

# UNIVERSITY OF GOTHENBURG **SCHOOL OF BUSINESS, ECONOMICS AND LAW**

# **A Retake on Productivity Growth, Technical Progress and Efficiency Change using Malmquist Productivity Indexes**

*Replicating a Färe, Grosskopf, Norris and Zhang study from 1994*

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## **Abstract**

This thesis follows methods employed by Färe *et al*. (1994) in their influential article 'Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries', published in the *American Economic Review*. The study is conducted using measures of output-oriented gross domestic product, the number of people working and the capital stock for 17 OECD countries from Penn World Tables (PWT), version 8.0, for 2002 to 2011. This retake use the same countries and the same data source as Färe *et al*. (1994) albeit their data was from the PWT, Mark 5 from 1991.

Productivity is defined as a ratio of outputs and inputs and this particular productivity analysis is performed using an output-oriented Malmquist productivity change index, an index that can be decomposed into technological change and efficiency change components. This is done using data envelopment analysis techniques meaning that a technological frontier is constructed using non-parametric linear programming given assumption of the returns to scale characteristics. The frontier is the efficient frontier that all data points are evaluated against using distance functions. In total, 612 linear programming problems need be computed per data set for which the mathematical programming software MATLAB was used. The methods were first tested on PWT data set that Färe *et al*. (1994) used. To yield the expected results, the returns to scale assumption had to be changed from constant returns to scale (CRS) to non-increasing returns to scale (NIRS). This is in contrast to the explicit description from Färe *et al*. (1994) which state CRS as the results clearly reveal that NIRS must have been used.

The same methods and assumptions were then used for the PWT version 8.0 data set. The results differed from those of Färe *et al*. (1994) with regards to which countries that established the frontier while the rate of productivity growth had slowed down. Depending on scale assumption, the determining countries were Ireland, Norway, Sweden and the United States under NIRS or Ireland and Sweden for CRS. Regardless of scale assumption, Sweden was the sole determinant of the frontier for the last year of 2011. Just as the 1994 results by Färe *et al.* (1994), productivity growth was driven by technological improvements rather than efficiency gains. Sweden was notably the worst performing country with respect to technology and the best performer regarding efficiency. Norway was the best performer with regards to overall productivity growth due to good results for both of the subcomponents.

Finally, the same techniques were applied to PWT 8.0 data for the same time period and countries as in the 1994 study and the results were significantly different. Canada, Ireland, Norway and the United States determined the frontier using NIRS meanwhile only Canada and Ireland were on the frontier given CRS. The overall productivity growth was slightly lower at 0.61 instead of 0.7 percent annually. That technological improvements were the main productivity driver, a conclusion by Färe *et al*. (1994), was reversed and Japan went from the best performing country to the fourth. Several countries shifted places and the discrepancies between the results for PWT Mark 5 and PWT 8.0 were wide-spread and vast.

Keywords: Productivity, Data Envelopment Analysis, Efficient Frontiers, Malmquist index, Technical Efficiency, Technological Change, Penn World Tables, OECD countries.

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## **1. Introduction**

<span id="page-5-0"></span>Färe *et al*. (1994) wrote an article on productivity published in *The American Economic Review* in March 1994. Productivity was measured as a geometric mean of Malmquist productivity indexes which enabled a decomposition of productivity growth into changes in technical efficiency and technological shifts over time. The empirical study by Färe *et al.* (1994) covered 17 OECD countries during 1979-1988 based on the Penn World Tables (PWT) Mark 5 (PWT5). Färe *et al.* (1985, p. 2) explained their outset in the following way:

It is our view that the neglect of inefficiency in the modern mainstream literature, the rather disparate development of a heterogeneous fringe literature on efficiency measurement, and the role played by efficiency considerations in a wide range of applied fields, all point to the need for a development of a coherent theory of the producer in the presence of inefficiency. This is our goal.

Productivity is of central importance as Krugman (1997, p. 11) wrote that 'productivity isn't everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker.' According to a recent report from the Boston Consulting Group, Sweden is among the top ten countries in the world in terms of work-force productivity. Although the amount of working hours per Swede has gone down, the living standards have improved which can be attributed to productivity gains. However, as the present situation is comparatively well for Sweden from an international perspective, it is estimated that the Swedish people are at a risk of a slowing productivity growth by 0.4 percentage points. (Alsén *et al*., 2013)

As imperceptible as this decrease might seem, as noticeable could the long-term effects be on a national level. Unless the current situation is remedied, the Swedish population might have to either reduce the yearly vacation time to two weeks, increase the pensionable age by three years or raise taxes by three SEK, *ceteris paribus*, to finance the same welfare as the population currently enjoy. (Alsén *et al*., 2013) The issue of productivity is thus a highly contemporary concern. It is thus interesting to assess the most recent productivity development, from 2002 to 2011 by means of the methods used by Färe *et al*. (1994) to provide a further perspective Sweden's development compared to other OECD nations.

#### **1.1 Purpose**

<span id="page-5-1"></span>As this thesis revolves around a replication and follow-up of a published article within economics and more specifically productivity analysis, the purpose could be described as twofold. First, apply economic models on real-world data in a manner closely resembling that of economic researchers within the area of productivity analysis. Secondly, to contribute to the research area by conducting a similar study based on more recent data.

#### **1.2 Research questions**

<span id="page-5-2"></span>The research questions assume that productivity measuring methods follow Färe *et al.* (1994).

- R1. How can the productivity development for 2002 to 2011 be characterized?
- R2. How does this compare with the findings from 1979 to 1988?
- R3. Given an updated data set, are there any implications for the 1979 to 1988 findings?

## **2. Methodology**

<span id="page-6-0"></span>This paper revolves around a specific way of measuring productivity and further decomposing productivity changes into technical changes and efficiency improvements. As this is a unique feature for the models that will be applied, it can be useful to start broadly and narrow in on particularities and technicalities. First, productivity is briefly discussed as Färe *et al*. (1994) methods are placed in a broader context of productivity measurements. Second, the outputbased Malmquist productivity change index is described by equations and figures. Third, the mathematical representations of the associated linear programming problems are explained. Fourth, the effects of scale assumptions are considered. Fifth, the index is rewritten for constant returns to scale. Sixth, the formulas are rewritten into a form that is congruent with the applied computing software. Seventh and finally, the data selection for the productivity measurements are described. As this chapter is rather technical and specific, hopefully it will be useful by providing the prerequisite understanding needed regarding the methods applied and remain on the specialized language side of Krugman's (1994, p. ix) notion that:

Like any academic field, economics has its fair share of hacks and phonies, who use complicated language to hide the banality of their ideas; it also contains profound thinkers, who use the specialized language of the discipline as an efficiency way to express deep insights.

#### **2.1 Productivity and how it can be measured**

<span id="page-6-1"></span>First off, productivity can be defined as the ratio of outputs to inputs (e. g. Coelli *et al*., 2005; Cooper *et al*., 2007). This means that an increased level of output for a given level of input or conversely a decreased level of input for some level of output or any combination yielding a higher ratio all imply improved productivity. It is a classic economic subject, recall for instance Adam Smith and the pin factory, and it is a contemporary subject of vast importance for our very wellbeing on a societal level as explained in the introduction. Within the specific economic area of productivity analysis, the measures and methods are more sophisticated than the ratio provided above although that is the very kernel of productivity. As given by the output to input ratio one can measure productivity with an output- or input-orientation and a further step would be to analyze the drivers behind productivity improvements.

There are four main means of economic analysis of productivity according to Coelli *et al*.  $(2005)^1$ . Among these, a major sub-categorization can be made between parametric and nonparametric methods. Least-squares econometric production models and stochastic frontiers belong to the former while total factor productivity (TFP) indices, referring to Törnqvist and Fisher, and data envelopment analysis, often DEA, belong to the latter. The models in this report belong to data envelopment analysis which thus is a non-parametric method meaning that it does not rely on statistical methods. Compared with TFP, data envelopment analysis requires fewer inputs as it require input and output quantities where TFP also need input and output prices. Data envelopment analysis is suitable for panel data and does not deal with time series data as TFP does. Regarding the measures that can be produced, data envelopment analysis holds advantages as it can be used to measure for instance technical efficiency which is needed for the application in this report. (Coelli *et al*., 2005)

 1 See page 312 in Coelli *et al*. (2005) for a comprehensive overview and comparison

Data envelopment analysis involves the practice of taking a data set containing inputs and outputs and establishes a frontier that often is referred to as the efficient frontier. A unit of analysis is often denoted as a decision making unit, abbreviated DMU (e.g. Charnes *et al*., 1978).<sup>2</sup> The frontier touches at least one data point and envelops all points, creating a feasible output versus input ratio region. Cooper *et al*. (2007, p. 3) explains this by highlighting that 'the name Data Envelopment Analysis, as used in DEA, comes from the property because in mathematical parlance, such a frontier is said to "envelop" these points.' Instead of statistical habits such as describing data using mean values data points are evaluated against the frontier consisting of the best known possible combinations. Such frontiers are not static as technical change can alter the position of the frontier (Coelli *et al*., 2005)

The method of evaluation is typically through some distance measure. One example could be the distance from the origin of coordinates to the frontier divided by the distance along the same line to some data point. This could then be considered a ratio-based measure of productivity. (Cooper *et al.*, 2007) As for the techniques to actually perform these analyses, data envelopment analysis relies on linear programming techniques to construct nonparametric piecewise surfaces by which data points are evaluated. If a data point is on the frontier it is considered technically efficient whereas any distance to the frontier implies some degree of inefficiency. (Coelli *et al*., 2005) Such measures can be considered in an inputoriented model which either '…aims to minimize inputs while satisfying at least the given output levels' or an output-oriented model that '…attempts to maximize outputs without requiring more of any of the observed input values.' (Cooper *et al*., 2007, p. 41) This essentially means whether one takes distance measures for technical efficiency horizontally or vertically respectively for input- and output-oriented models.

