An Empirical Analysis of World Health Production with Cross-Country Heterogeneity*

Shao-Hsun Keng** and Yang Li***

Abstract

The goal of a health care system is to maximize population health and reduce health inequality. Encountered by rapidly rising medical costs, policy makers have raised concerns over possible overinvestment in health care and have increasingly made the regular evaluation of health care systems central to their work. This study examines the performance of world health care systems by recognizing the multiple-output nature of health production and the existence of cross-country heterogeneity. A pure measure of the technical efficiency that is free from the influence of cross country heterogeneity is estimated. The empirical results show that the effect of the adjustment for heterogeneity significantly alters the efficiency ranks of worldwide health care systems.

Keywords: Health Production, Health Expenditure, DEA, Slack Variable, Heterogeneity
JEL Classification: I12, C13

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I. Introduction

The ultimate goal of a health care system is to maximize population health and alleviate health inequality. As countries across the globe allocate more resources to health care, health policy makers are becoming increasingly concerned with the overall performance of the health care system. An evaluation of efficiency that fails to control heterogeneity across countries (Evans et al., 2000) may overestimate (underestimate) the efficiency of a heath care system under favorable (unfavorable) operating conditions. Consequently, we might penalize good performers operating under an unfavorable environment and reward poor performers that operate in a favorable environment. Furthermore, previous studies consider only a single output production function (Evans et al., 2000; Hollingsworth and Wildman, 2003; Greene, 2004), which is unable to fully characterize the multiple dimensions of human health. Hence, by using a multiple output production function, this study intends to evaluate the performance of worldwide health care systems and to obtain a pure measure of the technical efficiency which is free of the influence of the external operating environment.

The World Health Report 2000 might have been the first attempt to conduct a systematic worldwide assessment of the effectiveness of health care delivery. Built on the work of Evans et al. (2000), the report provides an efficiency ranking for the health care systems in 191 countries between 1993 and 1997. This ranking is based on a panel data fixed-effect model in which technical efficiency is assumed to be time invariant. The results reveal a wide variation

in efficiency scores across countries. The main criticism of World Health Organization (WHO) study, however, is that it is silent with regard to the cross-country heterogeneity which reflects differences in the operating environment facing each country. The report has implicitly assumed that the countries analyzed were operating under a similar environment. However, the data cover countries that differ vastly in their political systems, culture, and stages of economic development. Placing countries such as the U.S. and Bangladesh in the same league will be problematic.

Hollingsworth and Wildman (2003) relax the assumption of time-invariant technical efficiency and estimate DEA-based Malmquist indices of productivity change. Although their model does not explicitly incorporate unmeasured heterogeneity, they do in fact address the heterogeneity issue by stratifying the data according to OECD membership. The results show that over a five-year period (1993-1997), OECD countries are more efficient and regress less quickly in technology than non-OECD countries. Non-OECD countries also exhibit more variations in efficiency measures than OECD countries. Their findings suggest that treating WHO member countries as a homogeneous sample may be incorrect. The ability of a country to transform health inputs into health outputs is influenced by technical efficiency and the external operating environment, which varies significantly across countries.

Greene (2004) adopts a stochastic frontier approach with panel data and proposes several specifications that incorporate measured heterogeneity indicators into either the production function or the distribution of inefficiency term. The heterogeneity indicators include a measure for the democratization and freedom of a country, the Gini coefficient, government effectiveness, tropical location, per capita GDP, and the government's share of health care expenditure. He compares the model with no heterogeneity to one with heterogeneity that incorporates both the production function and inefficiency. Both the estimated standard deviation in the distribution of the inefficiency term and the means of the estimated inefficiencies decrease after heterogeneity is accounted for. This is consistent with the conjecture that uncontrolled heterogeneity appears as inefficiency in the WHO analysis. Moreover, the efficiency rankings also change considerably. Greene concludes that heterogeneity is an important issue when estimating the global rankings of health care systems.

