	9.6	6.8	8.2
	Max	1,451.1	1,577.3	1,617.6	1,665.2	1,723.4

Table 3 Descriptive Statistics of the Malmquist *(M)*, Efficiency change *(EC)* and technological change *(TC)* original and biased corrected (*Mb*, *ECb* and *TCb*).

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
		2003-2004		
M	1.03	0.10	0.86	1.41
Mb	1.03	0.10	0.85	1.36
EC	1.07	0.12	0.89	1.55
ECb	1.01	0.13	0.92	1.57
TC	0.96	0.03	0.89	0.99
TCb	0.93	0.04	0.84	0.98
		2004-2005		
M	1.06	0.12	0.83	1.57
Mb	1.06	0.12	0.83	1.57
EC	0.93	0.10	0.71	1.28
ECb	0.89	0.10	0.68	1.19
TC	1.14	0.04	1.11	1.26
TCb	1.18	0.06	1.13	1.34
		2005-2006		
M	1.01	0.11	0.79	1.42
Mb	1.02	0.11	0.81	1.40
EC	1.06	0.11	0.81	1.47
ECb	1.07	0.10	0.85	1.45
TC	0.96	0.02	0.87	0.98
TCb	0.94	0.03	0.83	0.97
		2006-2007		
M	1.01	0.11	0.81	1.32
Mb	1.01	0.11	0.81	1.32
EC	0.96	0.11	0.78	1.27
ECb	0.95	0.11	0.77	1.25
TC	1.05	0.02	1.03	1.11
TCb	1.06	0.03	1.05	1.18
		2003-2007		
M	1.13	0.23	0.71	1.87
Mb	1.12	0.21	0.72	1.65
EC	1.03	0.22	0.65	1.73
ECb	0.99	0.18	0.66	1.47
TC	1.10	0.01	1.07	1.12
TCb	1.11	0.03	1.08	1.19

Table 4 Regression Results -- Malmquist Measures (DW=Durbin Watson)

Dependent variable: **$Mb^{2006,2007}$**	Estimate	t-statistic	p-value
Intercept	0.67	2.01	0.05
$Mb^{2005,2006}$	-0.25	-1.6	0.11
$Mb^{2004,2005}$	0.14	1.01	0.32
$Mb^{2003,2004}$	0.43	2.55	0.02
R^2 =0.20	DW = 1.63		
Dependent variable **$Mb^{2004,2005}$**			
Intercept	1.41	7.35	0.0001
$Mb^{2003,2004}$	-0.33	-1.81	0.08
R^2 = 0.07	DW = 2.26		
Dependent variable **$Mb^{2005,2006}$**			
Intercept	1.32	9.60	0.0001
$Mb^{2004,2005}$	-0.28	-2.23	0.03
R^2 = 0.10	DW = 2.21		
Dependent variable **$Mb^{2006,2007}$**			
Intercept	1.29	7.85	0.0001
$Mb^{2005,2006}$	-0.27	-1.70	0.10
R^2 = 0.07	DW = 1.48		
Dependent variable: **$ECb^{2006,2007}$**	Estimate	t-statistic	p-value
Intercept	0.76	2.29	0.02
$ECb^{2005,2006}$	-0.24	-1.56	0.12
$ECb^{2004,2005}$	0.09	0.52	0.62
$ECb^{2003,2004}$	0.32	2.58	0.01
R^2 =0.19	DW: = 1.58		
Dependent variable: **$ECb^{2004,2005}$**			
Intercept	1.21	10.39	0.0001
$ECb^{2003,2004}$	-0.29	-2.75	0.01
R^2 = 0.17	DW = 2.40		
Dependent variable: **$ECb^{2005,2006}$**			
Intercept	1.40	9.78	0.0001
$ECb^{2004,2005}$	-0.37	-2.30	0.03
R^2 = 0.10	DW 2.02		
Dependent variable: **$ECb^{2006,2007}$**			
Intercept	1.19	7.10	0.0001
$ECb^{2005,2006}$	-0.22	-1.46	0.15
R^2 = 0.05	DW = 1.43		
Dependent variable: **$TCb^{2006,2007}$**	Estimate	t-statistic	p-value
Intercept	1.65	4.30	0.0001
$TCb^{2005,2006}$	-0.62	-5.95	0.0001
$TCb^{2004,2005}$	0.005	0.04	0.96
$TCb^{2003,2004}$	-0.009	-0.04	0.97
R^2 =0.56	DW: = 2.18		
Dependent variable: **$TCb^{2004,2005}$**			
Intercept	2.63	32.73	0.0001
$TCb^{2003,2004}$	-1.56	-18.05	0.0001
R^2 = 0.89	DW = 1.68		
Dependent variable: **$TCb^{2005,2006}$**			
Intercept	1.23	15.84	0.0001
$TCb^{2004,2005}$	-0.25	-3.69	0.001
R^2 = 0.25	DW = 2.45		
Dependent variable: **$TCb^{2006,2007}$**	Estimate	t-statistic	p-value
Intercept	1.66	19.98	0.0001
$TCb^{2005,2006}$	-0.63	-7.19	0.0001
R^2 = 0.56	DW = 2.17		