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Health production and the socioeconomic determinants of health in OECD countries: the use of efficiency models

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ABSTRACT

It has been proposed that cross-country comparisons of the technical efficiency of health production, estimated using data envelopment analysis (DEA), have useful applications for policy makers. In theory such an analysis utilises measures of the socioeconomic determinants of health relevant to all social policy, not just health policy. Using OECD and WHO data, this paper critically analyses a number of outstanding theoretical questions regarding the use of DEA in this setting. It concludes that until such questions are addressed, the resultant implications for policy will be based on misleading information.

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Introduction

The production of health in a population is a multifactorial and complex issue. Consideration of the socioeconomic determinants of health in cross-country economic analyses has previously been somewhat limited by the lack of available data and suitable analytical techniques. The collation of more comprehensive cross-country databases in recent years provides an opportunity to apply so called 'cutting-edge' techniques to analyse the technical efficiency of health production at a country level [1-3]. In theory, such analysis could provide important information for policy makers. However a number of outstanding theoretical questions limit the interpretation of the results into policy implications [4], although some have attempted to do so [5].

Using Organisation for Economic Co-operation and Development (OECD) health data (2004) and the analytic technique data envelopment analysis (DEA) based Malmquist indexes, this paper extends a framework to analyse the technical efficiency of health production at a country level and describes the limitations inherent in using such an analysis as a policy tool.

Background

Causal pathways between the social determinants of health and health outcomes are not well understood. Some believe increases in life expectancy are strongly linked to healthcare spending [6]. Other authors suggest that differentials in life expectancy and infant mortality between populations are due to other factors including lifestyles and preferences [7-9], social class and occupation [10, 11], and environmental factors [12, 13].

Further insights can be found in social epidemiology. Lynch and Kaplan note that "economic and social policy have much to do with the levels of resources and exposures that individuals and communities experience; they represent important loci for intervention and are the upstream determinants of health" [14]. The level of community resource and social structure are thought by some to affect the health of the population to a greater extent than the sum of individual determinants [15]. Further, aggregate measures of socioeconomic status, such as income at a community level, have shown to be associated with health status [16].

From this it may be argued that all social policy tools controlled by governments (as well as macroeconomic indicators) impact directly or indirectly on the health of populations [17, 18]. If the production of health is influenced by the policy mix instituted by governments (and not simply the percentage of gross domestic product (GDP) spent on healthcare systems), it stands to reason that governments would aim to produce health in the most efficient manner possible. By identifying the "inputs", that is, the socioeconomic determinants influenced by government that produce the health "output" of a country, it is possible to measure how technically efficient (TE) a country is at 'producing' health. This analysis can be extended to produce cross-country comparisons which at first sight appear to provide insights into the policy mix of the countries that produce health most efficiently.

Work to identify the most indicative measures of the socioeconomic determinants of health continues to be controversial [19, 20]. In the absence of recognised measures, a conceptual framework of the socioeconomic determinants of health has been identified, which is largely based on scientific evidence, to guide the choice of variables for this analysis and is shown in Figure 1 [21].

Upstream or macro level determinants are directly or indirectly affected by government policy. Other midstream or intermediate-level factors, including lifestyle factors, also impact significantly on life expectancy [22-24]. Whilst acknowledging these associations, measures of health behaviours can be less robust and are not routinely measured [25], subject to significant cross-cultural differences [26], and difficult to disentangle from measures of income [27]. Whilst the collection of data such as that by the OECD, to describe some of these factors has improved significantly in recent years, analysis of this kind is still greatly limited by the lack of sufficient appropriate data (witness the furore over the data used in the World Health Report, 2000) [28].

Similarly, measures of specific health service usage, such as the number of medical staff or technologies, are also classified as intermediate level factors in the production of health. Similar to health behaviour measures, health service use measures are less reliable than measures of upstream factors, and the evidence for use of a particular set of indicators is unconvincing [29, 30]. This is partly due to real differences in health care systems across countries. For example, access to affordable primary health care has been positively associated with an increase in life expectancy and is generally considered more cost effective in producing population health than access to tertiary services and the latest technology [31]. So countries with a greater proportion of primary health care services potentially have more efficient health production.