Färe *et al.* (1985) set out to address what they perceived as a prevalent productivity and efficiency measurement neglect towards the possibility that there could be significant inefficiencies within production. Earlier, a notion that producers might conduct their operations inefficiently was traditionally dismissed within neoclassical production theory. Through various optimizations from the producers' point of view, different types of inefficiencies such as technical, behavioral, structural and allocative were dismissed. In 1985, soon to be 30 years ago, the literature regarding inefficiencies within production was described as thin and inhomogeneous. (Färe *et al*., 1985) Upon developing data envelopment analysis methods and applying them in various fields, Färe *et al*. (1994) applied these methods on macro level data to assess productivity growth for OECD countries by use of Malmquist indices of TFP growth. A paper described as 'very influential' by Coelli *et al*. (2005, p. 290). When calculating the Malmquist index, it is significantly easier if all decision making units, in this case nations, would be technically efficient. Being technically inefficient however, means that a productivity change could be either due to changed technical efficiency or an altered underlying technological base. (Coelli *et al*., 2005). This is just what this paper will do. It will assess productivity, thus the ratio of outputs to inputs, while estimating the subcomponents of productivity change namely technological and efficiency changes.

 2 This notation is not used throughout this report; the remark was rather made for general orientation within data envelopment analysis. In the case of this report, countries should be considered as decision making units.

#### **2.2 The output-based Malmquist index of productivity change**

<span id="page-8-0"></span>The index used in this report, following Färe *et al*. (1994), is referred to as an output-based Malmquist index of productivity change. The Malmquist index of productivity change is in itself a geometric mean of two Malmquist indices which are denoted CCD indices, referring to Caves, Christensen and Diewert. Caves *et al*. (1982) had developed a method for productivity measurement using discrete index numbers rather than a measure based on continuous time for which they used Malmquist indices. For productivity indexes there are two main approaches. Either, the maximum output given a level of input or a minimum level of input given a level of output. These are denoted output-oriented and input-oriented measurements respectively. (Caves *et al*., 1982) As mentioned, this report follows Färe *et al*. (1994) in their output-orientation. This means that the benchmark of productivity for any data point will be its relative position to the maximum possible output given the level of input. To characterize the maximum, thus best practise, level of output a frontier is established, see figure 1 below for such frontiers denoted by  $S^t$  and  $S^{t+1}$ . These are to be interpreted as the maximum possible output level, y-values, given the input level, x-values, for time periods t and t+1 in that order.



**Figure 1: A graphical interpretation of technological frontiers and the calculation of theta**

<span id="page-8-1"></span>The frontier can be interpreted as the production technology for a given point in time, which can be written such as that  $S^t = \{(x^t, y^t): x^t \text{ can produce } y^t\}$  when  $t = 1,...,T$  denote time period and x and y denote inputs and outputs respectively. To measure productivity, distance functions are utilized where theta  $(\theta)$  is of integral importance. Theta is a measurement of technical efficiency as it measures the output at a given input level compared to what is technically possible given the underlying production technology described by the frontier. Figure 1 above visually describe how theta can be computed as the ratio of the distances through straight lines from the horizontal axis at  $x^t$  to the output value  $y^t$ , marked as a, and the horizontal axis at  $x^t$  to the output at the frontier marked b. Theta is thus a divided by b. (Färe *et al*., 1994)

This implies that theta assume values that are less or equal to one. If theta is equal to one, it infers that production is fully technically efficient whereas lower values imply inefficiencies. As could be seen in [Figure 1](#page-8-1) above,  $x^t$  is not bound by  $S^t$  for other time periods than at time t. The corresponding computation of theta at  $x^{t+1}$  and  $y^{t+1}$  for  $S^t$  would result in a theta value of exceeding one. This is allowed as it means that there has been technological progress which allow for higher levels of output at the same levels of input. Conversely, if the values for  $x<sup>t</sup>$ and y<sup>t</sup> were used to compute theta against  $S^{t+1}$ , the value of theta would be smaller than for  $S^t$ if there had been technological progress.

Mathematically, distance functions are characterized by Färe *et al*. (1994) as by equations 1 and 2 below respectively, calculating theta for  $x^t$  and  $y^t$  for  $S^t$  as well as  $x^{t+1}$  and  $y^{t+1}$  for  $S^t$ . Note that equation 2 is a mixed period distance function. Together, these two distance functions are the constituents of the CCD Malmquist productivity index  $M<sup>t</sup>$  as expressed by equation 3.

(1) 
$$
D_0^t(x^t, y^t) = \inf \left\{ \theta : \left( x^t, \frac{y^t}{\theta} \right) \in S^t \right\}
$$

(2) 
$$
D_0^t(x^{t+1}, y^{t+1}) = \inf \left\{ \theta : \left( x^{t+1}, \frac{y^{t+1}}{\theta} \right) \in S^t \right\}
$$
  

$$
M^t = \frac{D_0^t(x^{t+1}, y^{t+1})}{\theta}
$$

(3) 
$$
M_{CCD}^t = \frac{D_0(x^t, y^t)}{D_0^t(x^t, y^t)}
$$

Similar to equation 1 and 2 above, the distance functions needed to compute the CCD Malmquist productivity index at t+1,  $M^{t+1}$  describe the  $x^{t+1}$  and  $y^{t+1}$  distance to  $S^{t+1}$  as well the  $x^t$  and  $y^t$  compared to  $S^{t+1}$ . The ratio of these two distance functions, denoted by equation 4 and 5 respectively, constitute the CCD index described by equation 6.

(4) 
$$
D_0^{t+1}(x^{t+1}, y^{t+1}) = \inf \left\{ \theta : \left( x^{t+1}, \frac{y^{t+1}}{\theta} \right) \in S^{t+1} \right\}
$$
  
\n(5)  $D_0^{t+1}(x^t, y^t) = \inf \left\{ \theta : \left( x^t, \frac{y^t}{\theta} \right) \in S^{t+1} \right\}$ 

(6) 
$$
M_{CCD}^{t+1} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}
$$

The constituents of the Malmquist index of productivity change are now explained as it is the geometric mean of the product of equation 3 and 6 as presented by equation 7 below. This can then be rewritten as equation 8 before being decomposed into efficiency change and technical change as described by equations 9 and 10 below. For a further explanation of this decomposition see Coelli *et al*. (2005, p. 70-72). Note that this is a central property for the analysis put forth by Färe *et al*. (1994), this is what allows for the mutually exclusive and collectively exhaustive measures of changes in technical efficiency, catch-up, and technological shifts over time.

(7) 
$$
M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left[ \left( \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \right) \left( \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)} \right) \right]^{1/2}
$$

$$
(8) \ M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \left[ \left( \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \right) \left( \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right) \right]^{1/2}
$$

(9) 
$$
Efficiency change = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}
$$

(10) 
$$
Technical \ change = \left[ \left( \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \right) \left( \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right) \right]^{1/2}
$$

#### **2.3 Mathematical representation for linear optimization**

<span id="page-10-0"></span>As the previous section contained the models to be used, this section first describe the mathematical foundation for data envelopment analysis as presented by Färe *et al*. (1994), with slightly altered notations, before explaining how the mathematical expressions have been transformed into a linear programming problem. Data envelopment analysis is modelled through a frontier envelopment of data points. The data set is characterized by  $n = 1,...,N$ inputs producing  $m = 1,...,M$  outputs for each time period  $t = 1,...,T$  which will be used throughout this section. For this productivity purpose, the frontier is constructed as a technological frontier  $S^t$ , determined by three main restrictions where x and y denote input and output values respectively as stated by equation 10.

(11) 
$$
S^{t} = \begin{Bmatrix} (x^{t}, y^{t}): \\ y_{m}^{t} \leq \sum_{k=1}^{K} \lambda^{k,t} y_{m}^{k,t} & m = 1, ..., M \\ \sum_{k=1}^{K} \lambda^{k,t} x_{n}^{k,t} \leq x_{n}^{t} & n = 1, ..., N \\ 0 \leq \lambda^{k,t} & k = 1, ..., K \end{Bmatrix}
$$

Lambda  $(\lambda)$  is an intensity variable which reflects the returns to scale assumptions made. Equation 11 implies constant returns to scale (CRS). However, the presumed returns of scale can, quite easily, be altered to assume non-increasing returns to scale (NIRS) or variable returns to scale (VRS). This is accomplished by adding one of the following equations 12 or 13 as a fourth restriction to those presented by equation 11 above:

(12) 
$$
\sum_{k=1}^{K} \lambda^{k,t} \le 1 \quad (NIRS)
$$
  
(13) 
$$
\sum_{k=1}^{K} \lambda^{k,t} = 1 \quad (VRS)
$$

Figure 2 below provides an illustration of how the technological frontier  $S<sup>t</sup>$  varies with returns to scale assumptions. The CRS frontier has its origin at the point of the origin of coordinates and allows no data points to the left. An intuitive interpretation of this frontier is that it is determined by a point which allows for a straight line from the origin of coordinates to envelop all other data points. This is an equivalent to being determined by the data point with the largest tangential angle from the origin of coordinates. As can be seen, the CRS frontier coincides with the NIRS frontier until they reach data point A vertically. The NIRS is estimated differently as the sum of the intensity variables, lambdas, is not allowed to assume values greater than one. Visually, this means that the NIRS frontier will not exceed the maximum in-sample y-value. It does however, just as the CRS frontier, set out from the origin of coordinates. The VRS frontier is the frontier that most closely envelopes its data points. It is established by straight lines through the outermost data points within the sample. As can be seen, neither the CRS nor the NIRS use the value B to construct the frontier as the VRS do.



