

Determinants of Health System Efficiency in OECD countries

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Abstract

While the scope of inefficiency of health systems around the world has been subject of investigation recently, the sources of inefficiency remain unexplored. Two methods of analyzing sources of health system inefficiency are applied, a two stage stochastic frontier approach, and a one stage stochastic frontier approach. While efficiency estimation and subsequent ranking of health systems is quite sensitive to choice of model, results with respect to desirable health system characteristics are fairly consistent between models. Efficiency is higher in public contract systems, and increases with the number of acute care beds available coupled with shorter stays. Capitation of physician reimbursement leads to greater efficiency as opposed to fee-for-service arrangements.

1. Introduction

Since the World Health Organization estimated the efficiency of health systems in 191 countries around the world, subsequently ranking those countries by efficiency (Evans et al., 2000), their approach has become a popular topic. The practice of such ranking has been criticized on both conceptual Navarro (2000) and methodological grounds (Hollingsworth et al., 2003, Gravelle et al., 2003, Greene, 2003).

So far little attention has been given to the arguably main flaw of the WHO analysis of efficiency, namely the failure to include characteristics of the health care system in estimations. Health system characteristics include the extent of public financing in the health system, the type of remuneration agreement with providers, the degree of system integration, and the existence of gatekeeping arrangements. While the WHO report seems to advocate private health care provision, this is done without grounding in empirical evidence. (Navarro, 2000) Health system characteristics are exogenous influences on the production process that are neither inputs nor outputs, but influence the efficiency with which inputs are turned into outputs. Failure to include characteristics can be an econometric problem under specific circumstances, and regardless of circumstances, is a problem from the perspective of policy design.

First, to the extent that health system characteristics are correlated with health expenditures, failure to include the former leads to an omitted variable bias in the estimation of effects of health expenditures on health outcomes. Omission of variables that are correlated with other regressors leads to biased estimates of the coefficients on those regressors that have been included. Evidence is not conclusive as to the impact of health system characteristics on health expenditures. Barros (1998) concludes that health system characteristics have no significant impact on health spending, Roberts (1998) finds that the share of public expenditures in total expenditures increases total expenditures, and Gerdtham et al. (1998) discover that health expenditures are reduced though public coverage, the share of public to total beds, gatekeeping arrangements, physician supply and capitation. Other health system characteristics are not shown to have significant impact on expenditures. Hence it is not clear how significant the omitted variable bias is in the WHO report.

Supposing that the omission of health system characteristics is defensible econometrically, results produced by Evans et al. (2000) nonetheless do not deliver useful policy advice. In the WHO report Oman ranks first, while Zimbabwe ranks last – does the policy maker conclude that it is better to be an oil exporter, or that it is better to not be a part of Africa, or just that it is better to be rich? Of interest are the reasons for Oman’s superior performance over Zimbabwe. Specifically the policy maker is interested in those sources of inefficiency that are under her/his control. This paper fills a large gap in literature by focusing on the estimation of sources of inefficiency. Two estimation techniques are used and compared in terms of their results. Emphasis is placed on health system characteristics as determinants of health system efficiency.

2. Literature

A strand of literature surrounding the estimation of efficiency of health care systems around the world has sprouted in the last four years. Following the original report produced by Evans et al. (2000) for the WHO, several researchers have embarked on questioning or improving the estimation methods. (Holligsworth et al., 2003, Gravelle et al., 2003, and Greene et al., 2003, Wranik-Lohrenz, 2004a). This is a much needed addition to health econometric literature at the macro level. Studies prior to the WHO report have focused primarily on determinants of health outcomes, or determinants of health spending. (Wranik-Lohrenz, 2004b).

Evans et al. (2000)¹ use health and related data from 191 WHO countries between the years 1993-1997 to create a production frontier using a panel data fixed effect model. Health system inputs, as measured by health expenditures, and other health determinants, as measured by education, are regressed on health outcome. Individual country fixed effects are indicators of inefficiency. The country with the highest intercept is used as the yardstick of full efficiency: deviations from this level are measures of inefficiency in other countries. The model used is:

¹ Evans, Tandon, Murray, and Lauer as a group authored two reports. The first report uses a health indicator as a dependent variable, while the second report uses a composite indicator of health system output. Since the model used is the same, references to Evans et al. (2000) encompass both reports.

$$Y_{it} = \alpha + X'_{it} \beta + v_{it} - u_i \quad [1]$$

$$Y_{it} = \alpha_i + X'_{it} \beta + v_{it} \quad [2]$$

where

$$\alpha_i = \alpha - u_i \quad [3]$$

$$\hat{u}_i = \max\{\hat{\alpha}\} - \hat{\alpha}_i \quad [4]$$

Where Y_{it} is health in country i at time t , X_{it} is a vector of health determinants, and α_i is the country specific fixed effect. The u_i 's, which measure the deviation of each country from the top performing country, are used to estimate efficiency scores. Equations [1] and [2] are the standard fixed effects model, where each country is assigned a different intercept α_i , the country fixed effect. The country with the highest intercept is defined as efficient, all other countries in the sample are measured relatively to the efficient country. The authors define technical efficiency as a country's actual performance expressed as a percentage of its potential performance.

$$TE_i = \frac{E(Y_{it}|u_i, X_{it})}{E(Y_{it}|u_i = 0, X_{it})} \quad [5]$$

Technical efficiency captures the ability of a health care system to deliver specific health levels at the lowest cost. In order to account for the fact that health levels would not be zero in the absence of a health care system, Evans et al. (2000) modify the index in [5] by incorporating health levels as they would be had there been no health care system. Subsequent studies drop this consideration for lack of reliable estimates of such counterfactual health levels. An alternative specification of technical efficiency described in Khumbakar et al. (2000) and used by Gravelle et al. (2003), Hollingsworth et al. (2003), Greene et al. (2003), Wranik-Lohrenz (2004), and adopted here is:

$$TE_i = \exp\{-\hat{u}_i\} \quad [6]$$

The model specification in Evans et al. (2000) is a nested version of the translog model. Determinants of health include health expenditures and levels of education. National income is not included, since its effects on health are believed to be channeled primarily

through education. Since the exact functional form of the health production relationship is not known on the basis of theory, the best fitting nested version of the first order Taylor series expansion is used, where x_1 is total health expenditure, and x_2 is the level of education.