Data on upstream factors such as education, employment and income are more readily available for the OECD countries. Indicators that describe occupation (as a proxy for working conditions) and the availability and quality of housing are not available. There is evidence to show that omitting these indictors from the final model for analysis could be problematic [12, 32]. Other factors that measure environmental factors in which a population lives, such as air pollution, are also not readily available (and extremely difficult to measure).

Life expectancy at birth was chosen as the output measure for this analysis. These figures are routinely collected and a relatively robust measure for comparison across countries. Quality of life data, such as self-reported health, or a utility measure (such as quality adjusted life years (QALYs)) arguably provide a measure that is more responsive to changes in government policy, especially in the shorter term, and would be more appropriate for this analysis. However these data are not routinely collected, and when they are reported, can be subject to large variations in methodological rigour and interpretation. As quality of life measures across countries become more readily available in the future, such an indicator would be valuable to include in any future analysis.

Methods

Detailed descriptions of DEA, and the economic theory of production and efficiency measurement which underlie it, can be found in a number of sources [5, 33, 34], only a general description is given here. Frontier type analysis has been used almost 200 times in analysis of health care [2], so we do not intend to describe it again, but point the interested reader to the above references.

Efficiency can change over time, and indeed we would suggest the examination of a single cross section of data when estimating production efficiency with regard to health, gives us only a snapshot of what is really going on. Only analysis of a panel of data can show real effects. DEA based Malmquist indices are used to measure this concept of productivity.   The Malmquist productivity index [35, 36], is defined as (with reference to Figure 2, a two input, one output model):

$$MPI = \left[\frac{OE/OG}{OC/OB} \, x \, \frac{OF/OG}{OA/OB} \right]^{0.5} \qquad (1)$$

The index is the geometric mean of two indices. The first takes the production frontier of period 1 as given and measures the distance of the two production points, G and B (representing a country in the two different time periods) from it. The second index is similar except the reference frontier is that of period 2. A score greater than unity indicates productivity progress as a country delivers a unit of output in period 2 using less inputs. In other words, the country in period 2 is more efficient relative to itself in period 1. Similarly, a score less than unity implies productivity regress and constant productivity is signalled by a unit score. The index can be decomposed:

$$MPI = \frac{OE/OG}{OA/OB} \left[\frac{OA}{OC} \, x \, \frac{OF}{OE} \right]^{0.5} \qquad (2)$$

The component outside the brackets is the ratio of technical efficiency in each period and measures efficiency change when moving from period 1 to period 2 (P1 and P2 in Figure 2). It indicates whether the unit gets closer to its production frontier, ie becomes more efficient (with a score greater than unity), or moves further away from the frontier, ie becomes less efficient (with a score of less than unity), or stays the same (with a unit score). The second component of the Malmquist index in equation (2) captures technological change evaluated from both time periods, that is, movements of the actual frontier itself – the technology with reference to which a sample operates. The frontier (technology) can progress (with a score greater than unity), regress (with a score of less than unity), or stay in the same position (with a unit score).

Data and Variables

This analysis predominantly uses OECD health data (2004), which was developed jointly between the OECD secretariat and IRDES (Institut de Recherche et d'Etude en Economie de la Santé), a research institute specialised in health economics and health statistics [37]. The sources and methods of collection details are described elsewhere [38].

As stated above, the choice of input variables for the final model used in the analysis was largely based on a framework of the socioeconomic determinants of health [21]. Ideally, measures for each of the five indicators would be used in the model: education, employment, occupation, income and housing. The level of education is estimated by school expectancy years, which is the expected years of schooling under current conditions, excluding education for children under the age of five. Unemployment rates are a percentage of the total workforce. Gross Domestic Product (GDP) per capita (US$, purchasing power parity (PPP)) is used as a measure of income, and total health expenditure for each country was also included (per capita, US$, PPP). Variables were not available for classification of occupation (which acts as a proxy for working conditions) or housing availability or standards, thus these inputs were omitted.

Life expectancy (years) at birth was the chosen output. Attempts to include infant mortality as a parallel output proved spurious for a number of reasons discussed later. The years of analysis chosen were based on maximising the use of available data. The model was trialled on single year (1995) data. As a demonstration, panel data with two time points (1995 and 2000) was used in the final model. In reality a much longer panel would be most useful. Missing data points were dealt with in one of two ways: the most recent data point before the missing entry was used (no greater than five years prior) or the country was excluded from the analysis. Luxembourg and the Slovak Republic were excluded due to irreconcilable data deficiencies, which left 28 of 30 OECD countries in the final analysis.

