Efficiency of New Zealand's District Health Boards at Providing Hospital Services: A stochastic frontier analysis

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Abstract

The majority of secondary and tertiary healthcare services in New Zealand are provided through public hospitals managed by 20 local District Health Boards (DHBs). Their performance were measured by a set of indicators established by the National Heath Targets including elective surgeries, cancer treatment, and Emergency Department waiting times etc. Due to data issues and ill-judged generic public perceptions, efficiency studies for the NZ health system is insufficient in spite of its common international applications within the field of applied production economics. This inevitably leads to criticisms about the perverse incentives created by the Health Targets and its final abolishment by the newly elected Labour Government in January 2018.

Utilizing a multifaceted administrative hospital dataset, this study is the first to measure both the technical and cost efficiency of NZ public hospitals during the period of 2011-2017. More specifically, it deals with the question of how hospital efficiency varies with activities reported under the National Health Targets after controlling for local patient structure. There is no evidence in the empirical results to suggest the proportions of elective surgical discharges or Emergency Department visits are increased at the expenses of lowering the overall efficiency of hospital operations. The national technical efficiency is averaged at 86 percent over the period and cost efficiency is 85 percent. The results are derived by stochastic input distance function and cost frontier in order to accommodate multiple outputs and limited number of census observations. Efficiency ranking is sensitive to specifications of the inefficiency error term, but reasonably robust to the choice of functional form and different proxies for capital input.

Keywords: NZ hospitals, Stochastic Frontier Analysis, Technical Efficiency, Cost Efficiency

JEL classification: D24; I11; I18

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1. Introduction

The majority of health care systems worldwide, including New Zealand, face challenges imposed by tight public budgets, an aging population, and more chronic diseases. In 2017, total health expenditures in NZ amounts to $24.5 billion and 9.2% of GDP (OECD Health Statistics), health spending sits in the second place right after social security and welfare in the core Crown expenses book with a share of 21% (Treasury, 2017). Debates about system inefficiency resulted in a series of major structural changes since the 1990s (Ashton, 2005 and 2009; Cumming *et al.* 2014 and Mays *et al.* 2013), nearly two decades of chaos before settling down in 2000 under the Public Health and Disability Act. Nonetheless, proper measures of the productivity and efficiency performance are yet to be established in the health sector.

This paper, to the best of our knowledge, is the first to analyse the efficiency of NZ hospital services during the stabilized post reform period. It investigates two issues: (1) how efficient are NZ hospitals and (2) does perverse incentives exist under the National Health Targets established in 2008 for the purpose of performance monitoring.

Obtaining data accurately reflects inputs usage is a major challenge for studies of this kind, we constructed a dataset from the monthly financial statements provided by the Ministry of Health. To deal with the issue caused by balancing the accounts, monthly data was integrated into annual observations.[1] An input distance function analysis is adopted to accommodate the problems of multiple outputs and potentially non-optimising behaviour under the NZ regulatory framework. A stochastic cost frontier is constructed to estimate cost efficiency. A number of robustness checks are performed, such as the choice of different functional forms and distributional assumptions, as well as the use of different variables to approximate the flow of capital services.

Healthcare services in NZ is mainly funded through taxation. Publicly owned hospitals provide most of the secondary and tertiary healthcare services such as surgery, specialist

[1] A non-negligible number of observations incurred negative expenditures on key inputs such as outsourced medical staff, nurses and allied professionals etc. This will cause problems when the quantity of input is derived from total expenditures on that category. The Ministry of Health indicates these negative records are the results of balancing the accounts. For example, a hospital might contract medical doctors to work on high level administrative duties and these outsourced services are recorded as outsourced medical expenditures when the right place to go is the outsourced management account. This will generate an imbalance in the monthly financial statement and be corrected in the following months by debiting the corresponding amounts from outsourced medical and crediting the account for outsourced management.

treatments and emergency services. General practitioners, practice nurses, pharmacists and other health professionals working within a Primary Health Organization (PHO) are contracted by the government to provide primary healthcare services. There were 21 District Health Boards (DHBs) initially established in 2000, responsible for providing health and disability services to their corresponding geographically defined local communities. DHBs own public hospitals as their provider arms and are funded by the MOH through a population-based funding formula (PBFF).[2] Two DHBs were merged in 2010, the analysis is therefore built upon the stabilized post-merge period from 2011 to 2017. Profiles of the 20 DHBs are presented in ***appendix 1***. They vary considerably in size, with Waitemata being the largest DHB serving over half a million population and West Coast being the smallest DHB with a population just over 30,000.

Performance of the DHBs were monitored by the MOH through quarterly assessment of the six targets presented in ***appendix 2***. Those targets were first introduced in 2008 and although designed to improve the performance of the health sector, they are primarily driven by partial output measures and there is no control for inputs usage. Many dimensions of healthcare services, such as acute hospital admissions and non-Emergency Department (ED) outpatient visits, are completely unaccounted for. The degree to which the current health target could potentially introduce perverse incentives by diverting resources away from unmeasured services to measured ones are unknown. In other words, there were risks that the Health Targets were achieved at the expenses of lowering overall productivity and efficiency. For instance, many concern that the hospitals might discharge acute patient earlier in order to accommodate more elective surgeries, and/or admit patients for elective surgeries when the condition could be treated at a primary or secondary level.

In this study, the performance analysis of DHB hospitals is based on standard production theory in economics (Fare, 1988; Heathfield and Wibe, 1987; Rasmussen, 2011 and Ronald, 1970), a frontier representing the current production technology (i.e. best practice) will be estimated using observed data and serves as the benchmark against which to evaluate the extent of resource utilization. Farrell (1957)'s input-based technical efficiency measures the maximum proportional reduction of all inputs (e.g. doctors, nurses, capital etc.) given the

[2] The PBFF tries to allocate resources between DHBs based on a core model which assesses the relative healthcare needs of the local populations via historical average expenditure for different demographic groups. The PBFF also incorporates adjusters to account for factors such as populations with low access to healthcare services, rural areas and overseas visitors and refugees.

observed outputs (e.g. inpatient and outpatient volumes). This definition of inefficiency assumes that inputs are more easily influenced by DHB hospitals than outputs which are primarily driven by local population demand for hospital care. No assumptions about cost minimizing behaviour need to be imposed when estimating technical inefficiency. The data required to construct the *production frontier* that maps minimum feasible inputs for producing a certain level of output(s) are *quantities* of inputs and outputs observed for each DHB. Whereas cost inefficiency can be defined as the DHB's deviation from the constructed *cost frontier*, which maps minimum feasible costs given exogenous input prices and demand driven outputs. One has to acquire data on input prices and assumes all DHBs seek to minimize expenses when measuring cost efficiency, even though these might be unsuited to the heavily regulated health system in NZ.