$$\ln Y_{it} = \alpha_i + \beta_1 \ln(x_1)_{it} + \beta_2 \ln(x_2)_{it} + \beta_3 \ln(x_3^2)_{it} + v_{it} \quad [7]$$

Navarro (2000) questions the underlying fundamental assumptions behind Evans' approach. Efficiency estimation rests on the assumption of a health production function, i.e. a strong relationship between the health system and health outcome. Navarro (2000) argues that such relationship is not documented in the literature; instead literature points to a strong link between health and income distribution. Wranik-Lohrenz (2004) demonstrates that the choice of measures of health system inputs and other health determinants significantly influences the estimation of the health system – health relationship. Depending on the measures chosen, the relationship can be positive or negative, and statistically significant or not. Without a health production function, an estimation of the efficiency of health production is meaningless.

Hollingsworth and Wildman (2003) criticize the WHO approach for failing to extract all information from their data set. They propose alternative estimation techniques that reveal additional information. The authors modify the original estimation by including a time variable to show that efficiency varies over time. They also find inefficiency scores by use of data envelopment analysis (DEA) and conclude that inefficiency estimation is sensitive to choosing a parametric or a non-parametric approach. The DEA technique measures efficiency as the ratio of the weighted sum of outputs to the weighted sum of inputs. This approach was rejected in the WHO analysis for its inability to separate true inefficiency from random error. (Evans et al., 2001) The DEA approach may therefore over-estimate inefficiency, as it penalizes those countries with a small country fixed effect. (Jacobs, 2001)

Specifically, time is added to the panel data fixed effects estimation in the manner proposed by Cornwell et al. (1990). The model replaces is extended in the following manner:

$$\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2 \quad [8]$$

The task is accomplished by regressing residuals from the original fixed effects panel data model on a constant, time and time squared. The fitted values then provide an estimate of county fixed effects in different time periods. Wranik-Lohrenz (2004a) incorporates time by replacing α_i with the whole expression in [8], an arguably more efficient method, since the estimation takes place in one rather than two stages. Hollingsworth and Wildman discover, that the model as used by Evans et al. (2000) and Tandon et al. (2000) is mis-specified for OECD countries. They suggest that these countries should be analyzed separately, as is attempted in the present study. Another study of OECD countries alone reveals that the inclusion of time significantly changes efficiency estimates. (Wranik-Lohrenz, 2004a).

Gravelle et al. (2003) compare alternative specifications of the model that can be used to estimate efficiency. Their goal is to alert readers to the sensitivity of results to various specifications, rather than to choose the correct specification. Efficiency scores are re-estimated using a fixed effects panel data estimator without the use of minimum health levels as used in Evans et al. (2000) and Tandon et al. (2000). They also apply a between estimator, estimate the model in natural units, include year dummies, and add other expenditure to the model. Efficiency scores for countries' differ depending on the model estimated. The authors also suggest that estimation might be biased by the small number of time periods chosen in the WHO report. This concern is of lesser importance in the present study, since the period chosen captures data from 23 years for 22 countries. Variation in data is present both within and between countries.

Greene (2003) builds on the findings of Evans et al (2001a, 2001b, 2000). He argues that stochastic frontier analysis using a fixed effects estimator is not able to distinguish between inefficiency and between-country heterogeneity. Alternative methods are presented. Greene surveys available panel data estimators in the stochastic frontier context. He presents results from a two stage procedure, where the estimates of inefficiency are regressed on potential determinants. As an alternative, he proposes to incorporate the regressors from the second stage, termed country variation, as regressors in the original estimation of the stochastic frontier. The approach is suggested in Khumbakar and Lovell (2000) and discussed in detail in section 3. The preferred

specification includes country variation as regressors, and in addition as determinants of the mean of the inefficiency score.

Wranik-Lohrenz (2004a) applies the model from Evans et al. (2000) to OECD data from 22 countries for the years 1970-1998. The model is extended to incorporate time effects. Three versions of the model are estimated. First is $Y_{it} = \alpha_i + X'_{it} \beta + v_{it}$, the Evans' model, where X includes health expenditures, and education. In the second version, X includes health expenditures, education and time. The third version uses the extension $\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2$ proposed by Cornwell et al. (1990), and used by Hollingsworth et al. (2003). The following model is estimated $Y_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2 + X'_{it} \beta + v_{it}$ where X includes health expenditures and education². Because the inclusion of t^2 proves of no statistical value, the term is dropped. The approach allows estimating a panel of efficiency scores for each health care system in each time period. The final model, also used here, becomes:

$$\ln y_{it} = \theta_{i1} + \theta_{i2}t + \ln x_{it}' \beta + v_{it} \quad [9]$$

$$\text{where } \theta_{i1} = \theta - u_i \quad [10]$$

$$\hat{\alpha}_{it} = \hat{\theta}_{i1} + \hat{\theta}_{i2}t \quad [11]$$

$$\hat{u}_{it} = \max_i (\hat{\alpha}_{it}) - \hat{\alpha}_{it} \quad [12]$$

$$TE_{it} = \exp \{ -\hat{u}_{it} \} \quad [13]$$

where x_{it} includes total health expenditures, education levels, and both their squared terms. From [11] one can see that country effects are allowed to change with time. This opens up the possibility that the most efficient country, the one with the highest country effect, changes from one time period to the next. Expression [12]³ ensures, that the maximum country effect is found for each time period separately – each country's deviation from the maximum country effect is found for each time period. This creates a panel of efficiency scores, where countries are evaluated relatively to the best performer in each time period.

² Note that this is a one stage procedure, as opposed to the two stage method used by Hollingsworth et al. (2003), and hence should be more efficient.

³ This type of problem has not been found in the literature, hence the notation *max*, meaning that a maximum is taken separately for each time period t , has been invented by the author.