Model assumptions and validity

DEA was performed to assess the relative technical efficiency of each country in producing health (life expectancy). An output oriented model was assumed for the analysis. An input oriented model would be inappropriate as the underlying assumption is the desirability to maximise health gains, not hold health gains constant and minimise inputs. When analysing a panel of data, the Malmquist total factor productivity (TFP) index is used to measure productivity change, which in turn is used to determine the productivity change and technical efficiency change. The construction of Malmquist indices requires the calculation under both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions [39] therefore it is of no consequence which option is chosen. However it should be noted for cross sectional analysis the BCC DEA model is appropriate when ratios are being used [40].

Internal validity testing [41] was performed on the results by comparing the rank order of countries technical efficiency (TE) for years 1995 and 2000. A high correlation coefficient would be expected as the output variable (life expectancy) does not show great variation over relatively short time periods such as five years.

As a measure of external validity, the same analysis performed on the OECD dataset was conducted using data, selected from the OECD sub-sample of WHO data [42], from 191 countries which contains alternate sources and methods for collecting total health expenditure per capita (1997 international dollars) [43] and average years of schooling in the adult population (different to the OECD measure of school expectancy). Disability adjusted life expectancy (DALE) was used as the output measure, obtained from the burden of disease study [44]. Unemployment data were sourced from the OECD website [45] and GDP per capita (US$, PPP) was again sourced from the OECD health dataset, 2004 [37]. Panel data and time points available corresponding as closely as possible to those used in the OECD subset were chosen (1993 and 1997), with the assumption that rankings would not change significantly between countries over two years. Spearman rank correlation coefficients were calculated to assess the correlation of the resulting technical efficiency rankings between both datasets.

Results

A summary of the mean and standard deviations of the variables used in both the OECD and WHO models is shown in Table 1. As expected, small increases in the mean are shown for life expectancy (OECD) and DALE (WHO) measures, as well as GDP and total health expenditure (both datasets). A large amount of variation in health expenditure is also shown.

A summary of results listing the technical efficiency (TE) change, technological change and total factor productivity (TFP) change for each country are shown in Table 2. The Malmquist index average or mean is also listed. Results for individual countries can be compared to the performance of other countries, and the group as a whole.

TE change provides a measure of how far each country has moved from the efficient frontier over the time period of interest. The mean value of 0.961 for the OECD dataset suggests that overall, member countries have moved slightly away from the frontier, representing a decrease in technical efficiency. Similarly, the mean technological change value of 0.995 would suggest that that the technology with respect to which individual countries are producing health has declined slightly, that is, the efficiency of the whole sample has remained steady (or declined slightly), and that over this time period absolute output values have decreased. The TFP value of 0.956 may be interpreted as reflecting the sum of movements. Good internal validity was shown by a spearman rank correlation coefficient of 0.85 between TE for years 1995 and 2000.

Results using the WHO dataset move conversely to results for the OECD dataset. Overall, TE has improved (1.041), the efficient frontier has retracted (0.974) and TPF has increased (1.014). Results for TE scores for each time period are listed in Table 3 and Table 4. TE scores lie between zero and one. Countries that have a TE score of one are deemed most efficient at producing health given the input variables, and lie on the efficient frontier.

From table 2 it can be shown that 6 and 8 of the 28 counties in the analysis for 1995 and 2000 respectively were nominated as efficient in the OECD dataset. The countries that have a TE score of one were notably found lower in the rankings of GDP per capita (OECD 1995 data), as shown in Table 3, and spent less on health per capita, as shown in Table 4. Notable exceptions to this trend were Iceland, Japan and Switzerland. Overall, the range of TE scores for countries is narrow (0.940-1) indicating the relatively small difference between outputs and inputs between countries over this short panel. Results of the DEA using the WHO data are also summarised in Table 2 and Table 3. Good correlation between the countries found on the efficient frontier (TE=1) using both datasets is shown.