For empirical construction of the best practice frontier, parametric stochastic frontier analysis (SFA) and non-parametric data envelopment analysis (DEA) are the two traditional research methods. SFA uses econometric methods to fit a best practice frontier into the observed data points, the estimated frontier is assumed to follow a specific functional form and subject to statistical error (Aigner *et al.* 1977; Kumbhakar and Lovell, 2000). DEA, on the other hand, is a linear programming technique which fits a deterministic piece-wise frontier over the observed data points using minimal extrapolation principle (Charnes *et al.* 1995; Cooper *et al.* 2007). Discussions of both methods and their relative merits are well documented (Coelli *et al.* 1998; Bogetoft and Otto, 2011). In general, SFA has the advantage of accommodating data noise, representing production relationships via established models and allowing the conduct of statistical tests on both the efficiency estimates and coefficients characterising the underlying production technology. DEA, on the contrary, is preferred for the opposite causes. There is no need to impose a specific functional form to approximate the shape of the production frontier or a particular distributional form for the error terms.

As pointed out in Bogetoft and Otto (2011), ideally, one would like to have the benefits of both, a frontier with flexible form to reflect the characteristics of the industry (instead of relying excessively on arbitrary textbook assumptions) and is also robust to random noise (i.e. the estimation results are not sensitive to data noise). This leads to the development of stochastic DEA (Land *et al.* 1993; Olesen and Petersen, 1995; Fethi *et al.* 2001) that incorporates stochastic elements into the deterministic frontier. However, approach like this comes at the cost of imposing strong distributional assumptions and the estimation requires a larger dataset, which essentially offset the advantages offered by traditional DEA. Another set of developments in DEA involves using techniques such as Jackknife and Monte Carlo simulation (Dyson and Shale, 2010; Kao and Liu 2009; Sandiford *et al.* 2017) to introduce stochastic elements into the efficiency estimates, the bootstrap technique in particular, has gained considerable momentum in hospital efficiency studies (Simar and Wilson, 1998, 2000 and 2007; Blank and Valdmanis, 2010; Chowdhury and Zelenyuk, 2016; Cristian and Fannin, 2013;).

Although a rich body of empirical literatures exist for hospital efficiency analysis using both SFA and DEA, there are only a few that uses census data (i.e. observations of the whole industry) for regions of small size with just a dozen of hospitals (Gannon, 2005; Knotodimopoulos *et al.* 2006). The NZ health sector provides unique challenges for performance studies. There are only 20 DHBs nationwide, each serves a distinctly defined geographical population. Studies of any kind are most likely to be based on census data containing observations of all DHBs and as a result, will not be suited for a bootstrap DEA study in which the dataset is supposed to represent a sample of hospitals drew from the larger population. In addition, one will have most of the DHBs operating exactly on the piece-wise frontier constructed using DEA with limited scopes for improvement. Sandiford *et al.* (2016) measured the efficiency of these 20 DHBs at producing *life expectance gains* with DEA. The input they used is the funding each DHB received and output is the change in Maori and European life expectance between the 2006 and 2013 census waves. Although the benefits of using Monte Carlo simulation are not clear for a census dataset with only 20 observations, studies like Sandiford *et al.* (2016) shows such analysis is feasible and could provide valuable insights. To the best of our knowledge, there is no research of this type has been carried out to measure the efficiency of NZ DHBs at providing *hospital services*. This study attempts to fill the gap and adds additional perspectives to the existing performance monitoring. An input distance function approach is adopted to measure technical efficiency because of its two key advantages: (1) to deal with the issue of small size census data by pooling multiple years of observations together in construction of the best practice frontier; and (2) to avoid the problems of single output restriction, non-optimising behaviour, and potential regressor endogeneity, all of which are critical issues to consider under the current regulatory framework.

For determinants of hospital efficiency, attentions have been leaned towards organizational factors such as ownership, size and teaching status (Chang *et al.* 2004; Chowdhury and Zelenyuk, 2016; Herr 2008; Herr *et al.* 2011). This is understandable for they are parameters within the control of policy instruments, the relevance of which however is quite limited in the NZ context. District patient profile and measured activities under the National Health Targets are more pertinent since each DHB is assigned a geographical area to serve, how their performance vary with indicators which have been built into the targets versus those that haven't, will be investigated in this study via specifications of the inefficiency error component.

The rest of the paper is organized as following: Section 2 describes the empirical models to be estimated; Section 3 specifies the data and explains the constructed variables; Section 4 discusses the results; Conclusions, with potential policy implications, are provided in the last section.

2. Methodology

In the case of technical efficiency, an input distance function defined over M outputs and K inputs takes the form

$$d_{it}^{I} = d^{I}(x_{1it}, x_{2it}, \cdots, x_{Kit}, y_{1it,} y_{2it}, \cdots, y_{Mit}) \qquad (1)$$

where $i = 1,2,\cdots,N$ denotes observations; $t = 1,2,\cdots,T$ represents time periods; x_{kit} is the k-th input used by observation i in year t; y_{mit} is the m-th output produced; and $d_{it}^{I} \geq 1$ is the maximum amount by which the input vector can be radically contracted without changing the output vector. Important properties of the function are that it is non-decreasing, linearly homogeneous and concave in inputs, and non-increasing and quasi-concave in outputs.

Assuming a Cobb-Douglas functional form and allowing the existence of random error term to account for statistical noise, the stochastic input distance function is defined as

$$\ln d_{it}^{I} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + v_{it} \qquad (2)$$

where v_{it} is assumed to be an independently and identically distributed normal random variable with zero means and constant variances σ_v^2 ; This function is non-decreasing, linearly homogeneous and concave in inputs if $\beta_k \geq 0$ for all k and if

$$\sum_{k=1}^{K} \beta_k = 1 \qquad (3)$$

It is also quasi-concave in outputs if nonlinear functions of the first- and second- order derivatives of d_{it}^I with respect to outputs are non-negative. Imposing the homogeneity constraint (3) and smooth-neutral technological change on equation (2) will result in the following model:

$$- \ln x_{1it} = \beta_0 + \sum_{k=2}^{K} \beta_k \ln (x_{kit} / x_{1it}) + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \theta_1 t + \theta_2 t^2 + v_{it} - u_{it} \tag{4}$$

where t is a linear time trend and $u_{it} \equiv \ln d_{it}^I$ is a non-negative random variable capturing technical inefficiency. Different specifications of this systematic inefficiency component u_{it} exist in the literature, this study follows the well-establish inefficiency effects model (Battese and Coelli, 1995; Huang and Liu, 1994) in order to assess the impacts of observed heterogeneity on efficiency. Under this specification, u_{it} follows a normal distribution truncated at zero with the mean as a function of hospital-specific factors and constant variance σ_u^2:

$$u_{it} \sim N^+(\gamma' Z_{it}, \sigma_u^2) \tag{5}$$

where Z_{it} is a vector of variables characterizing the local population, such as the proportion of Maori and Pacific, the proportion of living in the most deprived 20 percent of small areas (Salmond *et al.* 2007), the proportion of small children (under 5 years old) and elderly (beyond 75 years old).[3] Equation (5) can be estimated simultaneously with the stochastic input distance function (4) using maximum likelihood. The input-oriented technical efficiency score for observation i in period t can be predicted using the conditional expectation:

$$TE_{it} = E[\exp(-u_{it}) | v_{it} - u_{it}] \tag{6}$$

Another well-established specification is the time-varying technical efficiency model proposed by Battese and Coelli (1992):

$$u_{it} = u_i \big[\exp\big(\eta(T - t)\big)\big]$$

$$u_i \sim iid N^+(\mu, \sigma_u^2) \tag{7}$$

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[3] These population demographics are projections provided by Statistics NZ and do not represent the actual patients seen by each DHB.