**Figure 2: Frontier construction for different return to scale assumptions**

<span id="page-11-0"></span>To establish these frontiers and estimating distance functions, linear programming techniques are used. For the Malmquist index under CRS, four linear programming problems needs to be solved for each country and year in the sample. This require  $612<sup>3</sup>$  linear programming problems to be solved as there are 17 countries and nine years for which mixed period distance functions can be computed. If the frontier instead would be constructed based on VRS, it require two additional linear programming problems which then results in the 918 linear programming problems that Färe *et al*. (1994) calculated. These linear programming problems will now be described after a brief discussion regarding the choice of scale returns for the linear programming.

**THE 1888**<br><sup>3</sup> The number of linear programming problems that needs to be calculated is the product of the number of countries, the number of years minus one and the amount of linear programming problems that are needed. In the case of 612, it is the product of 17 countries, nine years and four linear programming problems. 918 are then computed using six linear programming problems instead of four.

Regarding returns to scale assumptions, Färe *et al*. (1994, p. 74) state that '…we choose to calculate the Malmquist productivity change index relative to the constant-returns-to-scale technology'. However, it is also mentioned while discussing CRS that 'in our empirical work, that maximum is the "best practice" or highest productivity observed in our sample of countries…' (Färe *et al*., 1994, p. 69). This is a relatively dubious description, but it is clear from the results put forth by Färe *et al*. (1994) that they used NIRS frontiers for their CRS estimations as will be explained later in section 3.1. The measure of technical efficiency used to compute CCD indexes are determined by theta, which is the ratio of the vertical distance from a data point from the horizontal axis and the corresponding vertical distance to the frontier. For the present time period t, this means that the maximum value is one which occurs when the frontier is established by that data point. However, during mixed period computation, theta can exhibit values exceeding one if there has been technological progress and the frontier has shifted.

It is time to review the linear programming problems that will be used to retrieve the values of theta that are used to compute CCD indexes and thus in turn the Malmquist index. All computations needs to be conducted for k'=1,…,K countries. Following Färe *et al*. (1994), the first and second linear problem are equations 14 and 15 respectively corresponding to equations 1 and 2 in that given order:

(14) 
$$
(D_0^t(x^{k',t}, y^{k',t}))^{-1} = max\theta^{k'} \text{ subject to}
$$
\n
$$
\begin{cases}\n\theta^{k'} y_m^{k',t} \le \sum_{k=1}^K \lambda^{k,t} y_m^{k,t} & m = 1, ..., M \\
\sum_{k=1}^K \lambda^{k,t} x_n^{k,t} \le x_n^{k',t} & n = 1, ..., N \\
0 \le \lambda^{k,t} & k = 1, ..., K \\
\sum_{k=1}^K \lambda^{k,t} \le 1 & (NIRS)\n\end{cases}
$$

(15) 
$$
(D_0^{t+1}(x^{k',t+1}, y^{k',t+1}))^{-1} = max\theta^{k'} \text{ subject to}
$$

$$
\begin{cases} \theta^{k\prime} y_m^{k',t+1} \leq \sum_{k=1}^K \lambda^{k,t+1} y_m^{k,t+1} & m = 1, ..., M \\ \sum_{k=1}^K \lambda^{k,t+1} x_n^{k,t+1} \leq x_n^{k',t+1} & n = 1, ..., N \\ 0 \leq \lambda^{k,t+1} & k = 1, ..., K \\ \sum_{k=1}^K \lambda^{k,t+1} \leq 1 & (NIRS) \end{cases}
$$

Then, to compute the distance function for mixed periods, the linear programming setup needs information from two time periods. Equations 16 and 17 below explain the computations that are conducted for the linear programming problems three and four, which correspond to equations 3 and 4 presented earlier in that order:

(16) 
$$
(D_0^t(x^{k',t+1}, y^{k',t+1}))^{-1} = max\theta^{k'} \text{ subject to}
$$
\n
$$
\begin{cases}\n\theta^{k'} y_m^{k',t+1} \le \sum_{k=1}^K \lambda^{k,t} y_m^{k,t} & m = 1, ..., M \\
\sum_{k=1}^K \lambda^{k,t} x_n^{k,t} \le x_n^{k',t+1} & n = 1, ..., N \\
0 \le \lambda^{k,t} & k = 1, ..., K \\
\sum_{k=1}^K \lambda^{k,t} \le 1 & (NIRS)\n\end{cases}
$$

$$
(17) \quad (D_0^{t+1}(x^{k',t}, y^{k',t}))^{-1} = max\theta^{k'} \text{ subject to}
$$
\n
$$
\begin{cases}\n\theta^{k'} y_m^{k',t} \le \sum_{k=1}^K \lambda^{k,t+1} y_m^{k,t+1} & m = 1, ..., M \\
\sum_{k=1}^K \lambda^{k,t+1} x_n^{k,t+1} \le x_n^{k',t} & n = 1, ..., N \\
0 \le \lambda^{k,t+1} & k = 1, ..., K \\
\sum_{k=1}^K \lambda^{k,t+1} \le 1 & (NIRS)\n\end{cases}
$$

As can be seen, equations 16 and 17 above use t and t+1 opposite to each other. Equation 16, utilize the frontier established at t to evaluate the t+1 position whereas equation 17 use t positions which are evaluated against the t+1 frontier. Before equations 14 to 17 are used to line up linear programming problems used to reach the results in chapter 3, the effects of scale assumptions are discussed in section 2.4 before a rewriting of the indexes CRS are presented in section 2.5 to facilitate further understanding.

#### **2.4 How scale assumption affects the productivity measure**

<span id="page-13-0"></span>At this point, it is important to understand how scale assumptions impact the results that the presented methodology yields. Figure 3 below visualize why CRS and NIRS yield different results. First off, the vertical distance between data points B and C is the same regardless if the CRS or NIRS assumption is used. This is true for all data points enveloped by the triangle from the origin of coordinates to the x and y-coordinated for the CRS frontier data point with the largest y-value. However, to the right of this 'CRS equals NIRS'-triangle, the distance functions will yield lower values for theta as specified by the equations above and figure 2.



**Figure 3: Difference between CRS and NIRS thetas depending on horizontal position**

<span id="page-14-0"></span>It should be mentioned that this is a characteristic that is specific for output-based measures and NIRS, as Coelli *et al*. (2005) emphasizes that input- and output-based measures are equivalent under a CRS assumption. In figure 3 above, this could be understood in terms of triangles using the CRS frontier as the hypotenuse whereas the input or output inefficiency distances to the frontier determine the catheti. As the catheti are at right angles with the frontier the catheti are of equal length. This is not the case for the NIRS part as for point D. The horizontal distance to the CRS frontier is longer than the vertical distance to the NIRS frontier. For an output-based approach this discussion can be readily summarized such as that a NIRS assumption essentially returns a higher rate of efficiency than a CRS assumption.

As CRS and NIRS differ for certain regions, it also affects the ability of a Malmquist productivity change index to yield results coherent with the fundamental output to input ratio measure of productivity<sup>4</sup>. The geometric mean the two Malmquist indexes presented by equation 7 have flaws for non-CRS frontiers. This have been shown before, notably by Grifell-Tatjé and Lovell (1995, p. 175) stating that '… the mere presence of increasing or decreasing returns can cause each of the three productivity indexes to mis-measure actual productivity change.<sup>5</sup> In order to understand why, see figure 4 below on the following page.

According to the fundamental definition of productivity, productivity measures for the points marked for time t and t+1 would be 1.6 and 1.25 respectively. Clearly, the ratio at the time t is higher than that of t+1, almost 30 percent higher. Consider a case when the NIRS frontier remains for both time periods. The distance functions specified by 1, 2, 4 and 5 will thus all be equal to one as both t and t+1 are at the frontier during both periods. In turn, the Malmquist CCD indexes by equations 3 and 6 will be one and subsequently the geometric mean of these, the Malmquist productivity change index as specified by equation 7, will also be equal to one.

1

<sup>&</sup>lt;sup>4</sup> Thanks to Hans Bjurek for suggesting this example

 $<sup>5</sup>$  The three productivity indexes refer to equations 3, 6 and 7 in this report respectively.</sup>

Thus, it is seen that the Malmquist productivity change index is unable to accurately reflect changes in productivity for non-CRS frontiers. It has thus become biased using a NIRS frontier. To see that this is not the case for CRS, it can be shown that equations 1, 2, 4 and 5 would yield theta values of 1, 0.7813, 0.7813 and 1 respectively.<sup>6</sup> These theta values lead to both Malmquist CCD indexes being 0.7813, as specified by equations 3 and 6, while the geometric mean of the product of these also becomes 0.7813 according to equation 7. The Malmquist productivity change index thus identifies decreased productivity using a CRS frontier as opposed to a non-CRS frontier as this example has shown. To address this bias, Grifell-Tatjé and Lovell (1995) suggests either the introduction of a new productivity index or scaling the index to account for non-CRS. For an example of an index that remedies the returns to scale bias, see the Malmquist total factor productivity index put forth by Bjurek (1996).