In this study, we regard the cross-country heterogeneity as consisting of the differences in the operating environment that are exogenous to the production unit. We reexamine the WHO data using a four-stage nonparametric DEA procedure (Fried et al., 1999) to obtain a pure measure of technical efficiency which is free of the impact of the external operating environment. This approach allows us to statistically test the effect of cross-country heterogeneity on the efficient use of each input. Our approach extends and complements the previous literature in several ways. First, we specify a multiple-output production function rather than the single-output production function used in previous studies. The advantage of using a multiple-output production function is that it integrates the multiple dimensions of population health. Second, we are able to examine the effect of more than one environmental variable on the efficient use of each individual health input. Third, we are able to identify those good performers who operate in unfavorable environments as well as those poor performers who work in favorable environments. We can fairly evaluate the efficiency of the health care systems by putting them under the same environment conditions. In addition, we can examine whether external environments have an effect on the efficiency of health care systems. Our findings shed new lights on how government can improve external environments to enhance efficiency of health care.

The remainder of this paper is organized as follows: Section two discusses the data used in the analysis and the model's empirical specifications. The empirical results are presented in section three. Section four concludes the paper.

II. Data Source and Empirical Specifications

A. Data

The data used in this study are those used by the WHO. The WHO data collect information on the health outcome, health expenditure and human capital for 191 countries

between 1993 and 1997. Two health outcome variables are available: DALE and COMP. DALE is the disability adjusted life expectancy, which accounts for both mortality and the quality of life simultaneously. COMP is the composite index of success for five health goals, namely, the overall population health, health distribution, responsiveness, responsiveness in distribution, and fairness in financing. Two health inputs are used in our analysis, namely, health expenditure per capita (HEXP) and human capital (HC). Health expenditure is viewed as an input by the health care system, while human capital represents the input of the non-health-care system. Health expenditure is the total private and public health expenditure per capita in 1997 international dollars. The human capital variable is measured by the average years of schooling in the population aged 15 and above.

B. Empirical Model

Data envelopment analysis (DEA) is essentially a linear programming technique that converts multiple outputs and multiple inputs into a scale measure of efficiency. It was initially proposed by Charnes et al. (1978) (being referred to as the CCR model) and was based on the concept of technical efficiency of Farrell (1957). The efficiency of a decision making unit (DMU) is calculated by transforming inputs into outputs in relation to its peer group, provided that the technology exhibits constant returns to scale. Banker et al. (1984) extended the CCR model to account for variable returns to scale, which became known as the BCC model. An inefficient DMU in the BCC model is only benchmarked against DMUs of similar sizes. DEA has been widely used in many fields (Wang et al., 2008; Li et al., 2010; Huang and Huang, 2010; Ke et al., 2010; Lin et al., 2010).

There are several extended DEA models that incorporate the external environment in order to control for heterogeneity across DMUs. The frontier separation approach stratifies DMUs to form sub-samples according to a single categorical variable. The DMUs are evaluated relative to the sub-sample and pooled frontier in order to investigate the impact of the operating environment on efficiency. However, the approach only allows for a single and

categorical environmental variable. This all-in-one approach by contrast includes environmental variables directly in inputs or outputs to overcome the above problem. It requires that an external variable be classified as an input, which is treated as the unfavorable environment, or as an output, which is treated as the favorable environment, prior to the analysis. Nevertheless, a priori input or output classification may not be suitable when it comes to testing whether or not a particular operating environment is favorable or unfavorable. Furthermore, the radial score assumes that all inputs in the input-oriented model are shrinkable or that all outputs in the output-oriented model are expandable, which makes little sense for many of the external variables.

Some studies employ a two-stage approach to investigate the impacts of exogenous variables on efficiencies. The radial technical efficiency, obtained from the conventional DEA model in the first stage, is regressed on environmental variables that are exogenous to DMUs in the second stage. However, the second stage omits the information contained in the slacks in inputs or surpluses in outputs, which may bias the parameter estimates and result in an incorrect conclusion regarding the influence of exogenous environment on the production process (Fried et al., 1999). Moreover, the sample is a subset of the true production possibility set, which tends to overestimate technical efficiencies (Banker, 1993).