where u_i is a time-invariant hospital-specific inefficiency error term, follows a truncated normal distribution with constant mean μ and variances σ_u^2. η is an unknown parameter to be estimated which determines how inefficiency u_{it} varies over time.[4]

The more flexible translog functional form, which incorporates interactions between the independent variables, is often estimated simultaneously and tested against its simplified Cobb-Douglas functional form. These interaction terms capture different degrees of substitutability between inputs and allow for various returns to scale (Griffin *et al.* 1987). The translog input distance function with the usual symmetry restriction ($\beta_{kj} = \beta_{jk}$) is defined as:

$$\begin{aligned} -\ln x_1 = \beta_0 &+ \sum_{k=2}^{K} \beta_k \ln (x_k / x_1) \\ &+ \sum_{m=1}^{M} \alpha_m \ln y_m + \theta_1 t + \theta_2 t^2 \\ &+ \frac{1}{2} \sum_{k=2}^{K} \sum_{j=2}^{K} \beta_{kj} \ln (x_k / x_1) \ln (x_j / x_1) \\ &+ \frac{1}{2} \sum_{m=1}^{M} \sum_{h=1}^{M} \alpha_{mh} \ln y_m \ln y_h + \sum_{k=2}^{K} \sum_{m=1}^{M} \beta_{km} \ln (x_k / x_1) \ln y_m + v - u \end{aligned} \tag{8}$$

To measure cost efficiency for each DHB i, an input price vector $\boldsymbol{w}_{it} = [w_{1it}, w_{2it}, \cdots, w_{Kit}]$ must be obtained for each observation and the Cobb-Douglas cost frontier is specified as:

$$\ln \frac{C_{it}}{w_{1it}} = \beta_0 + \sum_{k=2}^{K} \beta_k \ln \frac{w_{kit}}{w_{1it}} + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \theta_1 t + \theta_2 t^2 + v_{it} + u_{it} \tag{9}$$

where C_{it} is the total costs incurred by observation i in year t. The error terms follow the same specifications under equation (5) and (7). Since a cost frontier must be linearly homogeneous in input prices, total costs and the other input prices are normalised by one

[4] If η >0, then u_{it} increases over time, suggesting deteriorated efficiency performance. If η <0, then u_{it} decreases over time, suggesting improved efficiency performance. A limitation of this specification is that it does not allow for a change in the rank ordering of DHBs over time - a DHB that is ranked n-th at the first time period is always ranked n-th (Coelli *et al.* 2005, p.278).

fixed input price w_{1it}. The choice of this one input price does not affect the estimation results.

3. Selection of variables and data

The data used in this study are provided by the MOH, which contains input information for each DHB in the form of monthly financial statements for the year 2011-2017. We constructed five input variables to estimate the input distance function: the number of Full Time equivalent (FTE) medical doctors, nurses, other staff, plus capital and intermediate input. A two-step procedure is used to derive measures accurately reflect input volumes: in the first stage, we calculated *the price* of medical service by taking the ratio of payments (aggregated over the year) made to *employed* medical staff to the FTE number of medical doctors on the DHB's payroll (averaged over the year). By examining the raw data, both the salary payments and FTE counts are good quality for employees. It is the expenditures on outsourced inputs often contain negative values as a result of balancing the accounts , any input measure derived from the monthly financial statement is unlikely to reflect the actual volume used in that month and there is no way to ascertain this deviation. The problem is dealt with by aggregating the expenditures for *outsourced* medical service across the whole financial year. The FTE counts for outsourced medical is then determined by the second stage, taking the ratio of this aggregate expenditures and the *price* of medical service, estimated in the first stage, assuming both hired medical and outsourced medical doctors receive similar remuneration. The final FTE counts are the sum of employed medical and estimated outsourced medical.

The total FTE counts for nurses and other staff are derived in the same way. Other staff is a weighted sum of applied professional staff, support staff and management staff, the weights used are the expenditure shares for each.

Capital is often more challenge to measure due to the lack of data to separate the flow of capital services from capital stock. The number of installed beds is a common proxy variable for capital input (Aletras *et al.* 2007; Ancarani *et al.* 2009; Brown, 2003; Chang *et al.* 2004; Friesner *et al.* 2008; Herr, 2008; Herr *et al.* 2011; Worthington, 2004;). Unfortunately, that information for NZ DHB is only collected for 2014-2016. Others resort to use measures like depreciation (Marcinko and Hetico, 2012; Zelman *et al.* 2009) and capital charges (Parkin and Hollingsworth, 1997). Depreciation intends to measure the reduction in the value of capital assets and is calculated using the straight-line method (i.e. assets depreciate by the same percentage each year) in NZ. Capital charges is considered to be the best proxy because it reflects the opportunity cost of capital employed in public services (NZ Productivity Commission, 2017). We therefore built the analysis on capital charges and check the robustness of the estimation results when switching to depreciation.

Finally, the expenditures on clinical supplies (pharmaceuticals, medical instruments, implants, etc.) is used as a proxy for intermediate input. The price for capital (and intermediate input), in the cost frontier, is approximated by the capital charges (and expenditures on clinical supplies) per inpatient discharge.

Output information are extracted from the National Minimum Hospital Datasets (NMDS) and National Non-Admitted Patient Collection (NNPAC) by the MOH. Two output measures are used to reflect the full range of hospital services provided: case-weighted inpatient discharges and price-weighted outpatient visits. As mentioned previously, public hospitals in NZ are run and owned by DHBs to provide a variety of publicly funded health and disability services, they can be broadly categorized into inpatient admissions and outpatient visits. Although detailed outputs information are available for both category (such as maternity, medical and surgical cases), the use of which comes at the cost of losing more degrees of freedom in such a small census dataset. Provided our inpatient discharges are adjusted using case-mix methodology that accounts for the complexity of the diagnosis as well as the relative resources for treatment, the resulting output measures are reasonably comparable across different hospitals in different DHBs, one can refer to Fraser and Nolan (2017) for details. Outpatient data is weighted with national prices from the National Cost Collection and Pricing Programme (NCCPP) which are calculated for the purpose of inter-district flows. The final dataset is a balanced panel containing 20 observations (all DHBs) each year, for the year 2011-2017.