Results indicate that the omission of time in the WHO model leads to misleading estimates of efficiency and subsequent rankings. Ranks change substantially when time is included in analysis. In addition, countries' health systems rank differently with respect to the efficient production of women's health as opposed to men's health. Gender is not considered in the WHO report. (Wranik-Lohrenz, 2004).

Not presented in the literature thus far is an analysis of exogenous influences on health system efficiency. Exogenous influences may either affect technology used to convert inputs into outputs, or affect efficiency with which inputs are converted into outputs. (Khumbakar, et al., 2000) While Greene's (2003) is the only attempt in the literature to include exogenous influences into the estimation of health system efficiency, exogenous influences chosen are not those of interest to the policy maker. Greene uses income inequality, political freedom, government effectiveness, geographical location, percentage of health care paid by government, income and OECD status as exogenous influences. These are important in the analysis of health determinants, but from the perspective of the health policy maker, they do not deliver concrete advice. Health policy makers can hardly prescribe to redistribute income more equally and join the OECD in order to increase health system efficiency. (Wranik-Lohrenz, 2004b) The purpose here is to identify correctable sources of health system efficiency. Health policy designers are interested in the most efficient remuneration system, the most efficient degree of health system integration, gate-keeping arrangements, and the most efficient mix of public versus private health spending. These health system characteristics are used as explanatory variables of health system costs, but not of efficiency, by Gerdtham et al. (1998) and Barros (1998).

3. Models of incorporating exogenous influences

Two methods of assessing the impact of exogenous influences on technical efficiency are discussed in theoretical and applied literature on efficiency estimation. Exogenous influences include factors that affect the ability of production units to turn inputs into outputs, but in themselves are neither inputs nor outputs. These can be analyzed in the second step of a two step approach to estimation, or alternatively can be incorporated in a one step procedure. The two step approach has been criticized on econometric grounds,

but has, nonetheless, an intuitive appeal. The one step approach is statistically superior; its interpretation, however, is more complex.

Given that the purpose of this paper is to gain as much insight as possible into the sources of health system efficiency, and to deliver concrete advice to health policy designers, both approaches are included. Consistency between results of the two approaches solidifies the validity of their results. Important is consistency of signs on coefficients of health system characteristics, while the size of coefficients is less interesting. If in both models, for example, the capitation system has a significant positive impact on efficiency, conclusions can be made that it is a desirable remuneration method. Divergence between results warrants further discussion.

3.1. Two step estimation of efficiency determinants

Exogenous influences can be included in a two stage process. In the first stage, efficiency scores are estimated, using a production frontier formulation. Inefficiency is captured by each producer's, in this paper health care system's, deviation from the production frontier. Literature on this subject was discussed in the previous section. This study uses inefficiency scores estimated in Wranik-Lohrenz (2004a), where a panel of efficiency scores was created.

In the second stage, inefficiency scores estimated in the first stage are regressed on exogenous influences. Which variables belong in the first stage of the analysis and which in the second stage is a difficult decision that has to be made on a case by case basis. Generally, variables over which the producer has no control during the time period under consideration belong in the second stage, e.g. ownership, source of payment, market level variables such as income, unemployment rate, and industry concentration (Rosko, 1999 quoting Lovell, 1993). In the current setting, exogenous influences are predetermined characteristics of the health care system. These are generally under the control of the health policy maker, but not under the control of decision makers in the production process, such as health care providers or administrators.

The second step can be estimated either via least squares, or using a Tobit model, as used in Fried et al. (1999) and Rosko (1999). Only Reinhard et al. (2002) use stochastic

frontier estimation for both the first and the second step of the analysis. The efficiency scores estimated using [9] to [13] become the dependent variable, such that:

$$TE_{it} = z_{it}\gamma + \varepsilon_{it} \quad [14]$$

Where z_{it} represent exogenous influences of inefficiency. Since the dependent variable assumes values between zero and one only, a limited dependent variable estimation technique is advocated in some of the literature.

A dependent variable is censored (from above or below) when it is not possible to observe some of its values, even though corresponding values of the explanatory variables are observable. Censoring does not change sample size, since observations are generally clustered at some lower or upper threshold. This is often contrasted with truncation, in which case it is not possible to observe values of both the dependent and explanatory variables for some observations. Truncation changes the sample size, because it is not possible to collect data for some units. Since no observations are missing in the data on efficiency scores, the truncated regression model is not appropriate. Models that are able to bind the dependent variable between zero and one are probit and logit models. While they can restrict predicted values of the dependent variable to fall within this range, the requirement is that observed values of the dependent variable are dichotomous in nature, which is not the case with efficiency scores.

The tobit formulation assumes that there is a latent dependent variable, in this case TE_{it}^* , that is not observed for some data points. The observed values of the dependent variable are TE_{it} , such that:

$$\begin{aligned} TE_{it}^* &= z_{it}\gamma + \varepsilon_{it} \\ TE_{it} &= 0 \quad \text{if} \quad TE_{it}^* \leq 0 \\ TE_{it} &= TE_{it}^* \quad \text{if} \quad TE_{it}^* > 0 \\ TE_{it} &= 1 \quad \text{if} \quad TE_{it}^* \geq 1 \end{aligned} \quad [15]$$

The tobit model is generally estimated using the maximum likelihood approach. Suppose that censoring occurs from below at zero. The following represents the log likelihood function for this model:

$$l(TE_{it}) = \sum_{TE_{it}=0} \ln \Phi \left(\frac{-z_{it}'\gamma}{\sigma_{TE}} \right) + \sum_{0 < TE_{it} < 1} \ln \frac{1}{\sigma_{TE}} \phi \left(\frac{TE_{it} - z_{it}'\gamma}{\sigma_{TE}} \right) + \sum_{TE_{it}=1} \ln \left(1 - \Phi \left(\frac{1 - z_{it}'\gamma}{\sigma_{TE}} \right) \right) \quad [16]$$

The first part of the sum applies to the situation when $TE_{it}=0$, the second to the situation when $TE_{it}=TE_{it}^*$. If there are no $TE_{it}=0$ observations, then the tobit approach is equivalent to the OLS approach (Greene, 2000).