Discussion

Although not presented here, it is also possible to obtain results of cross-sectional DEA for a particular year. Such results provide great detail for each country of the projected gain in output (health) if inputs were used as efficiently as the countries forming the frontier. A summary of peers, that is, the countries performing most similarly to each other, is also provided. It is tempting to use the results of such an analysis to address policy questions in the same way as others (for example, see [5, 28]. In theory, application of DEA techniques to determine optimal indicators of social policy holds promise. However, these techniques have yet to overcome a number of methodological issues and underlying assumptions that Smith and Street [4] believe make it unsuitable at this time to inform policy makers. Some of there are discussed further here.

DEA is data driven, it assumes little doubt that an identified set of inputs are largely responsible for the production of given outputs, which contrasts with the high level of uncertainty surrounding the “inputs” that produce health. As stated previously, there is scant concurring evidence to support the choice of particular socioeconomic inputs for the production of life expectancy for cross country analysis. A framework of the socioeconomic determinants of health formed the basis of choice of inputs for this analysis, with a focus on macro-level factors, but we are not claiming this is in any way complete.

This approach differs from the approach taken by others in two ways. There may be a problem using a combination of both upstream and midstream (as categorised by the framework used here) socioeconomic factors in the DEA model, as this may produce inaccurate results as it would be expected that upstream effects will incorporate midstream and downstream factors. Thus, the use of both in a model may overestimate the effect of a particular factor, or combination of factors, in producing health. For example, Retzlaff-Roberts [5] used the number of Magnetic Resonance Imager (MRI) units per one million population as a model input “to acknowledge the growth and importance of healthcare technology” in producing health. The problem with this approach is the underlying assumption to the inclusion of this variable in the model: that the availability and use of MRI technology has a significant impact on the output measure(s), namely life expectancy and the infant mortality rate. Perhaps the use of a more proximal output measure in the causal pathway would be appropriate for this case.

Secondly, when deciding on an input or output oriented model for analysis, the question of whether it is relatively more beneficial for a country to pursue enhanced health status or resource and cost-containment has arisen. In reality this question is politically untenable - the public want both (good health outcomes with resource and cost containment). Sound economic theory may help, telling us health production assumes maximisation of health, obviously within a budget constraint.

A number of other methodological issues are also highlighted by this research. DEA assumes that inputs and outputs are isotonic, that is, increased input reduces efficiency, whilst increased output increases efficiency. This is not the case for some variables, for example, the infant mortality rate (as an output), or smoking (as an input). More complex associations, such as a J-shaped association have been found for alcohol consumption and mortality [25]. A number of methods for handling non isotonic data have been proposed, such as to invert the non-isotonic variable, subtract the value of the variable from a large number, or move the variable to the opposing side of the model, but no clear protocol exists [46-48]. In trialling the use of the infant mortality rate as a second output for this model, all three options were used but none produced plausible results.

It has been claimed that solving the linear program model for each of the chosen outputs (life expectancy and infant mortality) produces more detailed results as the number of countries found to be efficient for each output is lower than when the model is solved for the combined outputs. It is yet unclear what this means when applying DEA techniques to health status outputs, if the outputs interact in some way.

The use of panel data has clear advantages over the use of cross-sectional data. Data were limited to five year time periods in this analysis due to missing data. However, as the amount of complete data increases over time, the opportunity to produce more detailed results also increases. Malmquist indices are calculated relative to each time period included, therefore Malmquist index averages differ if data are included for each of the five years of the time period (that is, four annual means are calculated) rather than the first and last years of the time period (one annual mean). This was demonstrated using the WHO dataset when five years of complete data were analysed (1993, 94, 95, 96, 97) and compared to the analysis of the first and last years of the time period only (1993, 97) (data not presented).

The OECD health dataset provides one of the best cross-country sources of comparative data available, however limitations still exist. It is unclear the level of uncertainty surrounding the sources and methods of data collection, missing data often limits analysis, and not all variables of interest are collected routinely. Two of the macro level factors of interest (housing and occupation) were omitted in this analysis as no appropriate measure could be found. Another variable of interest for future work includes a composite measure of country-based environmental status. In addition, variation in the genetic epidemiology of individuals could potentially account for significant differences in health outcomes both within and between countries. As the number of variables and rigour of data collection of the OECD database increases, such measures may be available in the future.