**Figure 4: Non-CRS frontiers affect the used Malmquist productivity change index**

<span id="page-15-0"></span>Further, as the Malmquist productivity change index as specified by equation 7 result in biased productivity measures, choosing VRS instead result in ever greater issues<sup>7</sup>. Figure 5 below provide an illustration of how this can occur. Notice how a point can move outside the feasible region from a previous time period if the input value contracts enough, which imply a leftward horizontal movement. If this occurs, the mixed period distance functions specified by equation 2 cannot be computed. The reason for this is trivial as there simply is no frontier from time period t that is either below or above the data point at time t+1. Thus, as NIRS result in biased productivity measures, VRS can result in an absence of solutions to the distance functions. This problem holds for input-oriented indexes as well but in that case the issues would occur given a significant enough increase in output. That would lead to a situation where a frontier could not be reached by moving leftward nor rightward in the diagram from the point at time t+1.

**<sup>.</sup>**  ${}^6D_0^t(x^t, y^t) = 1$   $D_0^t(x^{t+1}, y^{t+1}) = 0.78125$   $D_0^{t+1}(x^{t+1}, y^{t+1}) = 0.78125$   $D_0^{t+1}(x^t, y^t)$ <br>  ${}^7$  Thanks to Hans Bjurek for suggesting this example



**Figure 5: Why VRS frontiers could result in non-computable distance functions**

#### <span id="page-16-1"></span>**2.5 Rewriting distance functions and indexes using slopes for CRS**

<span id="page-16-0"></span>A CRS frontier characterizes a constant ratio of outputs to inputs and all data points can be reviewed through a productivity measure of their ratio of output to input. See Appendix I for MATLAB code when using the method described in this section. The point marked DMU is used to illustrate this. First, consider the calculation of theta from the distance function specified by equation 1. In figure 6, the equation calculate the vertical distance from the horizontal axis of DMU,  $y^{DMU}$ , at  $x^{DMU}$  before dividing this distance with the corresponding distance for y<sup>CRS</sup> at  $x^{DMU}$ . In this case theta would be 0.5 at  $x^{DMU}$  as  $y^{CRS}$  and  $y^{DMU}$  are 8 and 4 respectively. This ratio of 0.5 is equal to the ratio of the slope of the CRS-frontier divided by the slope of a line from the origin of coordinates through the point DMU.



<span id="page-16-2"></span>**Figure 6: Using slopes to calculate theta under CRS**

Every data point enveloped by a CRS frontier can be evaluated using a ratio of slopes. It then turns out that the Malmquist index of productivity change as specified in equation 7 can be calculated without estimating a frontier. In order to show this, the distance functions as well as the indexes used will be rewritten. For this purpose, figure 7 below provides notations that will be used subsequently throughout the rewriting process where slopes from the origin of coordinates for the data points are marked by the dotted lines.



**Figure 7: Notations used when rewriting indexes for CRS**

<span id="page-17-0"></span>Equations 18, 19, 21 and 22 show how the distance functions are rewritten while equations 20 and 23 display how the CRS frontier is eliminated as CCD indexes are formed. Then, the rewriting of the Malmquist productivity change index in equation 24 is computed without estimating a frontier. It is the productivity ratio for time period two multiplied with the inverse of the corresponding productivity ratio for the previous time period one.

(18) 
$$
D_0^t(x^t, y^t) = \frac{\frac{y_1}{x_1}}{\frac{y_{CRS_1}}{x_{CRS_1}}} = \frac{y_1 x_{CRS_1}}{x_1 y_{CRS_1}}
$$

(19) 
$$
D_0^t(x^{t+1}, y^{t+1}) = \frac{\frac{y_2}{x_2}}{\frac{y_{CRS_1}}{x_{CRS_1}}} = \frac{y_2 x_{CRS_1}}{x_2 y_{CRS_1}}
$$

(20) 
$$
M_{CCD}^t = \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} = \frac{\frac{y_2 x_{CRS_1}}{x_2 y_{CRS_1}}}{\frac{y_1 x_{CRS_1}}{x_1 y_{CRS_1}}} = \frac{\frac{y_2}{x_2}}{\frac{y_1}{x_1}} = \frac{y_2}{x_2} \left(\frac{y_1}{x_1}\right)^{-1}
$$

(21) 
$$
D_0^{t+1}(x^{t+1}, y^{t+1}) = \frac{\frac{y_2}{x_2}}{\frac{y_{CRS_2}}{x_{CRS_2}}} = \frac{y_2 x_{CRS_2}}{x_2 y_{CRS_2}}
$$

(22) 
$$
D_0^{t+1}(x^t, y^t) = \frac{\frac{y_1}{x_1}}{\frac{y_{CRS_2}}{x_{CRS_2}}} = \frac{y_1 x_{CRS_2}}{x_1 y_{CRS_2}}
$$

(23) 
$$
M_{CCD}^{t+1} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)} = \frac{\frac{y_2 x_{CRS_2}}{x_2 y_{CRS_2}}}{\frac{y_1 x_{CRS_2}}{x_1 y_{CRS_2}}} = \frac{\frac{y_2}{x_2}}{\frac{y_1}{x_1}} = \frac{y_2}{x_2} \left(\frac{y_1}{x_1}\right)^{-1}
$$

(24) 
$$
M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left( \left( \frac{y_2}{x_2} \left( \frac{y_1}{x_1} \right)^{-1} \right) \left( \frac{y_2}{x_2} \left( \frac{y_1}{x_1} \right)^{-1} \right) \right)^{1/2} = \frac{y_2}{x_2} \left( \frac{y_1}{x_1} \right)^{-1}
$$

 $\ddotsc$ 

(25) 
$$
Efficiency change = \frac{\frac{y_2 x_{CRS_2}}{x_2 y_{CRS_2}}}{\frac{y_1 x_{CRS_1}}{x_1 y_{CRS_1}}} = \left(\frac{y_2}{x_2} \left(\frac{y_1}{x_1}\right)^{-1}\right) \left(\frac{y_{CRS_1}}{x_{CRS_1}} \left(\frac{y_{CRS_2}}{x_{CRS_2}}\right)^{-1}\right)
$$

(26) Technical change 
$$
=\left[\left(\frac{\frac{y_2x_{CRS_1}}{x_2y_{CRS_1}}}{\frac{y_2x_{CRS_2}}{x_2y_{CRS_2}}}\right)\left(\frac{\frac{y_1x_{CRS_1}}{x_1y_{CRS_1}}}{\frac{y_1x_{CRS_2}}{x_1y_{CRS_2}}}\right)\right]^{1/2} = \frac{\frac{x_{CRS_1}}{y_{CRS_1}}}{\frac{x_{CRS_2}}{y_{CRS_2}}} = \frac{y_{CRS_2}}{x_{CRS_2}}\left(\frac{y_{CRS_1}}{x_{CRS_1}}\right)^{-1}
$$

Efficiency change and technical change are also rewritten in equations 25 and 26 below. The first component of efficiency change is the overall Malmquist productivity change index and the second is the inverse of the technical change component. Efficiency change depend on both frontiers as well as both data points from the time periods t and t+1. Technical change on the other hand is only concerned with the slope of the CRS frontier. Written in this form, it could readily be interpreted as the productivity at the CRS frontier according to the essential productivity definition for time t+1 multiplied with the inverse of the same measure at t. Now, the linear programming problems solved to yield the NIRS results in chapter 3 follow.

#### **2.6 Formulating and computing the linear programming problems**

<span id="page-18-0"></span>To be able to compute the linear programming problems defined by equations 14 to 17 different techniques could be applied. For this report, MATLAB 7.12.0 (R2011a) have been used for programming and Microsoft Excel 2010 for iterative testing and visualization purposes. The MATLAB code used is available in Appendix II. MATLAB uses the function *linprog<sup>8</sup>* which is explained by equation 27 below.

(27) 
$$
\int_{x}^{x} \frac{1}{x} \operatorname{supp} \int_{x}^{T} \operatorname{supp} \int_{x}^{x} dx \leq b
$$
  
 
$$
\int_{x}^{x} A \cdot x \leq b
$$

A is a matrix containing scalar weights for each row of a linear optimization problem. This matrix thus specifies the linear inequality constrains. The x denotes a vector with the unknowns to be determined by the linear optimization whereas b is a vector containing scalars denoting the right hand side of the equations characterizing the linear problem set. A and b are

 8 See http://www.mathworks.se/help/optim/ug/linprog.html for further information about *linprog*

used for inequality entries and Aeq and beq are used for equality constraints. This is not the form specified by Färe *et al*. (1994) whereby an explanation of how the linear programming problems have been rewritten to fit MATLAB notations follows. The rewriting is essentially the same for all distance functions whereby only the first linear programming problem is addressed here. Equation 14 is rewritten into equation 28 before the A matrix as well as the x and b vectors are specified by equation 29, 30 and 31 in that given order.