Noteworthy is the interpretation of estimated coefficients in the tobit model. The coefficients predict change in the underlying latent variable following a one unit change in the explanatory variable. To estimate the resulting change in the observed dependent variable, the coefficient estimate must be multiplied by the probability of $TE_{it} = TE_{it}^*$. Given that a and b and the upper and lower threshold limits.

$$\frac{\partial E[TE_{it} | z_{it}]}{\partial z_{it}} = \gamma \times p[0 < TE_{it}^* < 1]. \quad [17]$$

If the equation is estimated in logarithms, the coefficient represents an elasticity with respect to TE_{it}^* , and also must be multiplied by the probability of a non-censored observation to obtain the elasticity with respect to TE_{it} .

The underlying assumption behind a tobit model is that the dependent variable is censored, and there is some underlying latent variable that is not observed. In this situation, all values of TE_{it} are observed, there are no latent values. In addition, no TE_{it} score comes close to zero, and there is only one observation of 1 for each time period. Since the probability of TE_{it} taking on values between zero and one, $p[0 < TE_{it}^* < 1]$ is very close to one in this situation, tobit estimates will be very close to OLS estimates. For the above reasons, the linear regression model is used here:

$$TE_{it} = z_{it}'\gamma + \varepsilon_{it} \quad [18]$$

Kumbhakar and Lovell (2000) criticize the two step approach for two reasons. First, to ensure that efficiency estimates are not biased, it must be assumed that x_{it} 's and z_{it} 's are not correlated. If z and x are correlated, and z affects y , omitting z leads to biased estimates of β . Second, the approach is referred to as schizophrenic. In the first stage it assumes, that $E(u_i)$ are constant, and in the second stage they are assumed to vary with z_i . The two stage approach is rendered as econometrically not sound. Wang and Schmidt (2002) show that neglecting z in the first stage causes estimates of β to be biased downward. In addition, the dispersion of u in the first step is underestimated, leading to a lower dependence of u on z in the second stage.

In the case of health system efficiency estimation, both of the above arguments may not apply. First, it is stated that this approach is appropriate in a situation where health system characteristics are not correlated with health expenditures, education and nutritional indicators. This assumption can safely be made about the latter two sets of variables. Literature on the correlation between health spending and health system characteristics is not conclusive. (Barros, 1998, Gerdtham et al., 1998, Roberts, 1998).

Second, the assumption that u_i 's have a constant mean applies to estimation by way of the random effects model. If the fixed effects model is used in the first stage, efficiency scores are derived from country specific fixed effects that are not assumed to be identically distributed. There is no reason why they could not vary with health system characteristics in the second stage of the model. In the least squares dummy variable regression used in stage one (Wranik-Lohrenz, 2004) $y_{it} = \alpha_i + \beta' x_{it} + v_{it}$, the $E(v_{it})$ is assumed constant, but α_{it} , on which efficiency estimates are based, is not. The country specific effects are assumed identically distributed in a random effects specification, which was rejected on the basis of the Hausman test. (Wranik-Lohrenz, 2004a).

3.2. One step estimation of efficiency determinants

Judged econometrically superior by Khumbakar et al. (2000) and Wang et al. (2002) is a one step approach to the estimation of sources of inefficiency, where the one sided inefficiency error terms are assumed dependent on exogenous influences in the initial estimation of inefficiency. The earliest version of this approach, as presented in

Khumbakar et al. (2000) is Deprins' and Simar's, who specify the production frontier relationship as:

$$\ln y_{it} = \ln f(x_{it}; \beta) - \exp\{\gamma' z_{it}\} + \varepsilon_{it} \quad [19]$$

Where ε_{it} are assumed to have zero mean and constant variance. The performance of each producer is estimated by way of the following expression:

$$\exp\{\varepsilon_{it}\} = \frac{y_{it}}{f(x_{it}; \beta)} \cdot \exp\{\exp\{\gamma' z_{it}\}\}, \quad i = 1, \dots, I \quad [20]$$

The first term on the right hand side is an estimate of technical efficiency, whereas the second term is an adjustment term which estimates the contribution of the exogenous influences of z_i on the performance of each producer. Unfavorable production environments create large values of the adjustment term. The approach is criticized by Khumbakar et al. (2000) on account of its deterministic nature stemming from the lack of a systemic error component to capture random noise.

An extension to the above model is the use of error component models, where a regular error term is broken into two parts, one a measure of technical inefficiency, one a measure of random noise. This allows retaining the stochastic component.

$$y_{it} = f(x_{it}; \beta) + v_{it} - u_i \quad [21]$$

where v_i is the random error component, while u_i is a measure of technical inefficiency. A discussion of stochastic frontier estimation is presented in Khumbakar et al. (2000) and Wranik-Lohrenz (2004a).

Used here is a model proposed by Caudill, Ford and Gropper (1995), which belongs to the class of production frontier models with scaling properties, as described by Wang et al. (2002). Models with scaling properties take the following form.

$$y_{it} = x_{it}' \beta + v_{it} - u_i(z_{it}, \gamma) \quad [22]$$

Where $u_i(z_{it}, \gamma) \sim N(0, \sigma_u^2)^+$, while v_{it} is $N(0, \sigma_v^2)$. Wang proposes an alternative specification for $u_i(z_{it}, \gamma)$, where the expression can be broken into a scaling function $h(z_{it}, \gamma) \geq 0$, and an underlying basic distribution u^* , such that

$$u_i(z_{it}, \gamma) = h(z_{it}, \gamma)u^* \quad [23]$$

The scaling property is an attractive feature in models of production frontiers for three reasons. First, this type of model suggests that the shape of the distribution of u is the same for all countries, although the scale of the distribution varies with the scaling function. Second, it is relatively easy to find an expression for the effects of external characteristics on efficiency of production without the need to make assumptions about the basic distribution. Third, and related, it is possible to estimate the effects of inputs and external characteristics on the production function without making assumptions about the basic distribution.