This study applies the four-stage approach, proposed by Fried et al. (1999), to measure efficiencies by incorporating the exogenous operating environments. The advantages of this approach are as follows: (1) it can incorporate more than one external variable without specifying such variables as inputs or outputs prior to the analysis; (2) the influence of external variables on the efficient use of each input in the input-oriented model (or each output in the output-oriented model) can be tested; (3) the end result is a radial measure of managerial efficiency with the traditional interpretation; and (4) it can help us to identify those good performers who operate in unfavorable environments as well as those poor performers who work in favorable environments.

We only discuss the input-oriented model. The output-oriented model can be analyzed in a similar fashion. The first stage estimates the input-oriented DEA frontier, excluding the exogenous environmental variables, and calculates both the radial and non-radial input slacks.

In the second stage, a system of equations is specified to investigate the relationship between production efficiency and operating environments that are beyond the control of the DMUs. The dependent variable for each equation is the sum of the radial and non-radial input slacks, which will be regressed on those independent variables that measure the features of the external operating environments.

The third stage calculates the predicted input slacks according to the parameters obtained from the second stage in order to adjust the primary inputs. These predicted input slacks can be interpreted as the allowable slacks due to the operating environments being exogenous to the DMUs. Fried et al. (1999) suggest using the least favorable environment as the base in order to avoid the possibility of negative values for adjusted inputs. Hence, the adjusted input j for DMU h is defined as:

$$\hat{x}_{hj} = x_{hj} + \{\mathrm{Max}_h(Spred_{hj}) - Spred_{hj}\} \tag{1}$$

where x_{hj} is the primary input j for DMU h and $Spred_{hj}$ is the predicted sum of both radial and non-radial slacks for input j of DMU h. This creates a pseudo data set where input data are adjusted for the influence of external environmental conditions. The final stage is to rerun the DEA model using the adjusted data. The new radial efficiency measures are free of the influence of the external variables and thus allow us to identify good performers operating under unfavorable environments and poor performers that work in favorable ones.

C. Exogenous Environmental Variables

Indicators of cross-country heterogeneity include the measure of government effectiveness (EFFECT), measure of political freedom (FREEDOM), geographical location (TROPICAL), GDP per capita (GDP), and newspaper circulation (NEWS). EFFECT measures government effectiveness, bureaucracy, the credibility of government commitment and the quality of public services. FREEDOM represents civil liberties, political rights, and the extent to which citizens participate in the selection of the government. Both variables are available

from the World Bank's Aggregate Governance Indicators 1996-2002. The values of both variables range between –2.5 and 2.5, with higher values corresponding to better government governance. Since these two variables were observed only for 1997, we use 1997 values for earlier years. Given that political freedom and the quality of government governance usually do not change greatly within short periods of time, assigning 1997 values to all years should not cause serious bias.

TROPICAL is a binary variable indicating whether a country is located in a tropical location. GDP is per capita GDP in $US ppp 1997. NEWS is the daily newspaper circulation per 1,000 people and the data are available in the World Bank's World Development Indicators, 2004. After deleting observations with missing data, there are 141 countries of which 140 countries have a complete five-year panel and one country has a four-year panel. The descriptive statistics and standard deviations are reported in Table 1.

Table 1 Descriptive statistics and standard deviations (STD): 1993 – 1997

All Countries (n = 141)	Mean	STD	Minimum	Maximum
Output Variables				
COMP	74.391	12.043	45.931	93.447
DALE	57.332	12.238	28.380	74.827
Input Variables				
HEXP	479.357	638.786	16.229	3721.270
HC	6.075	2.731	0.927	11.500
Heterogeneity Variables				
EFFECT	0.106	0.913	−1.680	2.310
FREEDOM	0.038	0.931	−1.790	1.610
TROPICAL	0.475	0.499	0.00	1.00
GDP	7043.430	7195.830	450.832	30264.310
NEWS	109.339	129.099	0.00	608.302
OECD Countries (n = 30)				
Output Variables				
COMP	89.291	4.001	73.755	93.447
DALE	70.138	3.016	61.081	74.827

Table 1 Descriptive statistics and standard deviations (STD): 1993 – 1997 (continued)