$$
(28) (D_0^t(x^{k',t}, y^{k',t}))^{-1} = max\theta^{k'} \text{ is rewritten as}
$$
\n
$$
\begin{cases}\n\theta^{k'} y_m^{k',t} - \sum_{k=1}^K \lambda^{k,t} y_m^{k,t} \le 0 & m = 1, ..., M \\
\sum_{k=1}^K \lambda^{k,t} x_n^{k,t} \le x_n^{k',t} & n = 1, ..., N \\
-\lambda^{k,t} \le 0 & k = 1, ..., K \\
\sum_{k=1}^K \lambda^{k,t} \le 1 & (NIRS)\n\end{cases}
$$
\n
$$
(29) \quad A = \begin{pmatrix}\na_{1,1} & \cdots & a_{1,K+1} \\
a_{1,1} & \cdots & a_{1,K+1} \\
a_{1,1} & \cdots & a_{K+3,K+1}\n\end{pmatrix}
$$
\n
$$
a_1 = \begin{bmatrix}\ny_m^{k',t} & -y_m^{1,t} & -y_m^{2,t} & \cdots & -y_m^{K-1,t} & -y_m^{K,t}\n\end{bmatrix}
$$
\n
$$
a_2 = \begin{bmatrix}\n0 & x_n^{1,t} & x_n^{2,t} & \cdots & x_n^{K-1,t} & x_n^{K,t}\n\end{bmatrix}
$$
\n
$$
a_3 = \begin{bmatrix}\n0 & -1 & 0 & 0 & \cdots & 0 & 0\n\end{bmatrix}
$$
\n
$$
a_k = \begin{bmatrix}\n0 & 0 & -1 & 0 & \cdots & 0 & 0\n\end{bmatrix}
$$
\n
$$
a_{K+1} = \begin{bmatrix}\n0 & 0 & 0 & \cdots & 0 & -1 & 0 & 0\n\end{bmatrix}
$$
\n
$$
a_{K+2} = \begin{bmatrix}\n0 & 0 & 0 & \cdots & 0 & 0 & -1 & 0\n\end{bmatrix}
$$
\n
$$
a_{K+3} = \begin{bmatrix}\na_{K+4} & \lambda^{2,t} & \cdots & \lambda^{K-1,t} & \lambda^{K,t}\n\end{bmatrix}
$$
\n
$$
(30) \quad x = \begin{bmatrix}\n0^{k'} & \lambda^{1,t} & \lambda^{2,t} & \cdots & 0 & 1\n\end{bmatrix}
$$
\n
$$
b = \begin{bmatrix}\n0 & x_n^{k',t} & 0 & \cd
$$

There is one row in the A matrix per restriction which result in 20 rows given 17 countries, denoted by K. The number of columns is determined by the number of unknowns to be computed, which in this case are 18 as it is theta plus 17 lambdas. From this, the A matrix is multiplied from the left with the x vector consisting of one row and 18 row entries for the unknowns. This multiplication assigns the weighs for the unknowns that constitute the left side of the inequality equations that the linear programming needs to solve based on the vector b consisting of one row and 20 entries. The first row in A,  $a<sub>1</sub>$ , correspond to the first constraint in equation 28 just as the second row,  $a_2$ , correspond to the second constraint in equation 28. This is displayed by equations 32 and 33 below which exemplifies the vector cross products that determine the left hand side conditions. Rows from  $a_3$  to  $a_{K+1}$  correspond to the third restriction as the 17 rows state that each individual lambda needs to be greater or equal to zero, as the negative lambdas need to be less or equal to zero. This is exemplified by equation 34 below. The final row, equation 35 below, is determined by the returns of scale assumption which in this case is NIRS. Equation 28 has two non-zero right hand side entries which can be seen by the corresponding constituents of the right hand side vector b.

(32) 
$$
a_1 \times x = [y_m^{k',t} \theta^{k'} - y_m^{1,t} \lambda^{1,t} -y_m^{2,t} \lambda^{2,t} \cdots \cdots -y_m^{K-1,t} \lambda^{K-1,t} -y_m^{K,t} \lambda^{K,t}]
$$
  
\n(33)  $a_2 \times x = [0 \quad x_n^{1,t} \lambda^{1,t} \quad x_n^{2,t} \lambda^{2,t} \cdots \cdots \quad x_n^{K-1,t} \lambda^{K-1,t} \quad x_n^{K,t} \lambda^{K,t}]$   
\n(34)  $a_3 \times x = [0 \quad -\lambda^{1,t} \quad 0 \quad \cdots \quad 0 \quad 0]$   
\n $a_4 \times x = [0 \quad 0 \quad -\lambda^{2,t} \quad \cdots \quad 0 \quad 0]$   
\n $a_5 \times x = [0 \quad 0 \quad 0 \quad 0 \quad \cdots \quad -\lambda^{K-2,t} \quad 0 \quad 0]$   
\n $a_{K+1} \times x = [0 \quad 0 \quad 0 \quad 0 \quad \cdots \quad 0 \quad -\lambda^{K-1,t} \quad 0]$   
\n $a_{K+2} \times x = [0 \quad 0 \quad 0 \quad 0 \quad \cdots \quad 0 \quad 0 \quad -\lambda^{K-1,t} \quad 0]$   
\n(35)  $a_{K+3} \times x = [0 \quad -\lambda^{1,t} \quad -\lambda^{2,t} \quad -\lambda^{3,t} \quad \cdots \quad \cdots \quad -\lambda^{K-2,t} \quad -\lambda^{K-1,t} \quad -\lambda^{K,t}]$   
\n(36)  $f = [-1 \quad 0 \quad 0 \quad \cdots \quad 0 \quad 0]$ 

The equations 32 to 35 above exemplify and characterize the making of the linear optimizations left hand side. In order to solve the linear programming problems with respect to the right hand side characterized by the b-vector one further condition must be set. To change the returns on scale assumption to CRS the row  $a_{K+3}$  as well as the 20<sup>th</sup> entry in the b vector should be removed. If instead VRS is to be applied, the inequality sign between row  $a_{K+3}$  and the 20<sup>th</sup> entry in the b vector should be changed to an equality, as explained by equation 13. Equation 14 which portray the distance function as specified by Färe *et al*. (1994) state that theta is to be maximized. However, MATLAB's *linprog* syntax minimizes with respect to the function f. It is a vector of one row with 18 entries, K plus one, as it assigns scalar weights for the x vector. To produce the desired output from the linear programming, minus theta is minimized. This is achieved by the vector f as specified by equation 36 above. Theta, as illustrated in figure 1, is attained through taking the inverse of the theta that the MATLAB *linprog* computes. This concludes the description of mathematical representations and linear programming. Thus, it is time to review the data selection.

#### **2.7 Data selection for inputs and outputs**

<span id="page-21-0"></span>PWT, version 5, is described as following by Summers and Heston (1991, p. 1): 'its unique feature is that its expenditure entries are denominated in a common set of prices in a common currency so that *real* international quantity comparisons can be made both between countries and over time.' This is a work in progress as the data set have been updated several times since. The most recent version of the PWT is 8.0 (PWT8) provided by Feenstra *et al*. (2013b), for which Feenstra *et al.* (2013a) has provided a user guide. Inklaar and Timmer (2013) elaborate further specifically regarding capital and labor for the interested reader.

As the model used for the linear programming is one input and one output there are two measures that needs be obtained namely output per worker and capital per worker. Unless directly provided, a measure of output needs to accompany capital and worker measures. Regarding data and measurement issues, Coelli *et al.* (2005) describe labor and capital as considerably important primary inputs before discussing how these can be treated. For labor, a few common alternative measures are number of employed persons, hours of labor input, fulltime equivalent employees or total wages before stating that 'if we have to choose or recommend an appropriate measure of labour input, total numbers of hours worked is the best indicator of labour input.' (Coelli *et al*., 2005, p. 142)

As capital and labor inputs, Färe *et al.* (1994) used capital stock per worker<sup>9</sup> and real gross domestic product (GDP) per worker respectively. These were available as *KapW* and *RGDPW* in the PWT5 but are no longer directly provided. Therefore, they retrieved using intermediate variables. For real GDP per capita, *rgdpo*, measuring output-based real GDP at chained PPP's in million USD in 2005 prices is divided by *pop* which measured a country's population in millions. The measure thus represents USD per capita in 2005 prices. This output-based measure is a new feature in the PWT8. Overall, expenditure-based and output-based real GDP measures are comparable but some countries display significant differences; five percent of the PWT sample had expenditure contra output discrepancies exceeding 20 percent. (Feenstra *et al*., 2013) Feenstra *et al*. (2013, p. 29) state that '… for analyzing productivity differences across countries, real  $GDP<sup>010</sup>$  would be the appropriate measure'.

The needed input variable is not GDP per capita but rather output per worker for which *rgdpo* is divided by *emp*, a measure of the number of people in millions that are engaged in the workforce. Although, the total amount of labor hours are available through *avh* in PWT8, *emp* is chosen as it more closely resemble the measure used by Färe *et al*. (1994). For capital per worker, *rkna* which represents a country's capital stock in millions USD expressed in 2005 years prices is divided by *emp*. The variable *rkna* is a Törnqvist aggregate of individual asset growth rates (Inklaar & Timmer, 2013). So, the measure denotes capital stock in USD, again in 2005 years prices, per worker. Feenstra *et al*. (2005) label this measure tangible capital stock per worker in USD. These are the inputs and outputs used for the linear programming which results are presented in section 3.

1

<sup>&</sup>lt;sup>9</sup> 'Capital stock does not include residential construction but does include gross domestic investment in producers' durables, as well as nonresidential construction. These are the cumulated and depreciated sums of past investments.' (Färe *et al*., 2004, p. 76)

 $^{10}$  GDP<sup>o</sup> denotes output-based real GDP

## **3. Results**

<span id="page-22-0"></span>This section contains the results of the methods applied to three sets of data which required 1836 linear programming problems to be solved as it is 612 per data set. First, the techniques are applied to the same data set as Färe *et al*. (1994) used. Secondly, the same techniques are applied to a more recent data set from the data base, albeit a much updated version. Finally, the techniques are applied to an updated data set from the same data base covering the same time period as Färe *et al*. (1994).