Another limitation in the OECD database (and other cross-country comparisons) at this time is lack of an objective measure of quality of life status, preferably measured at yearly intervals. Such a measure could be used as a second output for DEA purposes, providing a more proximal measure of the impact of social policy change. Life expectancy measured from five years of age, rather than birth, would also be a useful measure. Using a combination of the infant mortality rate and life expectancy at birth for DEA outputs may overestimate the overall mortality.

In addition there are concerns with interpreting the OECD sample as panel data because most of the series are not independent samplings, but rather some form of moving averages. It may be that any comparisons can only be meaningfully undertaken using micro-data, something we believe the OECD are pursuing.

Development of techniques to validate the results of DEA health applications would be beneficial to future work in this area. Good external validity was shown in this analysis when comparing the use of the OECD and WHO datasets. It is assumed that sources and methods of data collection for each dataset were discrete, yet the ranking of results showed high correlation, even though the time period differed by two years, and the overall movements were conflicting.

It is unclear as yet how applicable the use of DEA is to determining the countries most efficiently producing health. While the area of researching production of health using frontier methods is to be encouraged, methods are not yet robust enough to translate into potential policy implications. In their recent paper in *Health Policy* Retzlaff-Roberts et. al. [5] claim that “our results also provide useful policy recommendations”, however we would strongly disagree. The use of this analytical technique is emerging, with a number of questions of how best to use the technology still to be answered. As Smith and Street [4] note, “somewhat arbitrary choices may have an undue bearing on the efficiency judgements for individual organisations”. Currently, the most prudent use may be in hypothesis generation. Following our data analysis, we have attempted to provide a framework for discussion on the strengths and limitations of this technique in the health policy setting. We acknowledge that a number of hurdles still exist before it may be considered a useful policy tool (data quality, availability and comparability; missing variables; agreement on the most indicative social determinants of health; DEA questions such as the “best” number of countries on the frontier, solving for each output separately, variable inversion).

In addition the real advantage of DEA based techniques is the ability to handle a multiple input, multiple output model. If there is only one output used in the model, it is difficult to argue beyond using econometric techniques, with DEA perhaps used more as an additional validity measure. We did undertake a head to head comparison with stochastic frontier analysis (SFA), correlations between the ranking of the OECD results using DEA and SFA techniques were quite good (Spearmans correlation coefficients of between 0.69 and 0.71, $p<0.001$). Given that non-parametric measures do not account for measurement error, and variable distributional assumptions regarding SFA models, these results are not unreasonable.

To summarise, the use of DEA in cross-country comparisons of the technical efficiency of health production is currently limited due to a number of unanswered theoretical questions. After analysing a short panel of OECD data using a framework for the socioeconomic determinants of health, we conclude that policy makers should be aware of the limitations and uncertainty of using such techniques in production of health settings.

Figure 1: Framework of socioeconomic health determinants.