Apart from the demographic patient profile projected by Statistics NZ, we also incorporated variables which intend to capture the health needs of the local population into equation (5) to determine their marginal impacts on inefficiency u_{it}:

- Surgical ratio - the ratio of case-weighted surgical inpatient discharges over total discharges;
- ED ratio – the ratio of price-weighted ED outpatient visits over total visits;
- Elective ratio – the ratio of case-weighted elective inpatient discharges over total discharges;

- Average length of stay - total inpatient bed days divided by total inpatient discharges;
- Costs per discharge - total expenditures on all personnel, outsourced clinical services and clinical supplies per case-weighted inpatient discharge.

Descriptive statistics of the outputs and inputs for each DHB over 2011-2017 are presented in ***Table I***. Demographic projections and characteristics of local patients are reported in ***Table II***. There are three DHBs in the city of Auckland serving over one third of the national population together, they are Counties Manukau DHB, Waitemata DHB and Auckland DHB. Counties Manukau DHB has the highest average number of outpatients and Pacific population. On average, 22 percent of the local residents are Pacifica, compared with the national average of 4 percent. Tairawhiti DHB, with a population size of only 46,000, has the highest share of Maori, nearly half of the local residents are Maori. These two DHBs are also the most deprived DHBs with the highest share of under 5 years old. Another DHB with a significant high proportion of Maori and those living in the most deprived areas is the Lakes DHB. South Canterbury DHB, with a population just over 55,000, is characterized by having the highest share of over 75 years old and a corresponding high share of surgical discharges.

- Insert ***Table II*** and ***Table II*** about here -

The smallest DHB in NZ, West Coast DHB (population size 31,000), has the highest ratio of elective inpatient discharges (34% vs. 27.6% national mean) and the highest costs per discharge, averaged at $19,000 over the sample period. The largest DHB in NZ, Waitemata DHB, experiences the highest average length of stay, but the corresponding costs per discharge is only around $9,000. NZ DHBs are evidently serving populations with noticeably different characteristics.

4. Results and discussion

Estimation results for the Cobb-Douglas input distance functions as described in equation (4) are reported in ***Table III***, the error components model allows the DHB specific technical inefficiency error term to linearly change over time, as explained by equation (7). The inefficiency effects model allows us to assess the marginal effects of observed heterogeneity on performance, as illustrated by equation (5). Most of the coefficients associated with inputs and outputs are highly significant with expected signs, suggesting the estimated frontier is reasonably well behaved.

- Insert ***Table III*** about here -

However, the parameter estimates can differ a lot, in magnitude, between the error components model and the inefficiency effects model, suggesting the results might be sensitive to different specifications of the inefficiency error term u_{it}. This is confirmed by the correlation coefficient of negative 0.14 for the technical efficiency estimates obtained under each model. Further robustness tests suggest the error components model fits the data poorly, probably due to its restrictions on the rank ordering of DHBs over time, regardless the choice of the functional form. A DHB that is ranked n-th at the first time period is always ranked n-th. For a dataset contains very limited number of operation units that are homogeneous as a result of strict regulation, this specification is unable to recognize small changes in relative efficiency performance among these homogeneous units from one year to the next. In other words, valid comparison under the error components model hinges on the consistency of the performance over time in lieu the merit relative to others during the same year. We therefore decide to focus on the inefficiency effects model through the rest of the analysis. Estimation results for the translog input distance functions are reported in ***Appendix 3***, due to the incorporation of second-order parameters, the translog model is often suffer from multicollinearity with few coefficients being statistically significant.

Regarding the rate of technological change, the coefficients associated with the time trend variables are small in magnitudes and statistically insignificant most of the time, implying the absence of technical progress (or regress) within the time frame 2011-2017.

To evaluate the degree to which technical efficiency estimates and rankings will change with the choice of (1) functional forms; (3) proxy variables for input capital; and (3) parametric versus non-parametric methodological choice, the CD and TL input distance functions are estimated again after replacing capital charge with depreciation, we also performed a standard DEA analysis (as outlined in Fare *et al.* 1994; Coelli, 1996) by pooling the 7 years of data together (i.e. a common piece-wise frontier was constructed using 140 observations), which could be justified by previous observation of no technological change. The pairwise correlation matrix for the technical efficiency estimates obtained are presented in ***Table IV***, as well as the average efficiency score for each DHB over the sample period.

- Insert ***Table IV*** about here -

It shows that the performance line ups, for this particular dataset, are robust to the choice of functional forms imposed on production relationships, as well as the choice of measures for capital input, the correlation coefficients are in the range of 0.82 - 0.97. When a non-parametric DEA model which simultaneously estimates technical and cost efficiencies is used instead of SFA, the correlation still remain positive but dropped to 0.39-0.52. The average technical efficiency score is 86 percent across all DHBs over the entire period (except for the CD input distance function with depreciation which gives an average of 76 percent) and 93 percent under DEA. This implies that a frontier with flexible structure, as opposed to one following theoretical properties, produces a closer cover fit to this dataset. Bay of Plenty DHB, Lakes DHB and Counties Manukau DHB are among the most efficient performers. Another one with consistent above average performance is the Wairarapa DHB, the second smallest DHB across the whole country. On the contrary, West Coast, the smallest DHB located in the South Island, constantly sits at the bottom of the ranks. The argument that rurality and economies of scale are potential causes for this inefficiency is unlikely to be warranted based on comparison with similar DHBs.

Estimates of the stochastic cost frontiers for cost efficiency are presented in the same tables, i.e. the Cobb-Douglas cost frontier is reported in ***Table III*** and the translog cost frontier in ***appendix 3***, the results are more or less in line with the input distance function estimates. The Cobb-Douglas cost frontier is reasonably well behaved with most of the coefficients being significant with expected signs, but it can be easily rejected in favour of the translog functional form based on the likelihood ratio test. Parameter estimates in the translog frontier are less meaningful because most of them are statistically insignificant in the presence of multicollinearity. Summary of estimated cost efficiency is included in ***Table IV***, the correlation coefficient is 0.79 between the Cobb-Douglas and translog functional forms and 0.54-0.72 between DEA and SFA. The average cost efficiency across the nation is 85 percent during 2011-2017 based on both the translog cost frontier and DEA analysis.[5] The hospital specific results replicate what has been observed under estimates for technical efficiency, with the West Coast DHB being the least cost efficient.

In terms of the marginal effects of district population profile could have on efficiency performance, the results are presented in the second half of ***Table III*** and ***appendix 3***. The proportion of Maori and Pacifica, the proportion of surgical discharges and Emergency Department outpatient visits, as well as the average length of inpatient stay, are having negative associations with inefficiency, i.e. positive associations with technical efficiency performance. This is likely to be driven by output from the demand side and possibly

[5] The CD cost frontier returns an average of 94 percent, but it can be easily rejected in favour of the translog.

indicates public hospitals operating under current regulatory framework are reasonably well equipped to serve minority groups or the aging population with potentially higher demand for health care. There is neither evidence that increased proportion of surgical operations and Emergency Department patients were being handled at the cost of decreasing overall efficiency performance, nor would shorter hospital stay enable inputs savings. On the other hand, the percentage of those living in the most deprived areas and the average costs of inpatient discharges are having negative associations with both technical and cost efficiency performance. Therefore poverty, which has adverse effects on many aspects of people's lives, is likely to lead to hospitalizations of increasing complexity that are difficult to anticipate and manage efficiently.