#### **3.1 1979-1988 based on PWT5**

<span id="page-22-1"></span>To ensure that the interpretation of the models and the programming techniques applied are correctly applied, it was believed to be useful to perform the calculations on the same data which then should yield the same results. As this could be a sound approach, attaining the data set used 20 years earlier proved to be very difficult. The PWT version 5 (PWT5) was published as an appendix to the *Quarterly Journal of Economics* as a floppy disk (Summers & Heston, 1991). Swedish libraries as well as some international economics libraries were inquired but none of them had kept the floppy disk appendix. Neither could the publishing journal nor the digital publisher JSTOR assist. Not even the author, Alan Heston, knew how the data could be retrieved.

Upon extensive Googling, some economic researchers were found who had written about the PWT5. One of these researchers responded positively, namely Valerie Ramey, Professor of Economics at the University of California, San Diego, and the original data set was finally retrieved. This set containing the data used by Färe *et al*. (1994) from PWT5 is presented in Appendix III which is followed by Appendix IV which provides a selection of the results yielded by solving the linear programming problems in  $MATLAB<sup>11</sup>$ . These results are not copied from the article but rather reconstructed using the same linear programming techniques on the same data set.

Recall the discussion regarding the dubious description regarding which returns to scale constraints to apply. When applying linear programming techniques on the PWT5 data set, it is clear that Färe *et al*. (1994) established a NIRS frontier rather than a CRS frontier for the distance functions. Table 1 below presents results using the different returns to scale constraints regarding average annual index changes for the three most central indexes. The Malmquist productivity change index (MALM) is similar to the fourth decimal for all countries using NIRS as specified by equation 12 earlier. This holds true for technical change (TECHCH) as well. For efficiency change (EFFCH), Belgium and Finland differ with Färe *et al*. (1994) on the fourth decimal as they were 0.9932 and 1.0109 respectively while all other directly correspond. If CRS is used instead, thus not adding any constraints to those specified by equation 11, nine out of the 17 countries display deviating results. The explanations for eight of these are that they are situated to the right of the CRS frontier determining country as was the case for data point D in figure 3.

**<sup>.</sup>**  $11$  This set include example graphs for three years with their NIRS and VRS frontiers, theta values for the same period NIRS frontier as well as Malmquist productivity, efficiency and technical change indexes along their geometric means and cumulated changes. Such result data is available for all three subsections in this chapter.

Average Annual Changes, 1979-1988, PWT5									
		<b>Constant Returns to Scale (CRS)</b>		<b>Non-Increasing Returns to Scale (NIRS)</b>					
	<b>TECHCH</b> <b>MALM</b>		<b>EFFCH</b>	<b>MALM</b>	<b>TECHCH</b>	<b>EFFCH</b>			
Australia	0,9973	1,0009	0,9964	0,9973	1,0009	0,9964			
Austria	0,9981	1,0009	0,9972	0,9981	1,0009	0,9972			
<b>Belgium</b>	1,0017	1,0009	1,0009	1,0092	1,0161	0,9931			
Canada	0,9847	1,0009	0,9838	1,0151	1,0161	0,9990			
<b>Denmark</b>	1,0026	1,0009	1,0017	1,0026	1,0009	1,0017			
<b>Finland</b>	1,0030	1,0009	1,0021	1,0272	1,0161	1,0109			
<b>France</b>	0,9915	1,0009	0,9907	1,0081	1,0161	0,9921			
Germany	0,9946	1,0009	0,9937	1,0117	1,0161	0,9956			
Greece	0,9962	1,0009	0,9953	0,9962	1,0009	0,9953			
<b>Ireland</b>	0,9821	1,0009	0,9813	0,9821	1,0009	0,9813			
Italy	1,0072	1,0009	1,0064	1,0195	1,0161	1,0033			
Japan	0,9811	1,0009	0,9802	1,0287	1,0161	1,0124			
Norway	0,9977	1,0009	0,9968	1,0236	1,0161	1,0073			
<b>Spain</b>	0,9898	1,0009	0,9890	0,9898	1,0009	0,9890			
Sweden	1,0019	1,0009	1,0010	1,0019	1,0009	1,0010			
<b>United Kingdom</b>	1,0012	1,0009	1,0003	1,0012	1,0009	1,0003			
<b>United States</b>	1,0009	1,0009	1,0000	1,0085	1,0085	1,0000			
Mean:	0,9959	1,0009	0,9951	1,0070	1,0085	0,9986			

**Table 1: Comparing CRS and NIRS results 1979-1988, PWT5**

The ninth was the United States which determined the frontier. As the input data summary found in Appendix III displays increased capital per worker each year and decreasing output per worker for two years. Figure 8 below illustrate how such development moves point A towards the fourth quadrant in a plane using A as the origin of coordinates from  $A^t$  to  $A^{t+1}$ , effectively moving the data point to the zone where CRS and NIRS are not equal.



<span id="page-23-0"></span>**Figure 8: Why a frontier country can have different results using CRS and NIRS**

#### **3.2 2002-2011 based on PWT8**

<span id="page-24-0"></span>This section presents results using the same linear programming techniques used by Färe *et al*. (1994) on the most recent data available from the PWT data base, being version 8.0 (PWT8) as presented by Feenstra *et al*. (2013b). The sample consists of ten years, the same number of years as the 1994 study, and covers the time period between 2002 and 2011 for the same 17 countries. See Appendix V for the data set and for results see Appendix VI. The countries on the frontier were Ireland, Norway, Sweden and the United States. For NIRS frontier countries, see table 2 below. Although Ireland has a theta value of one for each year in the appendix table, these are rounded figures meanwhile the table below present years it was one.

Theta values equal to one at $D_0^t(x^t, y^t)$ for NIRS PWT8											
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Years
<b>Ireland</b>	1.0000	1.0000	1.0000		1.0000	1.0000	1.0000	1.0000	1.0000		8
Norway					1.0000	1.0000	1.0000				3
Sweden							1.0000	1.0000	1.0000	1.0000	4
<b>United States</b>	1,0000	1,0000	1,0000	1,0000				1.0000	1,0000		6

**Table 2: Frontier countries using NIRS 2002-2011, PWT8**

However, if one instead establishes a true CRS frontier, there is only one country at the frontier per year and neither Norway nor United States determined the frontier at any year. This is a quite remarkable difference. It is interesting to notice how Ireland determined the frontier between 2002 and 2007 only to pass the torch to Sweden in 2008 who remained the lone fully technically efficiency country for the remainder of the years in the sample. See table 3 below for a summary of the countries determining the frontier.

**Table 3: Frontier countries using CRS 2002-2011, PWT8**

Theta values equal to one at $D_0^{\ t}(x^t, y^t)$ for CRS PWT8											
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Years
Ireland	1.0000	1.0000	1,0000	1,0000	1.0000	1.0000					6
Norway											0
Sweden							1.0000	1.0000	1.0000	1,0000	4
<b>United States</b>											0

The full summary of theta values along the most important indexes are put forth by table 4 below on the following page. On average<sup>12</sup>, the annual Malmquist productivity index increased slightly less than 0.4 percentage points per year. Only three countries displayed deteriorating performance namely Greece, Ireland and the United Kingdom with decreasing average annual Malmquist productivity indexes. The best performing country was Norway with an increase of about 2.5 percent per year on average. It should be noted that this was the only result above two percentage points and there were only two countries with an average improvement about one percentage point.

1

 $12$  The geometric mean is used for average annual changes for individual countries as well as for the entire sample

	<b>Main results 2002-2011 PWT8</b>								
	Mean		Average annual		<b>Cumulated</b>				
	$D_0^t(x^t,y^t)$	<b>MALM</b>	<b>TECHCH</b>	<b>EFFCH</b>	<b>MALM</b>	<b>TECHCH</b>	<b>EFFCH</b>		
<b>Australia</b>	0,7978	1,0034	1,0115	0,9920	1,0306	1,1079	0,9302		
Austria	0,8105	1,0039	1,0125	0,9915	1,0355	1,1187	0,9257		
<b>Belgium</b>	0,8840	1,0000	1,0117	0,9885	1,0002	1,1099	0,9012		
Canada	0,8035	0,9955	1,0121	0,9837	0,9606	1,1139	0,8624		
<b>Denmark</b>	0,7428	1,0096	1,0131	0,9966	1,0898	1,1240	0,9696		
<b>Finland</b>	0,7524	1,0078	1,0114	0,9965	1,0727	1,1075	0,9686		
<b>France</b>	0,8075	1,0053	1,0115	0,9938	1,0488	1,1087	0,9460		
Germany	0,7524	1,0089	1,0145	0,9945	1,0829	1,1382	0,9514		
Greece	0,6788	0,9931	1,0039	0,9893	0,9394	1,0353	0,9073		
<b>Ireland</b>	1,0000	0,9857	0,9857	1,0000	0,8784	0,8784	1,0000		
Italy	0,7820	1,0011	1,0119	0,9893	1,0098	1,1127	0,9075		
Japan	0,6794	1,0044	1,0115	0,9929	1,0401	1,1086	0,9382		
Norway	0,9623	1,0248	1,0114	1,0132	1,2464	1,1076	1,1253		
<b>Spain</b>	0,7486	1,0123	1,0103	1,0019	1,1159	1,0969	1,0173		
Sweden	0,9091	1,0031	0,9816	1,0220	1,0284	0,8457	1,2160		
<b>United Kingdom</b>	0,8527	0,9953	0,9934	1,0019	0,9582	0,9422	1,0170		
<b>United States</b>	0,9921	1,0102	1,0109	0,9993	1,0960	1,1025	0,9941		
Mean:	0,8209	1,0037	1,0069	0,9968	1,0342	1,0642	0,9718		

**Table 4: Main results using NIRS from 2002-2011, PWT8**

Overall, changes were due to the technological improvement component rather than the efficiency increase component, similar to Färe *et al*. (1994). For technological improvement, 14 out of the 17 countries improved this aspect and Sweden was the worst performer and Germany the best. In terms of efficiency gains, five countries improved and Sweden was the best performer. Notably, the spread in annual performance seems larger with regards to efficiency than technology. Regarding the cumulative Malmquist productivity change index, Norway readily outperformed the other countries with their 24.6 percent, more than double that of the second country Spain. Figure 9 below illustrate differences between Sweden and Norway being the final frontier determinant and the best performing country respectively.