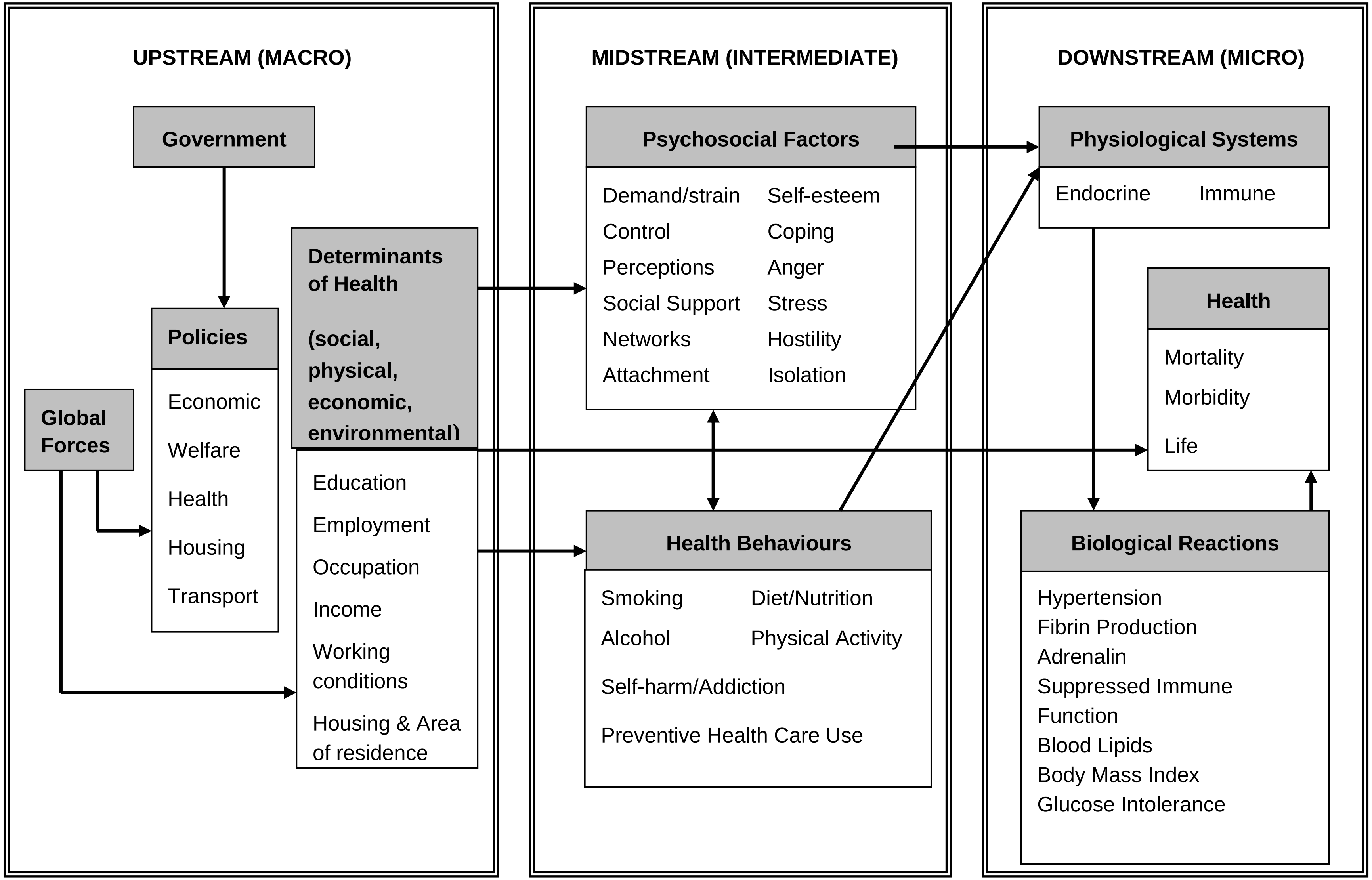

Figure 2: Malmquist Index

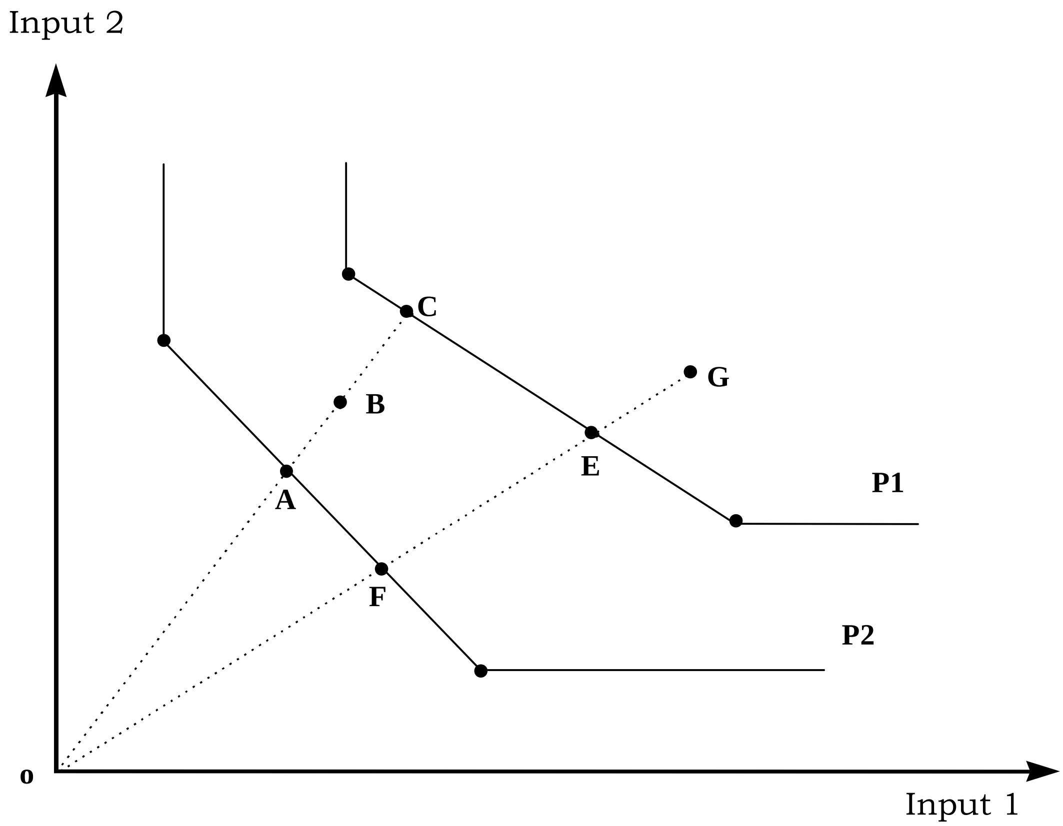

Table 1. Summary of model variables

Variable	Year	Units	Mean	Standard Deviation
OECD Dataset				
life expectancy	1995	years	76.00	2.85
	2000		77.30	2.77
gross domestic product (GDP) per capita	1995	US$, PPP	18,114	6019
	2000		22,833	7566
school expectancy	1995	years	15.15	1.67
	2000		16.74	2.07
total unemployment rate	1995	% labour force	8.22	4.39
	2000		6.46	3.47
total health expenditure per capita	1995	US$, PPP	1503	733
	2000		1923	886
WHO Dataset				
disability adjusted life years (DALE)	1993	years	69.48	3.23
	1997		70.35	3.03
gross domestic product (GDP) per capita	1993	US$, PPP	16,506	5585
	1997		19,905	6479
Schooling (average in adult population)	1993	years	8.78	1.67
	1997		8.98	1.56
total unemployment rate	1993	% labour force	8.69	4.00
	1997		7.59	3.38
total health expenditure per capita	1993	1997 international $	1,377	722
	1997		1,512	765

Table 2. Malmquist index summary of country means

	OECD Dataset 1995-2000			WHO Dataset 1993-1997		
	Technical efficiency (TE) change	technological change	total factor productivity (TFP) change	Technical efficiency (TE) change	technological change	total factor productivity (TFP) change