A special case of a production frontier model with a scaling property was used in Caudill et al. (1995) and is adopted here. The underlying idea is to specify the distribution for u_i , and then allow the parameter(s) of that distribution to depend on z_{it} . Suppose then that $u_i(z_{it}, \gamma) \sim N(0, \sigma_u^2)^+$, as stated above. The assumption is made that $\sigma_u = \sigma_u(z_{it}, \gamma)$, and specifically that $\sigma_u = \sigma_u \exp(z_{it}, \gamma)$. The estimated model has a heteroscedastic variance, which is determined by the external characteristics of the health care system. To verify the scaling property of this model, replace $u_i(z_{it}, \gamma) \sim N(0, \sigma_u^2)^+$, with $u_i(z_{it}, \gamma) = (\sigma \exp(z_{it}, \gamma)) \cdot u^*$, where $u^* \sim N(0, 1)^+$, a distribution that does not depend on z_{it} . (Wang, et al., 2002)

Using the scaling property in this model, the effect of health system characteristics on efficiency is captured by:

$$\gamma = \frac{\partial \ln(u_i(z_{it}, \gamma))}{\partial z_{it}} \quad [24]$$

regardless of the shape of the basic distribution. As mentioned above, the ability to solve for the effects of external factors on efficiency is one of the attractive features of the model.

4. Variables used

In this paper, two sets of variables are used. One is the variables in the underlying health production function, x_{it} , and the second are health system characteristics, z_{it} . The health production function is defined as the relationship between health system inputs and health, while controlling for other health determinants. Health system characteristics are features of the health system that cannot be classified as neither inputs nor outputs, but nonetheless have a hypothesized influence on the health production process.

Most variables in the health production function are taken from the OECD Health data base. Health – the dependent variable in the health production function – is measured in terms of potential years of life lost. This measure is inverted, to obtain a positive measure of health required to construct a production efficiency frontier (Wranik-Lohrenz, 2004). The WHO report and follow up studies use Disability Adjusted Life Expectancy as a measure of health outcome. The failure to establish a significant link between health and health spending, as cited by Navarro (2000) occurs in studies where crude measures of health are used, such as mortality or life expectancy.

Explanatory variables in the health production function include health system inputs, educational status, and nutrition. Following previous literature, health system inputs are captured in one single variable – total health expenditures. Total health expenditures are measured on a per capita basis valued in purchasing power parity US\$. This measure is shown superior to total health spending as a percentage of GDP by Wranik-Lohrenz (2004a).

Education is measured in terms of gross enrolment rates in secondary education. This measure is taken from the World Bank Group database of Gender Statistics. Secondary education is chosen over primary education, since primary schooling is mandatory in most OECD countries, and enrolment rates are 100% in nearly all countries for all periods. Gross enrolment rates measure the number of students enrolled in a particular level of education as a proportion of the total number of persons in the age group

corresponding to that education level. This measure can exceed one hundred percent, if all students who should be enrolled at this level and, in addition, some students who are either younger or older than the corresponding age group are enrolled at this level. Gross enrolment rates are not a perfect measure of educational achievement. One could argue that an increase in gross enrolment rates attributable to a large number of students staying behind at the secondary level despite their older age, would actually represent a decrease in educational status. Unfortunately, a more accurate measure of educational achievement is not available for all countries and all time periods.

Two control variables for nutritional status are included, total alcohol consumption measured in liters per capita, as well as total sugar consumption measured in kilograms per capita. Both are expected to have a negative influence on health. Studies of developing economies often use total calorie consumption as an indicator of nutritional status, since under-consumption of calories and starvation is generally a problem. In the Western world the opposite is more likely the case – one of the primary health concerns is obesity and over-consumption of sugary and fatty products.

Measures of health system characteristics are obtained from the OECD health data base, as well as from Gerdtham et al. (1998) and Barros (1998), who measure the impact of these characteristics on health care costs. They include:

- public health expenditure as a percentage of total health expenditure
- number of in patient care beds per 1000 population
- average length of stay in in-patient acute care settings
- percent of population with complete health coverage
- dummy variables for capitation versus fee-for-service reimbursement arrangements
- dummy variable for public reimbursement, contract and integrated systems.

A public reimbursement system is one where providers receive retroactive payments for services supplied. This system is often coupled with fee-for-service arrangements, and it can function with public and private providers. A public contract system is one where an agreement exists between health care providers and third party payers. This system is often found in social insurance systems with predominantly private non profit providers. Payment methods can include prospective budget, per diem and FFS arrangements. The public integrated system is one in which the same agency controls funding and the

provision of services. Salaries are pre-dominant in this type of system, and budgets are used to allocate resources.⁴ (Gerdtham, et al., 1998).

With respect to health care cost determination, the following has been discovered in the literature (Gertham et al., 1998, 2000, Barros, 1998). A higher proportion of public health spending in total health spending tends to generate lower expenditures. Health care costs are lower in countries where the physician to patient ratio is higher, but not in systems with fee-for-service arrangements. The percentage of population with health care coverage is shown to be an insignificant contributor to health care costs. With respect to the health system dummy variables, those that seem to lower health spending are capitation agreements, and public reimbursement systems. It is an interesting question, whether health system efficiency is affected in the same fashion.

This study is also interested in investigating, whether an acute care intensive health system, as measured by the average length of stay in in-patient acute care settings, is more efficient. Furthermore, it is also interesting whether a larger hospital sector, as measured by the number of in-patient care beds per 1000 population, positively contributes to efficiency.

5. Discussion of Results

In the first step of the two step procedure, a health production function was estimated, which was subsequently used to construct a production frontier. Country deviations from the frontier served as measures of relative inefficiency. The Lagrange Multiplier test rejected a pooled OLS regression. The random effects model assumes that there is no correlation between error terms, the individual effects, and other regressors. This assumption was rejected on the basis of a Hausman test, rendering the random effects model inconsistent (Greene, 1997). Therefore a fixed effects model was used.