	Mean	STD	Minimum	Maximum
Input Variables				
HEXP	1502.160	711.789	179.540	3721.270
HC	8.839	1.588	4.043	11.500
Heterogeneity Variables				
EFFECT	1.411	0.634	–0.200	2.220
FREEDOM	1.206	0.510	–0.650	1.610
TROPICAL	0.036	0.188	0.00	1.00
GDP	18131.860	6017.990	5006.740	30264.310
NEWS	282.834	146.916	23.927	608.302
Non-OECD Countries (n=111)				
Output Variables				
COMP	70.758	10.446	45.931	90.499
DALE	54.199	11.587	28.380	70.706
Input Variables				
HEXP	229.981	258.934	16.229	1821.050
HC	5.401	2.520	0.927	10.518
Heterogeneity Variables				
EFFECT	–0.212	0.650	–1.680	2.310
FREEDOM	–0.247	0.775	–1.790	1.310
TROPICAL	0.583	0.493	0.00	1.00
GDP	4339.890	4276.960	450.832	25322.54
NEWS	67.089	79.746	0.00	435.795

It is clear from Table 1 that there exist wide variations in all variables across countries. Stratifying the sample based on OECD membership shows that those variations within each group remain large. In general, OECD countries are healthier, wealthier, invest more in health production, and have more efficient governments, more political freedom and higher newspaper circulations.

III. Empirical Results

The empirical results are presented according to the sequence of the four stage procedures.

A. Stage One: Initial DEA Estimation

To compute the initial efficiency scores, we use input-oriented DEA and assume variable returns to scale technology. The results exhibit a wide variation in efficiency scores with a standard error of 0.203 and an average efficiency score of 0.709. We stratify the sample into OECD and non-OECD countries. OECD countries significantly outperform the non-OECD countries in the efficiency rankings. Among the 141 countries, the average efficiency score for OECD countries is 0.806 while the non-OECD countries have an average efficiency score of 0.685.

Total radial and non-radial input slacks represent potential input savings in health production. The average ratios of total input slacks to total input use (total input slacks/total input use) are 31 percent and 29 percent for HEXP and HC, respectively. That is, the potential savings in both inputs are close to one third of the current input use. For OECD countries, the ratios are 20 and 19 percent for HEXP and HC, respectively, while the corresponding ratios are 34 and 32 percent for the non-OECD countries. Without controlling for cross-country heterogeneity, health care systems in non-OECD countries are less efficient in terms of their health input use than OECD countries. Nonetheless, these potential input savings may not be realized because each country operates under different environments. In the next stage, we use total input slacks to quantify the effect of cross-country heterogeneity on the excessive use of both inputs.

B. Stage Two Estimation: Tobit Model to Quantify Cross-Country Heterogeneity

To control the effect of heterogeneity on efficiency, a random-effect tobit model is applied and the estimates are reported in Table 2. The random-effect model is preferred because the explanatory variables include time-invariant variables. There are two regression equations, one for each input. The dependent variables are the sum of the radial and non-radial input slacks. The independent variables are the indicators of cross-country heterogeneity, i.e., EFFECT, FREEDOM, NEWS, TROPICAL, and GDP. Since both equations contain identical explanatory variables, they can be estimated separately. A positive coefficient indicates an unfavorable operating environment and vice versa. The coefficients of these variables are all statistically different from zero except for NEWS in the human capital (HC) equation. This indicates that variations in the operating environment across countries do affect input use in the delivery of health services. The failure of DEA to account for heterogeneity is, however, due to its being unable to distinguish "good" performers operating under poor environments from "poor" performers operating under favorable conditions.

As expected, a more efficient government is associated with less excessive input use. On the other hand, a more democratic and egalitarian country has greater total input slacks than its counterparts. The explanation for this may be that political and civilian freedom requires greater compromise, negotiation, and coordination. Consequently, more resources are used than are otherwise needed. Newspaper circulation serves as a proxy for a country's information infrastructure. The results suggest that newspaper circulation has a negative effect on the excessive use of inputs. Hence, the operating environment is favorable in countries where the information infrastructure is well established. The indicator for tropical location has a significant negative sign, suggesting that tropical countries have a favorable operating environment in health production. That GDP per capita has a positive and statistically significant coefficient in both of its input slack equations suggests that high income countries tend to overinvest in health inputs, other things being equal. Our findings are consistent with

the literature in health economics that most developed countries have invested too much in health care such that the marginal productivity of health care is close to zero (Murphy and Topel, 2005; Cutler, 2004; Thornton, 2002).