Australia	0.832	1.048	0.872	1.123	0.982	1.103
Austria	0.903	1.076	0.972	1.011	0.961	0.971
Belgium	0.980	1.036	1.015	0.985	0.985	0.970
Canada	1.037	1.023	1.062	1.115	0.988	1.102
Czech Republic	0.787	1.042	0.820	1.001	0.949	0.949
Denmark	0.954	1.062	1.013	1.291	0.958	1.237
Finland	0.944	0.974	0.920	1.058	1.042	1.102
France	1.054	0.978	1.031	0.926	1.047	0.969
Germany	0.951	1.027	0.977	0.947	0.977	0.925
Greece	0.890	0.969	0.863	0.940	1.036	0.973
Hungary	0.993	0.976	0.969	1.032	0.994	1.026
Iceland	1.126	1.028	1.158	1.113	0.948	1.055
Ireland	1.149	1.004	1.153	1.108	1.010	1.119
Italy	1.084	0.948	1.028	0.891	1.062	0.946
Japan	0.889	1.083	0.963	1.000	0.873	0.873
Korea	0.780	1.022	0.797	1.000	0.985	0.985
Mexico	1.000	0.987	0.987	1.000	0.967	0.967
Netherlands	1.137	1.029	1.171	1.103	0.957	1.055
New Zealand	0.917	1.054	0.967	1.178	0.972	1.145
Norway	0.872	1.092	0.952	1.193	0.953	1.137
Poland	1.046	0.722	0.778	0.848	0.903	0.766
Portugal	0.982	1.063	1.044	0.921	0.985	0.907
Spain	1.001	0.933	0.934	1.039	0.936	0.973
Sweden	0.864	1.039	0.898	1.051	0.966	1.016
Switzerland	0.995	1.045	1.040	1.057	0.940	0.993
Turkey	1.000	0.647	0.647	1.000	0.975	0.975
United Kingdom	0.891	1.040	0.927	1.179	0.995	1.173
United States	0.940	1.074	1.010	1.177	0.945	1.113
mean*	0.961	0.995	0.956	1.041	0.974	1.014