5. Conclusion

The nature of the hospital sector in NZ presents unique challenges for efficiency measurement standardized in production theory in terms of the (1) limited number of units (i.e. 20 local District Health Boards) operate in a strictly regulated environment; (2)each serves a geographically defined local population; and (3) multiple outputs measured with different weights. Consequentially this study employed the input distance function approach to measure technical efficiency and the stochastic cost frontier for cost efficiency.

Robustness of the estimates are tested across different specifications of the inefficiency error term, different functional forms and proxy measures for capital input, as well as between the parametric SFA and non-parametric DEA approach. The empirical results indicate the inefficiency effects model (Battese and Coelli, 1995) yields more stable results compared to the error components model (Battese and Coelli, 1992), potentially due to the fact that our operation units are more homogenous in nature so does their performances. There is no DHB whose efficiency performance consistently deviate a lot from the rest, they move within close range from each other year by year. While focusing on the inefficiency effects model, the estimates are highly robust between the Cobb-Douglas and translog functional form, as well as capital charge versus depreciation as a measure for the flow of capital services. The average technical efficiency is estimated to be 86 percent by SFA and 93 percent by DEA, while the mean cost efficiency is around 85 percent.

Higher share of Maori or Pacifica population is associated with higher efficiency performance, the same applies to the share of surgical inpatient discharges, emergency department outpatient visits, and the average length of inpatient stay. This could be explained by demand factors because the minority and elderly are often requiring more hospital care services which the current system has no difficulties to accommodate. The proportion of those living in the most deprived areas and the average costs of inpatient discharge are having negative associations with efficiency, signalling potential barriers to utilize preventive health services might exist for the poor with comorbidity that are costly to handle at the hospitalization level.

Table I. Mean and stand deviations of outputs and inputs for each DHB over 2011-2017

DHB	Outpatients	Inpatients	FTE medicals	FTE nurses	FTE other staff	Depreciation (in $1000)	Capital Charge (in $1000)	Clinical Supplies (in $1000)
Auckland	24,205	***130,053***	***1,636***	3,374	***1,474***	44,040	***37,282***	***234,331***
	(1,764)	(4,796)	(97)	(120)	(61)	(5,008)	(3,818)	(16,123)
Bay of Plenty	14,294	38,537	323	1,118	430	18,249	6,326	55,331
	(920)	(2,723)	(22)	(42)	(26)	(1,576)	(1,174)	(3,468)
Canterbury	25,387	92,574	950	***3,542***	1,258	***53,569***	13,809	130,110
	(2,088)	(4,281)	(51)	(158)	(57)	(6,191)	(4,122)	(9,199)
Capital Coast	17,655	65,528	795	2,059	749	38,211	8,364	117,972
	(805)	(3,240)	(83)	(88)	(16)	(4,023)	(1,311)	(3,750)
Counties Manukau	***29,923***	84,317	983	2,589	909	27,194	14,708	112,911
	(1,265)	(3,183)	(57)	(117)	(41)	(4,323)	(2,702)	(7,685)
Hawke's Bay	10,458	27,152	312	858	376	13,369	4,193	43,301
	(656)	(762)	(22)	(40)	(10)	(758)	(1,557)	(2,971)
Hutt Valley	10,585	23,130	251	729	354	11,621	6,207	28,044
	(506)	(1,131)	(13)	(26)	(12)	(1,469)	(1,196)	(927)
Lakes	6,986	17,440	170	485	208	9,809	3,410	23,982
	(324)	(1,169)	(14)	(21)	(10)	(1,028)	(671)	(1,858)
MidCentral	11,605	28,133	308	960	422	13,115	8,529	50,022
	(564)	(791)	(20)	(29)	(8)	(1,658)	(1,776)	(2,527)
Nelson Marlborough	9,746	21,402	191	644	454	11,516	6,104	35,960
	(1,203)	(582)	(10)	(9)	(8)	(569)	(1,085)	(1,987)
Northland	10,243	27,483	272	973	421	11,586	7,926	43,814
	(974)	(1,326)	(30)	(45)	(14)	(825)	(1,788)	(3,441)
South Canterbury	4,427	8,604	67	327	105	3,650	620	11,268
	(276)	(200)	(6)	(6)	(4)	(496)	(117)	(779)
Southern	19,508	52,084	519	1,593	632	19,502	8,607	81,917
	(2,397)	(1,761)	(23)	(51)	(9)	(2,475)	(1,679)	(4,328)
Tairawhiti	3,102	7,388	77	268	140	2,747	2,269	14,179
	(192)	(226)	(4)	(14)	(3)	(240)	(493)	(1,228)

Taranaki	7,859	17,588	154	571	245	13,015	5,826	25,457
	(419)	(762)	(5)	(22)	(8)	(2,957)	(733)	(2,915)
Waikato	23,412	82,131	725	2,384	986	35,680	15,568	136,098
	(1,455)	(4,089)	(52)	(124)	(39)	(5,121)	(1,800)	(9,456)
Wairarapa	3,559	6,174	49	212	87	1,710	487	9,457
	(425)	(214)	(4)	(16)	(6)	(76)	(167)	(908)
Waitemata	25,550	72,621	877	2,579	1,150	24,055	17,122	99,284
	(4,154)	(6,568)	(74)	(194)	(60)	(2,645)	(4,546)	(14,065)
West Coast	3,227	3,783	60	320	138	4,308	746	7,751
	(195)	(183)	(5)	(12)	(13)	(461)	(116)	(319)
Whanganui	4,924	11,157	114	391	155	4,915	1,801	15,477
	(364)	(287)	(4)	(10)	(4)	(377)	(372)	(351)
National Average	**13,333**	**40,864**	**442**	**1,299**	**535**	**18,093**	**8,495**	**63,833**

Table II. Mean and stand deviations of patients projections and characteristics over 2011-2017