Table 2 Random effect tobit model of total input slacks for HEXP and HC

	Dependent Variables	
Variables	HEXP	HC
Intercept	65.279 (3.153)***	1.655 (0.029)***
EFFECT	−27.772 (3.019)***	−0.339 (0.029)***
FREEDOM	32.119 (1.983)***	0.336 (0.022)***
NEWS	−14.489 (1.367)***	−0.011 (0.016)
TROPICAL	−172.822 (2.865)***	−0.496 (0.026)***
GDP	291.062 (3.718)***	0.373 (0.037)***
σ_v	50.054 (0.804)***	0.361 (0.004)***
σ_u	185.477 (0.819)***	0.927 (0.007)***
Countries (No. of observations)	141 (704)	141 (704)
χ^2 Statistic	1188.486	1351.202
Pseudo R^2	0.143	0.545

Note: *** significant at 1% significance level. ** significant at 5% significance level.
* significant at 10% significance level.

C. Stage Three Estimation: Initial Data Adjustment

Following equation (5), the tobit estimates obtained from Stage two are used to adjust the initial data. Such an adjustment alleviates the cross-country heterogeneity and places every country in the least favorable operating environment. Table 3 summarizes the maximum predicted input slack and average predicted input slacks for both inputs according to OECD and non-OECD countries. A country with the maximum predicted input slacks means that it has the least favorable operating environment. The results indicate that the maximum predicted

input slack is located in non-OECD countries in the cases of both inputs. The average predicted input slacks for both inputs are also larger for non-OECD countries as opposed to OECD countries.

Table 3 Predicted input slacks by OECD membership: 1993 – 1997

	Mean	STD	Minimum	Maximum
All Countries (n = 141)				
HEXP	219.524	207.928	29.209	888.512
HC	1.669	0.415	0.886	2.606
OECD Countries (n = 30)				
HEXP	179.115	174.934	29.209	824.362
HC	1.592	0.385	0.886	2.557
Non-OECD Countries (n = 111)				
HEXP	229.376	214.191	31.451	888.512
HC	1.687	0.419	0.907	2.606

D. Stage Four Estimation: Recalculate the Efficiency Scores Using Adjusted Data

We recompute the efficiency scores using the adjusted data. These new efficiency scores incorporate environmental heterogeneity across countries and are reported in Table 4. By comparing Stage four with Stage one, it can be seen that the average efficiency score has risen from 0.709 to 0.88, reflecting a 24 percent increase, and its standard deviation has declined considerably from 0.203 to 0.087. The evidence suggests that failing to account for heterogeneity, the efficiency scores for countries operating in favorable and unfavorable environments are overestimated and underestimated, respectively. Consequently, adjustments to the data remove these biases, thus causing the standard deviation to narrow.

Non-OECD countries have experienced greater gains in efficiency than OECD countries after adjusting the data. Consequently, the average efficiency score for non-OECD countries

(0.886) surpasses that for OECD countries (0.856) following the adjustment. Our findings indicate that the underestimation in efficiency for non-OECD countries is greater than that for OECD countries. The efficiency rankings also change significantly. Table 5 shows the effect of the adjusted data on the rankings of the top 35 countries in our initial DEA estimates. The country with the greatest advance in rankings is Swaziland that moves from 140 to 43, followed by Turkmenistan moving from 118 to 30, Vietnam advancing from 136 to 50, and Tajikistan proceeding from 131 to 51. On the other hand, Germany experiences the largest drop in ranking slipping from 62 to 130, followed by Sweden declining from 52 to 117, Switzerland falling from 55 to 118 and the Netherlands sliding from 44 to 106.