Table 1 presents the estimated health production function coefficients. Also listed are individual country fixed effects, as well as the coefficients of country dummies crossed

⁴ Countries with public contract systems include: Austria, Germany, Greece (until 1983), Luxembourg, Switzerland, and the United States. Public reimbursement systems are predominant in Australia, France, Italy (until 1978), Japan, Netherlands, Portugal (until 1977), and Spain (until 1983). Remaining countries feature predominantly a public integrated system. (Gerdtham, et al. 1998, Barros, 1998)

with time. The squared country time dummies turned out to be statistically insignificant individually and jointly⁵, and were dropped from the estimations. Similarly, it was discovered that the nutritional indicators add no explanatory power to the regression, hence they were dropped from further estimations. Finally, the cross product between education and health spending was found statistically insignificant and was dropped from further estimations. The final form to be estimated is captured in [9].

Using the country fixed effects and time country dummy coefficients, a panel set of efficiency scores was constructed, used as the dependent variable in the second stage of the analysis. The efficiency score for county i in time t was found using [13]. Results are available from the author upon request. Efficiency levels and country rankings change over time and are different between women and men. Nonetheless one can observe that Japan and Sweden rank in the top three for all time periods and for both the sexes, while Portugal and New Zealand rank towards the bottom in this OECD sample. (Wranik-Lohrenz, 2004a).

Note that health spending has a positive effect on both women's and men's health, a result that is statistically significant. This result runs in contrast with studies that find the effect of health spending on population health to be weak or null. The quadratic health spending term is negative and statistically significant, suggesting that health spending is subject to diminishing returns. Note that the coefficient on education is negative, but cannot be interpreted as suggesting that education has a negative effect on health. The squared education term, which is actually the only statistically significant variable of the two, has a positive impact. Hence the marginal effects of education on health are positive after gross enrolment rates reach a minimum level, which in the two step health production model is around 4 for all estimations. Since gross enrolment rates in secondary education do not fall below 34 in any country in any time period, one can safely conclude that education has a positive effect on health in OECD countries.

⁵ Individual t-statistics for all t-squared terms were below critical values. An F-test could not reject the null hypothesis of no joint significance of all t-squared terms.

Table 1
Health production function – two step estimation

	coefficient		goodness of fit	
	women's health	men's health	women	Men
health spending	.5803 **	.4442 **	R ² = .9769	R ² = .9757
education	-.8755	-.7255		
health spending ²	-.0539 **	-.0506 **		
education ²	.1035 **	.0907 **		
	country fixed effect		time country dummy coefficient	
	women	men	women	Men
Australia	3.1116 **	2.7844 **	.0362 **	.0413 **
Austria	2.9293 **	2.4890 **	.0422 **	.0476 **
Canada	3.0714 **	2.7412 **	.0387 **	.0449 **
Denmark	3.2076 **	2.9814 **	.0239 **	.0301 **
Finland	3.2387 **	2.5659 **	.0309 **	.0399 **
France	3.2792 **	2.6958 **	.0307 **	.0388 **
Germany	2.9987 **	2.6456 **	.0413 **	.0452 **
Greece	3.0907 **	2.8558 **	.0353 **	.0323 **
Ireland	2.9816 **	2.7493 **	.0357 **	.0366 **
Italy	3.0049 **	2.7194 **	.0428 **	.0433 **
Japan	3.2568 **	2.9545 **	.0396 **	.0427 **
Luxembourg	2.8819 **	2.5563 **	.0456 **	.0470 **
Netherlands	3.4129 **	3.0427 **	.0234 **	.0348 **
New Zealand	2.9695 **	2.6760 **	.0285 **	.0346 **
Norway	3.3982 **	2.9209 **	.0272 **	.0385 **
Portugal	2.5466 **	2.2178 **	.0443 **	.0412 **
Spain	3.1082 **	2.7993 **	.0353 **	.0301 **
Sweden	3.4275 **	3.1219 **	.0284 **	.0359 **
Switzerland	3.3290 **	2.9739 **	.0328 **	.0372 **
UK	3.1151 **	2.8422 **	.0293 **	.0362 **
US	2.9919 **	2.6919 **	.0358 **	.0410 **

** indicates significance at the 0.01 level

* indicates significance at the 0.05 level

Table 2 presents estimates of the health production function using the heteroscedastic one step model. The model is estimated via maximum likelihood. While the size of the coefficients in the production function is quite different from the two step procedure, signs are the same. Health spending has a positive and statistically significant impact on health, with diminishing returns. Education, again, has a positive effect on health after the minimum level for gross enrolment rates in secondary education is reached, which in the one step health production function is at 4.27 for women, and 3.93 for men. Since the lowest observation in the entire data set is at 34, education is positively associated with health in all countries and through all time periods.

Table 2
Health production function – one step estimation

	coefficient			
	women's health	men's health		
health spending	.7764 **	.1535 *		
education	-.7365 **	-1.3713 **		
health spending ²	-.0710 **	.01634 *		
education ²	.0863 **	.1745 **		
	country fixed effect		time country dummy coefficient	
	women	men	Women	men
Australia	2.3548 **	4.4421 **	.0493 **	.0369 **
Austria	2.3323 **	4.3316 **	.0465 **	.0314 **
Canada	2.4783 **	4.5544 **	.0448 **	.0280 **
Denmark	2.6967 **	4.8038 **	.0242 **	.0124 **
Finland	2.6346 **	4.3970 **	.0359 **	.0250 **
France	2.6207 **	4.6589 **	.0393	.0167
Germany	2.6527 **	5.3301 **	.0360	-.0098
Greece	2.4030 **	4.6944 **	.0428 **	.0232 **
Ireland	2.4945 **	4.5545 **	.0320 **	.0279 **
Italy	2.4090 **	4.5607 **	.0500 **	.0302 **
Japan	2.5701 **	4.7268 **	.0511 **	.0346 **
Luxembourg	2.2822 **	4.4641 **	.0505 **	.0276 **
Netherlands	2.8102 **	4.8685 **	.0300 **	.0186 **
New Zealand	2.4003 **	4.5500 **	.0306 **	.0196 **
Norway	3.0120 **	4.9937 **	.0179 **	.0064
Portugal	1.9983 **	4.0544 **	.0447 **	.0346 **
Spain	2.4692 **	4.7301 **	.0404 **	.0147 **
Sweden	2.8428 **	4.9200 **	.0331 **	.0210 **
Switzerland	2.7076 **	4.9191 **	.0421 **	.0135
UK	2.4978 **	4.6793 **	.0348 **	.0243 **
US	2.7564 **	4.3513 **	.0316 **	.0274 **

** indicates significance at the 0.01 level

* indicates significance at the 0.05 level

Country fixed effects and time country coefficients are also presented. Their value in discussion lies in the possibility to rank countries in terms of their relative efficiency. Country rankings found using the two step and one step estimation procedures are presented in table 3. Countries are ranked for both sexes in 1999, the last year for which observations were available for all relevant variables in all countries.