DHB	Maori ratio	Pacific Ratio	Deprived Q5 ratio	Under 5 ratio	Plus 75 ratio	Surgical discharge ratio	Outpatient ED visits ratio	Inpatient Elective discharges ratio	Average LOS per discharge	Costs per discharge (in $1000)
Auckland	7.99	11.07	19.05	6.24	4.31	51.46	9.96	28.29	2.43	8.63
	(0.21)	(0.29)	(0.35)	(0.27)	(0.19)	(0.74)	(1.15)	(0.78)	(0.10)	(0.44)
Bay of Plenty	24.95	1.51	24.54	6.76	8.31	49.50	15.15	26.89	2.87	7.54
	(0.15)	(0.19)	(0.17)	(0.21)	(0.38)	(1.10)	(1.62)	(0.89)	(0.18)	(0.17)
Canterbury	8.43	2.34	11.98	6.20	6.85	52.14	14.15	28.85	2.41	8.31
	(0.38)	(0.09)	(1.16)	(0.34)	(0.19)	(0.38)	(1.30)	(0.49)	(0.11)	(0.32)
Capital Coast	11.11	7.33	13.69	6.47	5.24	51.35	8.92	28.71	2.33	8.26
	(0.18)	(0.22)	(0.63)	(0.29)	(0.21)	(0.64)	(1.14)	(1.03)	(0.15)	(0.23)
Counties Manukau	16.38	***22.31***	***34.98***	***8.15***	4.10	50.24	9.34	21.44	2.77	8.24
	(0.45)	(0.80)	(0.59)	(0.36)	(0.25)	(0.55)	(0.76)	(1.11)	(0.05)	(0.44)
Hawke's Bay	25.49	3.41	26.29	7.18	7.25	46.94	16.31	24.00	2.91	8.44
	(0.30)	(0.25)	(0.64)	(0.21)	(0.38)	(1.38)	(1.16)	(1.02)	(0.15)	(0.55)
Hutt Valley	17.46	8.18	21.41	7.18	5.64	53.35	15.78	29.41	2.68	8.52
	(0.34)	(0.29)	(0.71)	(0.36)	(0.72)	(2.52)	(0.79)	(2.00)	(0.10)	(0.19)
Lakes	34.83	2.47	30.86	7.45	5.93	49.64	21.70	22.61	2.67	7.65
	(0.28)	(0.06)	(1.56)	(0.36)	(0.38)	(0.95)	(2.35)	(1.01)	(0.20)	(0.14)
MidCentral	19.19	2.68	22.28	6.71	7.41	45.78	13.96	27.79	2.99	9.02
	(0.36)	(0.20)	(1.56)	(0.24)	(0.29)	(0.81)	(0.86)	(1.09)	(0.11)	(0.51)
Nelson Marlborough	9.74	1.39	7.53	5.94	7.95	55.39	19.04	33.85	2.33	9.60
	(0.37)	(0.15)	(0.63)	(0.28)	(0.43)	(2.16)	(3.02)	(0.95)	(0.04)	(0.41)
Northland	32.99	1.79	33.16	7.08	7.26	51.56	12.99	25.80	2.74	9.23
	(0.95)	(0.12)	(2.12)	(0.18)	(0.48)	(0.65)	(0.63)	(0.77)	(0.10)	(0.56)
South Canterbury	7.39	0.89	9.32	5.93	***9.81***	***57.49***	14.94	31.92	2.94	9.25
	(0.56)	(0.09)	(0.05)	(0.15)	(0.22)	(3.82)	(2.22)	(1.00)	(0.20)	(0.63)
Southern	9.30	1.64	13.14	6.06	7.03	54.98	17.09	30.10	2.48	8.37
	(0.45)	(0.20)	(0.57)	(0.16)	(0.19)	(1.30)	(3.08)	(0.54)	(0.13)	(0.39)
Tairawhiti	***48.80***	2.20	***45.72***	***8.07***	5.66	53.77	22.24	25.93	2.94	10.71
	(0.68)	(0.20)	(1.05)	(0.38)	(0.22)	(1.00)	(2.28)	(0.95)	(0.08)	(0.60)

Taranaki	17.71	1.08	16.81	7.10	7.70	51.25	***24.14***	27.20	2.82	9.04
	(0.62)	(0.05)	(0.65)	(0.22)	(0.16)	(1.84)	(1.06)	(1.25)	(0.14)	(0.30)
Waikato	22.14	2.63	24.15	7.30	6.35	52.76	14.92	27.43	2.47	8.17
	(0.42)	(0.19)	(0.47)	(0.29)	(0.24)	(0.90)	(1.22)	(1.97)	(0.08)	(0.31)
Wairarapa	16.09	1.93	16.10	6.50	8.67	49.87	18.43	23.96	2.72	8.56
	(0.74)	(0.08)	(1.89)	(0.39)	(0.28)	(3.61)	(4.50)	(2.54)	(0.12)	(0.45)
Waitemata	9.86	7.19	8.11	6.88	5.57	39.88	12.66	22.45	***3.05***	9.31
	(0.14)	(0.11)	(0.06)	(0.20)	(0.19)	(0.52)	(0.91)	(0.87)	(0.10)	(0.30)
West Coast	10.64	0.88	15.07	6.54	6.86	56.88	19.70	***34.20***	2.63	***19.04***
	(0.57)	(0.17)	(2.09)	(0.21)	(0.22)	(5.38)	(2.50)	(3.64)	(0.12)	(0.72)
Whanganui	25.99	1.93	34.42	6.87	8.39	54.44	13.70	30.26	2.73	8.73
	(0.33)	(0.43)	(0.96)	(0.15)	(0.28)	(2.44)	(1.56)	(1.47)	(0.07)	(0.52)
National Average	18.82	4.24	21.43	6.83	6.82	51.43	15.76	27.56	2.7	9.23

Table III: Cobb-Douglas Input Distance Function and Cost Frontier Estimates

-ln(FTE medical staff)	Error components model		Inefficiency Effects Model		ln (Adjusted costs/Price_medical staff)	Inefficiency effects model	
Input Distance Function Estimates					*Cost Frontier Estimates*		
constant	-1.3810	***	2.5780	***	**constant**	0.4049	
ln(nurses/medical)	0.6088	***	0.4862	***	**ln(Pirce_nurses)**	-0.0096	
ln(other staff/medical)	0.1208	***	0.0692	**	**ln(Pirce_other_staff)**	0.4152	***
ln(capital charge/medical)	0.0020		0.0420	***	**ln(Price_capital)**	0.0444	***
ln(clinical supplies/medical)	0.0993	***	0.3023	***	**ln(Price_intermediate input)**	0.3746	***
ln(outpatients)	-0.0516	***	-0.0253		**ln(outpatients)**	0.0233	
ln(inpatients)	-0.4022	***	-0.9865	***	**ln(inpatients)**	0.9258	***
t	-0.0144	***	-0.0017		t	0.0017	
t^2	0.0002		0.0014		t^2	0.0006	
Effects on Inefficiency					*Effects on Inefficiency*		
constant			-1.1537	***	**constant**	-1.8322	***
maori_ratio			-0.0046	***	**maori_ratio**	-0.0106	***
pacific_ratio			-0.0127	***	**pacific_ratio**	-0.0053	
deprived_Q5_ratio			0.0055	***	**deprived_Q5_ratio**	0.0000	
under5_ratio			0.0117		**under5_ratio**	0.1244	***
plus75_ratio			-0.0148	**	**plus75_ratio**	-0.0047	
surgical_ratio			-0.0067	***	**surgical_ratio**	-0.0019	
outpatiemt ED_ratio			-0.0041	***	**outpatiemt ED_ratio**	-0.0021	
inpatient Elective_ratio			0.0002		**inpatient Elective_ratio**	0.0020	
ln(average_LOS)			-0.1560	***	**ln(average_LOS)**	0.0054	
ln(costs per discharge)			0.8713	***	**ln(costs per discharge)**	0.6159	***
LLF	304.52		291.22		**LLF**	239.6627	
LR test of the one-sided error	421.43		394.82		**LR test of the one-sided error**	234.2236	