Table 4 Comparison of DEA (Stage 1) and heterogeneity-adjusted DEA (stage 4) efficiency scores and ranking by OECD membership: 1993 – 1997

	Stage 1	Stage 4
All Countries (n = 141)		
Average Efficiency Scores	0.709	0.880
Standard Deviation	0.203	0.087
Minimum	0.232	0.597
Maximum	1.00	1.00
OECD Countries (n = 30)		
Average Efficiency Scores	0.806	0.856
Standard Deviation	0.134	0.104
Minimum	0.540	0.597
Maximum	1.00	1.00
Non-OECD Countries (n = 111)		
Average Efficiency Scores	0.685	0.886
Standard Deviation	0.210	0.081
Minimum	0.232	0.619
Maximum	1.00	1.00
Mann-Whitney U test	−6.169	−2.954
OECD vs. Non-OECD	(<0.001)	(0.003)

Note: *P* values are in the parentheses.

While changes in ranking are quite substantial for some countries, the discussion however should focus on the implication of our findings rather than the ranking itself. In particular, countries experiencing the largest change in ranking are all located in both tails of the distribution of economic development. These countries also show considerable discrepancy in terms of political institutions and market structures, which play an important role in the efficiency of health production. More important, we find that the fall in the ranking among developed countries is mostly due to the large increase in efficiency scores among less developed countries. This implies that should less developed countries have the same operating environment as developed countries, they can use fewer inputs and still maintain the current output level. Our findings indicate the importance of controlling for cross-country heterogeneity when evaluating the performance of health care across countries given that environmental factors have a significant effect on the performance of the health care. Policy makers should focus on improving environmental variables, such as infrastructure and democracy that are important to the efficiency of the health care system.

Table 5 Comparison of selected country ranks based on stage 1 and stage 4 efficiency scores: 1993 – 1997

Country Name	Old Rank	New Rank
Malta	1	1
France	2	15
Oman	3	8
Singapore	4	18
Italy	5	2
Philippines	6	62
Yemen	7	39
Senegal	8	57
Morocco	9	4
Jamaica	10	11
Japan	11	7
Sri Lanka	12	56

Table 5 Comparison of selected country ranks based on stage 1 and stage 4 efficiency scores: 1993 – 1997 (continued)

Country Name	Old Rank	New Rank
Spain	13	22
Mali	14	9
Poland	15	12
Greece	16	17
Indonesia	17	65
Mozambique	18	37
Ukraine	19	16
Croatia	20	45
Benin	21	19
Chile	22	28
Egypt	23	3
Cape Verde	24	38
Niger	25	31
Columbia	26	73
United Kingdom	27	35
Cyprus	28	25
Ethiopia	29	72
Norway	30	52
Kazakhstan	31	21
Georgia	32	20

Note: Kendall's τ correlation coefficient = 0.454 with P-value < 0.001.

IV. Conclusion

We have reexamined the WHO data in this study using a four-stage procedure that isolates cross-country heterogeneity from true inefficiency. It utilizes information imbedded in

the input slacks produced by the initial DEA. It also provides statistical tests of the effect of heterogeneity variables on inefficiency for each input use.

The results suggest that a considerable degree of heterogeneity has been measured as inefficiency in previous studies using WHO data. The average efficiency score improves considerably and its standard deviation is reduced following the adjustment. These findings have two important implications for efficiency measures that are based on WHO data and fail to control for cross-country heterogeneity. First, the penalty for countries operating under an unfavorable environment is greater than the benefit to those countries operating under favorable conditions. Secondly, the efficiency score is found to be upward biased for countries operating in favorable circumstances and downward biased for those operating in unfavorable environments.

Stratification of the WHO data based on OECD membership reveals several important observations. Consistent with the World Health Report 2000, our initial DEA suggests that OECD countries are more efficient in terms of health production than non-OECD countries. However, we find that non-OECD countries are more efficient than OECD countries in terms of health production after heterogeneity is accounted for in the model. Although the efficiency scores for both groups are found to have increased following the adjustment, our results indicate that the underestimation in efficiency for non-OECD countries is much greater than that for OECD countries.

The effect of the adjustment for heterogeneity is found to significantly alter the technical efficiency of the 141 countries included in the initial DEA model. We conclude that the importance of the model's specification, such as the control of heterogeneity in this study, should not be overlooked when we compare the efficiency of the delivery of health outcomes across vastly different countries. Improving environmental factors crucial to the functioning of the health care system should be emphasized from the viewpoint of health care policy.