Rankings are affected by choice of model. While the position of top and bottom contenders remains relatively unchanged, rankings of some countries in the middle places are affected dramatically. In terms of women's health, the top four and bottom three ranks are taken by the same countries using either model. The pattern is less clear for rankings of health systems in terms of men's health.

Table 3				
Country rankings				
	<i>TWO STEP</i>		<i>ONE STEP</i>	
	Women	Men	Women	Men
Australia	10	7	5	3
Austria	11	13	10	12
Canada	7	4	6	7
Denmark	19	14	19	14
Finland	13	18	11	18
France	9	15	7	17
Germany	6	9	9	21
Greece	14	17	14	9
Ireland	17	16	18	8
Italy	3	8	3	4
Japan	1	1	1	1
Luxembourg	5	10	8	11
Netherlands	15	5	12	5
New Zealand	21	19	21	19
Norway	8	6	16	13
Portugal	20	21	20	20
Spain	12	20	15	16
Sweden	4	2	4	2
Switzerland	2	3	2	10
UK	18	11	17	6
US	16	12	13	15

Country rankings have been shown quite volatile to model specifications in previous studies (Gravelle et al., 2003, Wranik-Lohrenz, 2004a), suggesting that interpretation must be done with extreme caution. The analysis of efficiency determinants is complicated by the volatility of efficiency scores to model specification. Table 3a presents results of the Spearman's rank order correlation test.

Table 3a							
Spearman's rank order correlation coefficients							
		r_s^2					
Women - Men	One step	.58	**	Two step – One step	Women	.85	**
	Two step	.35	**		Men	.55	**
** indicates significance at the 0.01 level							
* indicates significance at the 0.05 level							

Spearman's r^2 values indicate, that there is statistically significant positive correlation between rankings produced by the different methods, however, the strength of correlation is generally low.

The logical next step is to investigate what the more efficient countries have in common that influences their ability to produce health. Again, this is accomplished using both the

two step approach and the one step approach. Results of the two models are compared and contrasted.

In the second stage of the two step approach, the panel of efficiency scores is used as the dependent variable and regressed on health system characteristics, as described in the previous section. Results of the second step regression are reported in table 4. A fixed effects model is used in place of a Tobit model, suggested by some in the literature. The tobit model is appropriate when an underlying latent variable exists that is censored. Hence values of the dependent variable cluster around the censored value. This is not the case in the current setting. There is no underlying latent variable; all efficiency scores are observed in their true value. While there is a value of 1 for each of the 23 time periods, it stands to argue that 23 ones in 483 observations is clustering, since the probability of TE falling between zero and one, $p(0 < TE < 1) = 0.952$, which is nearly 1. The random effects approach was rejected in favour of the fixed effects approach on the basis of high Hausman H values.

Table 4 also presents results of the one stage regression. Health system characteristics in this model determine the variance of the error term, which underlies the estimation of inefficiency. Interpretation of coefficients is as follows. A positive coefficient implies that the variation of the error term is increased by the variable in question. A greater variance results in larger deviations from the efficiency frontier, hence in greater inefficiency. Health system characteristics whose coefficients are positive are not desirable, while those with negative coefficients lead to higher health system efficiency.

Table 4				
Determinants of health system efficiency				
	<i>TWO STEP MODEL</i>		<i>ONE STEP MODEL</i>	
	women	men	women	men
public expenditures	.0024 **	.0020 **	.0946 **	.0224 *
beds per 1000 people	.0214 **	.0093 **	-.1399 **	-.1835 **
average length of stay	-.0053 **	-.0037 **	.0231	-.0160
health coverage	.0036 **	.0019 *	-.1114 **	-.0232 *
public reimbursement	-.1480 *	-.0457	-.1692	2.1282 **
public contract	.0753	.0814 *	-1.0519 **	-.3406
fee for service	-.0082	-.0036	1.6630 **	.2606

** indicates significance at the 0.01 level

* indicates significance at the 0.05 level

In general, results are consistent between the two estimation approaches. The same health system characteristics are identified as efficiency increasing. The only exception is the share of public expenditures in total health expenditures. While the two step model suggests, that a higher share of public spending is accompanied by higher efficiency, the one step model suggests the opposite. Recall that a positive coefficient in the two step model signifies a positive correlation with efficiency, while it signifies a negative correlation with efficiency in the one step model. Both results are statistically significant. It is disappointing that light cannot be shed on this particular variable, since it is the basis of on-going debates in among health policy makers. The share of public in total spending has been a bone of contention in the determinants of health spending literature, as well, where some suggest it leads to increased health spending, while others suggest the exact opposite. Studies also indicate that a higher public share of expenditures improves health outcome. There seems to be slightly more evidence in support of a publicly funded system (Wranik-Lohrenz, 2004, chapter b of this volume) This issue is not to be confused with public versus private delivery of health care, also subject to frequent debate. The latter is captured in the type of system, such as public integrated, contract, or reimbursement.

Debate with respect to the appropriate proportion of public expenditures in total expenditures is rooted in an underlying dichotomy in beliefs. Public health care funding is advocated for the sake of equality and access. Those who argue in favour of public health systems take the stance that health care is a right, and not a commodity, and hence should not be traded in the private market. The flipside of the argument revolves around quality of care, availability and efficiency. Advocates of privately funded systems point to the private sector as a solution to elimination of shortages, to improvements in quality and technology, and to increased efficiency. This argument is coupled with the ideology that health care is a good much like any other, and incentives in the health care market have similar effects as in other markets. This paper is not able to support either side of the debate.