* Malmquist index averages are geometric means

Table 3. Summary of VRS technical efficiency scores for each time point (Countries ranked in order of descending gross domestic product (GDP) per capita)

		OECD Dataset 1995-2000		**WHO Dataset 1993-97**	
	GDP per capita 1995 ($US, PPP)	Technical efficiency (TE) 1995	Technical efficiency (TE) 2000	Technical efficiency (TE) 1993	Technical efficiency (TE) 1997
Turkey	5,471	1	1	1	1
Mexico	6,727	1	1	1	1
Poland	7,557	0.987	0.990	1	1
Hungary	9,021	0.940	0.949	0.960	0.981
Korea	11,451	1	1	1	1
Czech Republic	12,015	0.980	0.984	0.997	1
Greece	13,182	1	1	1	1
Portugal	13,214	0.980	0.987	1	1
Spain	15,720	1	1	1	1
New Zealand	17,163	0.988	0.992	0.936	0.949
Ireland	17,789	0.973	0.955	0.953	0.953
Finland	19,031	0.970	0.970	0.950	0.952
United Kingdom	19,998	0.971	0.966	0.969	0.986
Italy	20,652	0.986	0.985	1	1
Australia	21,079	0.982	0.977	0.967	0.966
France	21,283	0.981	0.973	1	1
Sweden	21,290	0.993	0.982	0.981	0.983
Germany	21,411	0.964	0.964	0.942	0.949
Belgium	21,679	0.967	0.957	0.966	0.965
Netherlands	21,723	0.975	0.984	0.974	0.968
Iceland	22,040	0.981	1	0.964	0.971
Canada	22,292	0.981	0.978	0.965	0.968
Japan	22,396	1	1	1	1
Denmark	22,462	0.946	0.949	0.936	0.930
Austria	22,817	0.962	0.963	0.985	0.993
Norway	23,868	0.977	0.979	0.968	0.991
Switzerland	26,304	0.986	1	0.968	0.972
United States	27,559	0.951	0.951	0.941	0.940

Table 4. Summary of VRS technical efficiency scores for each time point (Countries ranked in order of ascending total health expenditure per capita)

		OECD Dataset 1995-2000		WHO Dataset 1993-97	
	Total health expenditure per capita 1995 ($US, PPP)	Technical efficiency (TE) 1995	Technical efficiency (TE) 2000	Technical efficiency (TE) 1993	Technical efficiency (TE) 1997
Turkey	184	1	1	1	1
Mexico	380	1	1	1	1
Poland	423	0.987	0.990	1	1
Korea	500	1	1	1	1
Hungary	674	0.940	0.949	0.960	0.981
Czech Republic	876	0.980	0.984	0.997	1
Portugal	1,080	0.980	0.987	1	1
Spain	1,195	1	1	1	1
Ireland	1,208	0.973	0.955	0.953	0.953
New Zealand	1,238	0.988	0.992	0.936	0.949
Greece	1,269	1	1	1	1
United Kingdom	1,393	0.971	0.966	0.969	0.986
Finland	1,428	0.970	0.970	0.950	0.952
Italy	1,524	0.986	0.985	1	1
Japan	1,530	1	1	1	1
Sweden	1,733	0.993	0.982	0.981	0.983
Australia	1,737	0.982	0.977	0.967	0.966
Netherlands	1,827	0.975	0.984	0.974	0.968
Denmark	1,843	0.946	0.949	0.936	0.930
Iceland	1,853	0.981	1	0.964	0.971
Austria	1,865	0.962	0.963	0.985	0.993
Belgium	1,882	0.967	0.957	0.966	0.965
Norway	1,892	0.977	0.979	0.968	0.991
France	2,025	0.981	0.973	1	1
Canada	2,044	0.981	0.978	0.965	0.968
Germany	2,263	0.964	0.964	0.942	0.949
Switzerland	2,555	0.986	1	0.968	0.972
United States	3,655	0.951	0.951	0.941	0.940

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