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References

Banker, R. D., 1993, "Maximum Likelihood, Consistency and Data Envelopment Analysis: A Statistical Foundations," *Management Science*, 39: 1265-1273.

Banker, R. D., A. Charnes, and W. W. Cooper, 1984, "Models for Estimation of Technical and Scale Inefficiencies in Data Envelopment Analysis," *Management Science*, 30: 1078-1092.

Charnes, A., W. W. Cooper, and E. Rhodes, 1978, "Measuring the Efficiency of Decision-making Units," *European Journal of Operational Research*, 2: 429-444.

Cutler, D. M., 2004, *Your Money on Your Life*, Oxford University Press: Oxford.

Evans, D. B., A. Tandon, C. Murray, and J. A. Lauer, 2000, "The Comparative Efficiency of National Health Systems in Producing Health: An Analysis of 191 Countries," *GPE Discussion Paper Series*, No. 29, World Health Organization.

Farrell, M. J., 1957, "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society*, A120: 253-290.

Fried, H. O., S. S. Schmidt, and S. Yaisawarng, 1999, "Incorporating the Operating Environment into a Nonparametric Measure of Technical Efficiency," *Journal of Productivity Analysis*, 12: 249-267.

Greene, W. H. 2004, "Distinguishing between Heterogeneity and Inefficiency: Stochastic Frontier Analysis of the World Health Organization's Panel Data on National Health Care Systems," *Health Economics*, 13: 959-980.

Hollingsworth, B. and J. Wildman, 2003, "The Efficiency of Health Production: Re-estimating the WHO Panel Data Using Parametric and Non-parametric Approaches to Provide Additional Information," *Health Economics*, 12: 493-504.

Huang, M. Y. and S. Y. Huang, 2010, "Productivity Evaluation of Taiwanese Semiconductor Companies Using a Three-stage Malmquist DEA Approach," *Taiwan Journal of Applied Economics*, Special Issue: 31-57.

Ke, T. Y., Y. H. Chiu, and T. H. Chen, 2010, "The Analysis of the Relationship between

Performance and Recession in Electronic Industry," *Taiwan Journal of Applied Economics*, Special Issue: 1-30.

Li, Y., J. C. Kuo, W. L. Lee, and M. H. Lin, 2010, "Group Performance Evaluation of Chinese and Indian Banking Industry," *Taiwan Journal of Applied Economics*, Special Issue: 78-116.

Lin, Y. M., W. H. Kong, and C. L. Chang, 2010, "Quasi-fixed Inputs and the Change of Productivity of Taiwanese International Tourist Hotels," *Taiwan Journal of Applied Economics*, Special Issue: 191-225.

Murphy, K. M. and R. H. Topel, 2005, "The Value of Health and Longevity," *Working Paper*, No. 11405, National Bureau of Economic Research.

Thornton, J., 2002, "Estimating a Health Production Function for the U.S.," *Applied Economics*, 34: 59-62.

Wang, C. L., Y. C. Hsu, and S. W. Tsui, 2008, "Performance and Efficiency of Municipal Government in Taiwan," *Taiwan Journal of Applied Economics*, 84: 71-120.

控制環境異質性的跨國間健康生產效率比較*

耿紹勛**、李揚***

摘要

健康醫療系統的目標是爲了達到全體人民健康狀況的極大化和減少健康的不均等情況。在面臨醫療成本急遽高漲的情況下，政策決策者開始關注醫療保健的過度投資問題，並且逐漸將定期的健康保健評估視爲最主要的工作。這篇文章主要是利用健康生產多樣產出的特性和國家間異質性來檢驗全球健康保險系統的表現。本研究透過三階段的計量模型得到不受國家異質性影響的醫療生產技術效率，實證結果顯示，調整異質性後會顯著的改變全球健康醫療系統的效率評等，相關分析應將國家間異質性納入模型，才能在相同的基礎上比較生產效率。

關鍵詞：健康生產、醫療支出、資料包絡分析、缺額變數、異質性

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