The number of beds available for in-patient care has a positive effect on health system efficiency in both models. It appears that, while additional beds are costly to the system, they have a positive effect on health that outweighs the additional costs. If the number of in-patient care beds per 1000 population is a good measure of the size of the hospital

sector, one can speculate that countries with larger hospital sectors are more efficient at producing health. The result is somewhat surprising, since much of the literature on the subject rejects the hypothesis that hospitals have any significant impact on population health improvements (Navarro, 2000, Evans, 1996, Wilkinson, 1998, citations of literature). This literature shows that the impact of the medical establishment on crude health indicators, such as life expectancy or mortality rates, is small or statistically insignificant. It may be that the alternative measure of health used here, arguably one that is more reflective of morbidity than the crude measures, is the reason behind this discrepancy.

Systems with higher focus on acute care, however, are the less efficient ones in the sample. The average length of stay in in-patient acute care settings decreases efficiency. This suggests, that while additional hospital beds improve health more than they increase costs, their beneficial effects take place primarily in the first few days of the hospital visit. Past the initial period of care and recovery, additional days spent in the acute care bed increase costs with insufficient health benefit. It would be interesting to investigate the effects of average length of stay in acute care settings on hospital level efficiency, a study similar to Rosko (1999).

Increases in the percentage of the population with health coverage have a positive impact on health system efficiency. There is concern in theoretical economic literature that health insurance creates a moral hazard problem. Persons with health insurance are less likely to take health precautions, resulting in health problems and increased health care usage. Gerdtham et al. (1998) show that health coverage does not lead to increased health care costs. Suspicions have also been expressed that insured patients are more likely to seek unnecessary testing and treatment, thereby increasing health care costs with no benefit to health. Such behaviour would be expected to lower health system efficiency. Results of this study indicate, that neither health problems and injury nor unnecessary care increase with higher health coverage. The idea is supported that patients are treatment averse and do not consume more health care when the price they pay declines. Efficiency is not negatively affected when more people obtain health insurance. This result is statistically significant for both sexes and in both models.

While health insurance does not appear to strain the health care market on the demand side, the supply side of the health care market does seem to respond to financial incentives. Theoretical literature has argued that doctors' behaviour is less noble in a fee-for-service system than in a capitation system. This may be a result of doctors knowingly prescribing too much care in order to maximize their income (Ellis et al., 1990, Lee, 1995); or it may be a result of the fee for service system creating lower incentive to exert diagnostic effort and prescribe appropriate care (Wranik-Lohrenz, 2004, chapter 2 of this volume, Jencks et al., 2001). Whichever effect takes place, results here support the idea that a fee-for-service system is less efficient than the capitation system. Unfortunately, this result is not statistically significant except for women in the one step model. Nonetheless, the result is consistent with empirical literature demonstrating capitation systems to be superior to fee-for-service systems. (Grignon et al., 2002, Krasnick, 1990, Wilensky et al., 1986).

The result that public reimbursement systems decrease efficiency is consistent with the previous result, since public reimbursements systems predominantly use fee-for-service remuneration agreements. Public contract systems seem to perform better in terms of efficiency. Looking at the two competing systems, public reimbursement, and public contract, between the two sexes and the two models, not all eight coefficients are statistically significant. Overall, however, it appears that a sufficient number of the hypotheses cannot be rejected, and indeed a public contract system can be favoured over a public reimbursement system. The public reimbursement system was found to lower health care costs in Gerdtham et al. (1998), but the public contract system appears to increase health outcomes sufficiently to warrant its higher costs. The public contract system is one, where some kind of agreement exists between health care producers and third party payers. It is generally found in social insurance systems with predominantly private non profit providers⁶. Canada, for example, has a public contract system (Gertham, et al., 1998), where the insurer, in this case the government, enters into an agreement with health care providers. A public reimbursement system predominates in the United States, where providers receive retroactive payments for services supplied. The other two systems can also be found in some part of the United States health care system. It appears then, that Canada's health care system outperforms the U.S. health

⁶ Hence while some support exists in favour of a publicly funded system, health service delivery appears to best be done privately.

care system. Canada consistently ranks higher than the United States for both sexes and across model specifications. In addition, the type of health care system that predominates in Canada is in general more efficient than the type that predominates in the United States.

6. Conclusions

This paper sheds light on the mysteries surrounding design of an efficient health care system. While economic literature to date ranked countries according to efficiency, and has discriminated between more and less costly types of systems, a clear guide to efficiency creating health system characteristics did not exist. This paper fills the gap. Results of the paper give meaningful advice to health policy makers. If efficiency is the goal, a public contract system is most desirable and should focus on ensuring the following:

1. A greater number of acute care beds coupled with fewer days spent in the hospital in acute care situations.
2. Increased health coverage for patients
3. Physician reimbursement on a capitation as opposed to a fee for service basis.

These results, of course, must be interpreted with care, since the efficiency scores are extremely volatile to model specification. Further testing might shed light as to which econometric specification is most appropriate for the data.

Much remains to be done in this area. It will be useful to check, whether an alternate variable, such as the share of white collar workers (used in Or, 2000) would perform better than education as an argument in the health production function. Unfortunately, this variable was not readily available. Secondary education might not be a good predictor of health in developed Western economies, as there might not be enough variation in gross enrolment rates over time and across countries.

Literature on the determinant of health expenditures has given much attention to the problem of stationarity of variables, where health spending and national income are tested for stationarity and cointegration. In the context of the health production function,

a natural question would be to ask, whether health and health expenditures are stationary. The possibility of a spurious relationship should not be excluded a priori, especially since the theoretical underpinnings of a health production function are extremely weak.

One might also be inclined to ask, whether health might be a determinant of health spending, where lower levels of health require higher health expenditures. Given that the potential of endogeneity in this context is large, some analysis should be devoted to the question. On the same note, one might want to include the lag of health outcome as a determinant of current health status. All improvements in the estimation of the underlying health production function will automatically lead to more reliable estimates of health system efficiency. Clearly, our understanding of health system efficiency determinants will be improved, as well.

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