*** Statistically significant at the 1% level
** Statistically significant at the 5% level
* Statistically significant at the 10% level

Table IV: Summary of Efficiency Estimates*

	TE_CD	TE_TL	TE_CD^D	TE_TL^D	TE_DEA	CE_CD	CE_TL	CE_DEA
TE_CD Model	1							
TE_TL Model	0.959	1						
TE_CD^D	0.963	0.972	1					
TE_TL^D	0.903	0.847	0.818	1				
TE_DEA	0.491	0.386	0.438	0.518	1			
CE_CD						1		
CE_TL						0.790	1	
CE_DEA						0.540	0.721	1
DHB								
Auckland	0.903	0.849	0.752	0.922	0.979	0.964	0.894	0.816
Bay of Plenty	***0.979***	0.982	***0.874***	0.940	0.990	0.996	0.979	***0.962***
Canterbury	0.841	0.891	0.765	0.870	0.884	0.934	0.879	0.821
Capital Coast	0.854	0.882	0.750	0.914	0.951	0.965	0.917	0.783
Counties Manukau	0.951	0.946	0.835	***0.990***	0.985	0.903	0.933	0.879
Hawke's Bay	0.872	0.893	0.764	0.852	0.915	0.983	0.899	0.827
Hutt Valley	0.924	0.916	0.808	0.923	0.986	0.938	0.895	0.892
Lakes	0.979	***0.997***	0.857	0.957	0.994	***0.997***	***0.981***	0.947
MidCentral	0.789	0.810	0.711	0.791	0.815	0.952	0.835	0.775
Nelson Marlborough	0.852	0.819	0.718	0.881	0.963	0.932	0.799	0.857
Northland	0.808	0.823	0.722	0.812	0.834	0.987	0.819	0.816
South Canterbury	0.910	0.868	0.831	0.908	0.970	0.926	0.810	0.907
Southern	0.911	0.912	0.801	0.889	0.944	0.978	0.900	0.870
Tairawhiti	0.730	0.773	0.650	0.749	***0.795***	0.981	0.742	0.731
Taranaki	0.878	0.892	0.801	0.859	0.933	0.928	0.839	0.898
Waikato	0.926	0.924	0.807	0.864	0.956	0.976	0.920	0.898
Wairarapa	0.898	0.905	0.799	0.946	***0.997***	0.983	0.875	0.929
Waitemata	0.842	0.789	0.717	0.840	0.887	0.834	0.844	0.803
West Coast	***0.447***	***0.450***	***0.409***	***0.527***	0.927	***0.565***	***0.427***	***0.674***
Whanganui	0.864	0.862	0.770	0.841	0.908	0.985	0.846	0.849
Total	0.858	0.859	0.757	0.864	0.931	0.935	0.852	0.847

* The TE_CD model refers to the technical efficiency estimates obtained from the Cobb-Douglas input distance function specified by equation (4)
The TE_TL model refers to technical efficiency estimates obtained from the translog input distance function specified by equation (8)
The CD^D and TL^D models are input distance functions estimated with depreciation
The TE_DEA model are technical efficiency estimates obtained using the DEA model explained in ***appendix 4***
The CE_CD model refers to the cost efficiency estimates obtained from the Cobb-Douglas cost frontier
The CE_TL model refers to the cost efficiency estimates obtained from the translog cost frontier
The CE_DEA model refers to the cost efficiency estimates obtained using the DEA model explained in ***appendix 4***

Appendix 1: New Zealand DHB

DHBs	Hospitals	Population
Auckland	Auckland City Hospital and Starship Children's Hospital..	460,000
Bay of Plenty	Tauranga Hospital and Whakatane Hospital.	220,000
Canterbury	Christchurch Hospital, Christchurch Women's Hospital, Burwood Hospital, The Princess Margaret Hospital, Ashburton Hospital and Hillmorton Hospital.	501,425
Capital Coast	Wellington Hospital and Kenepuru Hospital.	300,000
Counties Manukau	Middlemore Hospital and Manukau Super Clinic & Surgery Centre.	512,130
Hawke's Bay	Hawke's Bay Hospital.	150,000
Hutt Valley	Hutt Hospital.	140,000
Lakes	Rotorua Hospitals and Taupo Hospital.	108,000
MidCentral	Palmerston North Hospital and Horowhenua Health Centre.	166,000
Nelson Marlborough	Nelson Hospital and Wairau Hospital.	134,500
Northland	Whangarei Hospital, Bay of Islands Hospital, Dargaville Hospital and Kaitaia Hospital.	154,700
South Canterbury	Timaru Hospital.	55,626
Southern	Dunedin Hospital, Wakari Hospital, Lake district Hospital And Southland Hospital.	315,000
Tairawhiti	Gisborne Hopsital.	46,000
Taranaki	Taranaki Base Hospital and Hawera Hospital.	110,000
Waikato	Waikato Hospital.	360,000
Wairarapa	Wairarapa Hospital	40,000
Waitemata	North Shore Hospital and Waitakere Hospital	560,000
West Coast	Grey base Hospital	31,000
Whanganui	Whanganui Hospital	60,120

Appendix 2: Health Targets for 2017

Shorter Stays in Emergency Departments	95% of patients will be admitted, discharged, or transferred from an emergency department within six hours.
Improved Access to Elective Surgery	The volume of elective surgery will be increased by an average of 4000 discharges per year nationally. Each DHB is expected to meet the agreed number of elective surgeries annually.
Faster Cancer Treatment	85% of patients receive their first cancer treatment (or other management) within 62 days of being referred with a high suspicion of cancer and a need to be seen within 2 weeks.
Increased Immunisation	95% of 8-months-olds will have their primary course of immunisation (6 weeks, 3 months and 5 months immunisation events) on time.
Better Help for Smokers to Quit	90% of PHO enrolled patients who smoke have been offered help to quit smoking by a health care practitioner in the last 15 months.
Raising Healthy Kids	95% of obese children identified in the B4 School Check programme will be offered a referral to a health professional for clinical assessment and family-based nutrition, activity and lifestyle interventions by December 2017.