<span id="page-25-0"></span>**Figure 9: Swedish and Norwegian productivity development trajectories 2002-2011, PWT8**

Sweden displayed the worst and best performances for technological change and efficiency change respectively. Norway, outperforming Sweden by far regarding the overall Malmquist index, did so by performing reasonably well in both of the productivity subcomponents. In the Färe *et al*. (1994) study, Norway was the third best performer and Sweden placed eleventh in the same sample of countries. Interestingly, Sweden maintained that eleventh place while Norway advanced. Japan who was the best performer back then placed only eight for the 2002 to 2011 sample. Finally, it can be noted that the entire sample on average was about 17.9 percentages short of the vertical frontier for the same time frontier as the data points.

#### **3.3 1979-1988 based on PWT8**

<span id="page-26-0"></span>This section presents results when using the same methods, countries and time periods as Färe *et al*. (1994) on the PWT8 data set made available by Feenstra *et al*. (2013b). The data set is available in Appendix VII, for the full set of results see Appendix VIII. To evaluate if there are any implications of using an updated data set, it is useful to revisit the same pair of graphs used in figure 9 above for Japan and the United States. Figure 10 below presents the Malmquist productivity change index trajectories with its subcomponents below.



**Figure 10: Japanese and American productivity development trajectories 1979-1988, PWT5**

<span id="page-26-1"></span>As PWT is updated several times since Färe *et al*. (1994) used its Mark 5, the PWT5, some differences could be expected but the extent of differences between figure 10 above and figure 11 below are substantial. Japan had a cumulated Malmquist productivity improvement of about 12.5 percent based on PWT8 compared with the 29.1 percent reported using PWT5. This difference can mainly be accredited to a significant difference regarding the technological component which was 15.5 compared with 2.4 for PWT5 and PWT8 respectively. On top of this drastic decrease, there was a slight decrease from 11.7 to 10 for the efficiency component as well. The United States on the other hand had a cumulated Malmquist productivity improvement of 9.4 percent using PWT8 compared to 7.9 percent using PWT5. However, it is noteworthy that the United States as the sole determinant of the NIRS frontier for Färe *et al*. (1994), no longer determined the frontier all years as the change in the efficiency curve reveal in figure 10 above. Determining the frontier implies full technical efficiency, thus equal to one, for all years which is seen in figure 11 below to the right.



**Figure 11: Japanese and American productivity development trajectories 1979-1988, PWT8**

<span id="page-27-0"></span>As it could be deduced that the United States was not fully technically efficient for all years, it is thus interesting to evaluate which countries that determined the boundaries for the technological frontier using PWT8 data. Table 5 presents the countries at the frontier for the time period. Canada is at the frontier for all ten years compared to three years for the United States. Norway, who was a strong performer for Färe *et al*. (1994) as well, notes nine years and Ireland five.





Table 5 above is on one hand based on the same linear programming problems that yielded the same results as Färe *et al*. (1994), however to determine the magnitude of change regarding country determining the frontier it seems interesting to review the CRS case as well. These are presented by table 6 below. The results are very different from those presented in the 1994 study as the United States are not on the technological frontier for a single year. Instead, Canada and Ireland took turns at determining the frontier. Given these quite remarkable findings the main results of the data envelopment analysis based on the PWT8 data will be briefly reviewed.





Table 7 below presents a summary of the main results for 1979 to 1988 based on PWT8 and a NIRS frontier. First, it is noteworthy that the United States which did not determine the frontier one single year displays a mean theta value around 98.5 meaning that although they did not determine the frontier they were just beneath it. The mean Malmquist productivity improvement index was slightly lower than the 0.7 percent reported by Färe *et al*. (1994) at 0.61 percent. For technological improvements and efficiency, these results are to the contrary of Färe *et al*. (1994, p. 78) who stated that 'on average, that growth was due to innovation (TECHCH) rather than improvements in efficiency (EFFCH).' They reported a sample mean annual efficiency change below zero whereas the PWT8 data set yields a positive efficiency development around 0.5 percent. It seems as the conclusions from the PWT5 data set overestimated technological improvements as it yielded 0.9 compared to the 0.1 percentages based on PWT8 data.



**Table 7: Main results using NIRS from 1979-1988, PWT8**

Based on the new data, Japan was no longer the best performer with respect to Malmquist productivity improvement as Australia and Finland received higher cumulated values. Notably, Australia displayed the fourth worst cumulated productivity development for Färe *et al*. (1994) meanwhile Finland was the second best based on PWT5 as well. For the technological development component, the results are vastly different. Although Greece had a modest annual improvement about 0.6 percent it was enough to have the best cumulated value of 5.3 percent. As for efficiency development, Finland, Australia, Italy and Japan placed the highest in that given order. Besides Australia, they all displayed high values using PWT5 as well. However, Norway who had 15.5 percent and a shared first place was now second worst.

## **4. Conclusions**

<span id="page-29-0"></span>This section addresses the research questions stated in section 1.2 which are addressed in their stated order.

#### **R1.How can the productivity development for 2002 to 2011 be characterized?**

There was an average productivity improvement, based on the output-oriented Malmquist productivity change index, just short of 0.4 percent annually. Out of the 17 countries, only four saw deteriorating productivity. The main productivity driver was technological improvements, only five countries had an annual growth in efficiency. Depending on choice of scale, four or two countries determined the frontier for NIRS and CRS respectively. These were Ireland, Norway, Sweden and the United States with Sweden being the sole determinant of the frontier regardless of NIRS or CRS for the final year of 2011. Sweden was an interesting country in the sample as the country was the worst performer with regards to technological improvements meanwhile the best with regards to efficiency development. Norway was the best performing country with a 24.6 percent productivity improvement with solid performances regarding both technological improvement and efficiency.

#### **R2. How does this compare with the findings from 1979 to 1988?**

Compared with the 1979 to 1988 results from Färe *et al*. (1994) based on the PWT5 data set the productivity growth was about half, 0.4 compared with 0.7 percent, due to slightly lower results for the subcomponents. These resulted in 0.7 and 0.9 percent for technological improvements and minus 0.3 and minus 0.1 percent for efficiency for the 1979 to 1988 PWT5 and 2002 to 2011 PWT8 respectively. Although productivity growth was slower, the growth was due to technological improvements rather than efficiency gains just as for Färe *et al*. (1994).

#### **R3. Given an updated data set, what are the implications for 1979 to 1988 findings?**

There are significant differences. If assuming that the revisions of the PWT data have improved its reliance the new results could possibly be considered more accurate. However, it should be emphasized that the exact same categories of inputs and outputs no longer exist which likely impacted the results to some extent. Besides individual countries results, one major conclusion in Färe *et al.* (1994) was that growth from 1979 to 1988 was mostly due to technological improvements for OECD countries is not supported by the updated data set. This data set showed that it rather was efficiency gains that were the driver behind productivity improvements during this period. Also, it highlights the important of estimating the reliability of a data set that is used for analysis. The capital per worker measure is much higher for PWT8 compared with PWT5, as the estimations seemingly have changed quite a lot in retrospect during the almost 25 years since PWT5. And the differences are of significant importance, as Japan for instance went from being the furthest to the right to being midsample as time passed and the PWT was updated from PWT5 to PWT8.

#### **5. Discussion**

<span id="page-30-0"></span>Data envelopment analysis provides interesting techniques to determine positions relative to some best practice benchmark. Compared to statistical methods, it seems useful to compare something to the best known possible performance rather than the average performance. After all, in terms of GDP, the goal of a society is likely not to ensure that the GDP per capita is average or above average. Instead it seem more likely that a decision making unit such as a country would want to evaluate itself compared to countries with similar preconditions and strive to improve according to the findings. Although the data envelopment analysis use highly aggregated data in this report, it seems interesting to benchmark a country with similar countries in terms of capital per worker or industry structure. The sample was chosen based on the choices made by Färe *et al*. (1994). However their choices were not based on industry structure but rather because of the fact that the data sought for was available for just these particular countries.

In addition, the data envelopment analysis provided plenty of learning opportunities both regarding mathematical understanding but also more operational aspects of conducting the linear programming to reach the results that the methods can yield. Regardless of how solid the results presented based on such a seemingly rigorous mathematical foundation appears, the data set still determines the reliability of the results. In this case, the choice of data set and the version thereof proved to be of the utmost importance. Some changes were to be expected but the finding that the productivity growth for the best performing country of Japan would drop so significantly during the same time period was unexpected. Although it casts a shadow of doubt regarding the overall results derived based on the old data set, it simultaneously reduces the perceived reliability of the new analysis based on updated figures as well. Perhaps the main conclusion and learning from this example was the importance of a carefully chosen data set.

Turning to the methods, it was difficult to follow the methods described by Färe *et al*. (1994). To some extent, Krugman's notion of how highly specialized language can be used to hide the banality of an idea was one source for the threshold to follow the footsteps of the economists publishing in *The American Economic Review*. Another was that the information provided was inaccurate or at least dubious. When the results of an inexperienced economic student do not match those expected, it is easy to doubt the methodological understanding or the application. Which one to blame feels impossible to determine during the struggle. In this case, some results were right and others wrong. Upon greater understanding of the methods, the explanation was that the data points to the left of the frontier determining nation was correct as these yield identical results under CRS and NIRS assumptions.