Appendix 3: Translog Input Distance Function and Cost Frontier Estimates

$-ln(FTE\ medical\ staff)$	Inefficiency Effects Model		$ln(\frac{Adjusted\ Costs}{Price\_medical})$	Inefficiency Effects Model	
Input Distance Function Estimates			*Cost Frontier Estimates*		
constant	6.9640	***	**constant**	-3.1859	***
ln(nurses)	2.6153	**	**ln(Price_nurses)**	5.8348	***
ln(other staff)	-2.2342	***	**ln(Price_other staff)**	-7.1522	***
ln(capital charge)	0.0800		**ln(Price_capital)**	-0.2047	
ln(clinical supplies)	-1.0739		**ln(Price_intermediate input)**	2.0948	**
ln(outpatients)	-1.4786	**	**ln(outpatients)**	1.4867	
ln(inpatients)	-0.0196		**ln(inpatients)**	-0.3698	
t	0.0151	***	t	-0.0223	***
t^2	-0.0001		t^2	0.0005	
squared ln(nurses)	-0.1489		**squared ln(Price_nurses)**	-0.4457	
squared ln(other staff)	-0.0670		**squared ln(Price_other staff)**	-0.5330	
squared ln(capital charge)	0.0187		**squared ln(Price_capital)**	0.0084	
squared ln(clinical supplies)	-0.0112		**squared ln(Price_intermediate input)**	0.2430	*
ln(nurses)*ln(other staff)	-0.7921	***	**ln(Price_nurses)*ln(Price_other staff)**	0.7546	
ln(nurses)*ln(capital charge)	-0.0422		**ln(Price_nurses)*ln(Price_capital)**	0.0609	
ln(nurses)*ln(clinical supplies)	0.2097		**ln(Price_nurses)*ln(Price_intermediate)**	0.6262	
ln(other staff)*ln(capital charge)	-0.0228		**ln(Price_other staff)*ln(Price_capital)**	0.0095	
ln(other staff)*ln(clinical supplies)	0.5034	***	**ln(Price_other staff)*ln(Price_intermediate)**	-0.7239	
ln(capital charge)*ln(clinical supplies)	-0.0086		**ln(Price_capital)*ln(Price_intermediate)**	-0.0657	
squared ln(outpatients)	-0.2350	*	**squared ln(outpatients)**	-0.1624	
squared ln(inpatients)	-0.2738	***	**squared ln(inpatients)**	-0.0974	
ln(outpatients)*ln(inpatients)	0.5241	**	**ln(outpatients)*ln(inpatients)**	0.2516	
ln(nurses)*ln(outpatients)	0.5991	**	**ln(Price_nurses)*ln(outpatients)**	-0.1029	
ln(other staff)*ln(outpatients)	0.3607	**	**ln(Price_other staff)*ln(outpatients)**	0.0133	
ln(capital charge)*ln(outpatients)	-0.0379		**ln(Price_capital)*ln(outpatients)**	0.0885	

ln(clinical supplies)*ln(outpatients)	-0.0537		**ln(Price_intermediate)*ln(outpatients)**	0.1059	
ln(nurses)*ln(inpatients)	-0.7862	***	**ln(Price_nurses)*ln(inpatients)**	0.0111	
ln(other staff)*ln(inpatients)	-0.2370		**ln(Price_other staff)*ln(inpatients)**	0.2120	
ln(capital charge)*ln(inpatients)	0.0289		**ln(Price_capital)*ln(inpatients)**	-0.0720	
ln(clinical supplies)*ln(inpatients)	0.1461		**ln(Price_intermediate)*ln(inpatients)**	-0.2104	
Effects on Inefficiency			***Effects on Inefficiency***		
constant	-1.1604	***	**constant**	-1.7935	***
maori_ratio	-0.0021		**maori_ratio**	-0.0029	**
pacific_ratio	-0.0047	**	**pacific_ratio**	-0.0032	*
deprived_Q5_ratio	0.0030	***	**deprived_Q5_ratio**	0.0027	**
under5_ratio	-0.0140	*	**under5_ratio**	0.0080	
plus75_ratio	-0.0051		**plus75_ratio**	0.0070	
surgical_ratio	-0.0080	***	**surgical_ratio**	-0.0004	
outpatient ED_ratio	-0.0046	***	**outpatient ED _ratio**	-0.0005	
inpatient Elective_ratio	0.0032	*	**Inpatient Elective_ratio**	-0.0003	
ln(average LOS)	-0.0971	**	**ln(average LOS)**	-0.0573	
ln(costs/discharge)	0.8819	***	**ln(costs/discharge)**	0.8932	***
LLF	376.4718		**LLF**	419.6557	
LR test of the one-sided error	314.1459		**LR test of the one-sided error**	381.1663	

Appendix 4: The DEA Model

With price information and under the behavioural objective of cost minimization, both technical and cost efficiencies can be measured using the standard DEA model as outlined in Fare *et al.* (1994) and the software DEAP 2.1 developed by Coelli (1996).

First the input-oriented DEA model is run to obtain technical efficiencies (i.e. **TE_DEA** in ***table IV***), assuming there is data on K inputs and M outputs on each of N firms or decision making units (DMUs). For the i-th DMU these are represented by the vectors $\boldsymbol{x_i}$ and $\boldsymbol{y_i}$ respectively. The $K \times N$ input matrix, $\boldsymbol{X}$, and the $M \times N$ output matrix, $\boldsymbol{Y}$, represent the data of all N DMU's. The purpose of DEA is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier. This is accomplished by solving the corresponding variable returns to scale (VRS) linear programming problem:

$$min_{\theta,\lambda} \quad \theta,$$

$$st \qquad -\boldsymbol{y_i} + \boldsymbol{Y\lambda} \geq 0,$$

$$\theta \boldsymbol{x_i} - \boldsymbol{X\lambda} \geq 0,$$

$$\mathbf{N1}'\boldsymbol{\lambda} = 1,$$

$$\boldsymbol{\lambda} \geq 0,$$

where θ is a scalar and $\boldsymbol{\lambda}$ is a $N \times 1$ vector of constants for all N DMUs. $\mathbf{N1}$ is an $N \times 1$ vector of ones. The value of θ obtained will be the efficiency score for the i-th DMU. It will satisfy $\theta \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient DMU. Note that the linear programming problem must be solved N times, once for each DMU in the sample. A value of θ is then obtained for each DMU.

Next the following cost minimization DEA model is run to obtain cost efficiencies (i.e. **CE_DEA** in ***table IV***):

$$min_{\lambda,x_i^*} \quad \boldsymbol{w_i'x_i^*},$$

$$st \qquad -\boldsymbol{y_i} + \boldsymbol{Y\lambda} \geq 0,$$

$$\boldsymbol{x_i^*} - \boldsymbol{X\lambda} \geq 0,$$

$$\mathbf{N1}'\boldsymbol{\lambda} = 1,$$

$$\boldsymbol{\lambda} \geq 0,$$

where $\boldsymbol{w_i}$ is a vector of input prices for the i-th DMU and $\boldsymbol{x_i^*}$ (which is calculated by the Linear Programming) is the cost minimizing vector of input quantities for the i-th DMU, given the input prices $\boldsymbol{w_i}$ and the output levels $\boldsymbol{y_i}$. The total cost efficiency (CE) of the i-th DMU would be calculated as:

$$CE = \frac{\boldsymbol{w}_i'\boldsymbol{x}_i^*}{\boldsymbol{w}_i'\boldsymbol{x}_i}$$

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