Deviating from the CRS assumption was necessary to provide the results needed, however the implications for the productivity measure of such sidestep were not immediately obvious. Given scale changes, the Malmquist productivity change index had been criticized for its ability to satisfy the most fundamental productivity measure being the ratio of output to input. This measure is just as sophisticated in its simplicity as it is intuitive for the single input, single output case. However, the methods that were to be applied did no longer adhere to this definition. It is noteworthy that this was not mentioned by Färe *et al*. (1994).

Regarding the results, industrial nations such as Japan and Germany being widely known for their high level of productivity could be expected to place higher. The Färe *et al*. (1994) study was interesting in the aspect as it was able to pinpoint the sharp rise in productivity that Japan displayed during the 1980's. Although their position in terms of the cumulative Malmquist productivity change index results worsened, Japan still placed fourth. On the other hand, Norway who is not really known for their productive capabilities were the best performer with regards to cumulative Malmquist productivity change index results for the most recent sample from 2002 to 2011. As this might be accurate for living standards through an intermediary measure of GDP per worker, it does not necessarily have to do with neither technological improvement nor efficiency gains as it could be due to for instance oil findings. Another concern is how the model premiers less capital intense countries. A capital intense industry structure would mean that the country would be place far to the right in the input- and outputdiagram. This would, given a comparable GDP per worker level to a country with a less capital intensive industry structure, mean that the angle from the origin of coordinates would be lesser and the technical efficiency under CRS could be relatively low. Such characteristic could be interpreted as that the model favors less capital industries. An example would be that a country of Spotify-like companies would be considered more productive than a country of Volvo's and ABB's.

Although it should be considered bad that a method is presented in a manner by which it is very difficult to follow, back and forth struggles do lead to learning opportunities as many areas of the methods needs to be explored in order to yield the expected outputs. Through this understanding and upon guidance from a highly initiated and experienced supervisor, new heights of understanding could be reached. This enabled the slope CRS rewriting which is useful to understand some of the discrepancies regarding the results between PWT5 and PWT8 and some of the unexpected characteristics of the results in general.

As it was shown that technical efficiency under CRS only depend on the frontier which explains the clustering of technical change results for 1979-1988 under NIRS. For a CRS frontier, the technical change component does not vary. This alone could have revealed that Färe *et al.* (1994) did not use CRS. However it is not easily spotted without the rewriting in equation 26, showing that the frontier alone determines the component. The reason that a lot of countries had identical results for PWT5 was that many of these were positioned to the left of the frontier-determining country thus adhering to a CRS frontier. Although it is not shown in this report, the reason for all the other countries sharing the technical change component is most likely similar but for NIRS. If countries had moved back and forth between CRS and NIRS, different values would have been expected which was not the case.

To conclude, there were two main factors which altered the Malmquist index's ability to actually measure what it was supposed to measure. First, the choice of frontier of NIRS rather than CRS and second the inconsistencies over time for the data set when moving from PWT5 to PWT8. These kinds of issues do reduce the credibility of the findings. To remedy the first, the CRS frontier can be used which accurately reflect the ratio of output to input or some version of Malmquist productivity indexes put forth by the research communities. For the second, the findings during this thesis work point towards careful input data scrutinizing.

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## <span id="page-34-0"></span>**Appendix I: MATLAB code for CRS slope method**

This appendix contains the MATLAB code used to compute the Malmquist index and its subcomponents efficiency change and technical change under CRS without linear programming techniques. To identify the CRS frontier for each year, the output vector is divided term by term with the input vector and the highest value was chosen for each year. If this code is to be used, use the following steps to choose the desired data set:

- 1. Change 'MATLABinput.xlsx' to an MS Excel file placed in the same folder as the MATLAB m-file
- 2. Choose the desired sheet, default is 1
- 3. Select the area for the input and output
	- a. Input default is  $IB3:K19'$
	- b. Output default is 'M3:V19'

```
clear
clc
Xinput = xlsread('MATLABinput.xlsx',1,'B3:K19').'; 
Yinput = xlsread('MATLABinput.xlsx',1,'M3:V19').';
[T,K] = size(Yinput); % Set T as time periods and K as DMUs in sample
for t = 1:T-1,
  for k = 1:K,
       MALMcrs(t,k) =inv(Yinput(t, k)/Xinput(t, k)) * (Yinput(t+1, k)/Xinput(t+1, k));
        TECHCHcrs(t, k) =
inv(max(Yinput(t,1:K)./Xinput(t,1:K)))*max(Yinput(t+1,1:K)./Xinput(t+1,1:K)
);
       EFFCHcrs(t, k) =
(inv((Yinput(t, k)/Xinput(t, k))*inv(Yinput(t+1, k)/Xinput(t+1, k))))*((max(Yin(t+1, k)))put(t,1:K)./Xinput(t,1:K)))*inv(max(Yinput(t+1,1:K)./Xinput(t+1,1:K))));
    end
end
clearvars k t
```
#### <span id="page-35-0"></span>**Appendix II: MATLAB code for linear programming**

This appendix contains the MATLAB code used to compute the 918 linear programming problems computed by Färe *et al*. (1994), denoted FGNZ in the code. If this code is to be used, the following steps explain how a data set can be entered:

- 1. Change 'MATLABinput.xlsx' to an MS Excel file placed in the same folder as the MATLAB m-file
- 2. Choose the desired sheet, default is 1
- 3. Select the area for the input and output
	- a. Input default is  $IB3:K19'$
	- b. Output default is 'M3:V19'

```
% FGNZ: Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). 
Productivity Growth, Technical Progress, and Efficiency Change in 
Industrialized Countries. The American Economic Review, 84(1), 66-83.
% Stable URL: http://www.jstor.org/stable/2117971
%%% Code %%%
clear
clc
X1994PWT5 = xlsread('MATLABinputPWT.xlsx', 1,'B3:K19'); % K/L data, 1979-1988 from PWT5
Y1994PWT5 = xlsread('MATLABinputPWT.xlsx',1,'M3:V19'); % Y/L data, 1979-
1988 from PWT5
X1994PWT8 = xlsread('MATLABinputPWT.xlsx',2,'B3:K19'); % K/L data, 1979-
1988 from PWT8
Y1994PWT8 = xlsread('MATLABinputPWT.xlsx',2,'M3:V19'); % Y/L data, 1979-
1988 from PWT8
X2014PWT8 = xlsread('MATLABinputPWT.xlsx',3,'B3:K19'); % K/L data, 2002-
2011 from PWT8
Y2014PWT8 = xlsread('MATLABinputPWT.xlsx', 3, 'M3:V19'); % Y/L data, 2002-
2011 from PWT8
% Default input matrices: FGNZ PWT5 1979-1988 data
Xinput = X2014PWT8.'; % Choose and transpose input data source
Yinput = Y2014PWT8.'; % Choose and transpose output data source
Years = xlsread('MATLABinputPWT.xlsx',1,'B2:K2').'; % Gathering year list
% Default label vectors: FGNZ PWT5 1979-1988 data
[\sim, Countries] = xlsread('MATLABinputPWT.xlsx', 1,'A3:A19'); % Gathering
country list, ~ skips numeric output
Countries = Countries.'; % Transpose country list
[T,K] = size(Yinput); % Set T as years in sample and K as countries in
sample
clearvars X1994PWT5 Y1994PWT5 X1994PWT8 Y1994PWT8 X2014PWT8 Y2014PWT8; % 
Clear from Workspace
A = zeros(K+3, K+1); % Constraint matrix A
[Arow, Acol] = size(A); \frac{1}{6} Assess row and colum numbers for A
f = zeros(1, K+1); % Establish minimizing function vector
f(1) = -1; % Minimizing "theta" (first variable) function for linear
optimization
for k = 1:K,
   A(2+k, k+1) = -1;A(K+3, k+1) = 1;
```

```
Aeg = A(K+3,1:K+1); % VRS condition row for matrix A
beg = 1; % VRS condition for vector b
for t = 1:T, % Choosing year
    for k = 1:K, \textdegree Choosing country
         %%% t %%%
        A(1,1) = Yinput(t, k); % Setting ymkt as theta-weight at t
        A(1,2:Acol) = -Yinput(t, 1:K); % Assigning negative Y-weights for
lambda at t
        A(2,2:Acol) = Xinput(t, 1:K); % Assigning positive X-weights for
lambda at t
        b = zeros(1,K+3); % Clearing and establishing output restriction
vector at t
        b(1,2) = Xinput(t,k); % Setting nkt as right hand side for
restriction (2) at t
        b(1,K+3) = 1; % NIRS
        A(Arrow, 1: Acol) = zeros(1, 1: Acol); % CRS
        linprog(f, A, b); % Solves min f' * x such that A * x ? b. See
http://www.mathworks.se/help/optim/ug/linprog.html
        DI(t, k) = 1/ans(1); % CRS Dt at time t, FGNZ equation 16
         linprog(f, A, b, Aeq, beq);
        D5(t, k) = 1/ans(1); % VRS Dt at time t, FGNZ footnote 17
         %%% t+1 %%%
         if t<T
             t=t+1; % Setting t to t+1 for mixed-period comparison
            At = A;bt = b;At(1,1) = Yinput(t,k); % Setting ymkt as theta-weight at t+1
            bt(1,2) = Xinput(t,k); \frac{1}{2} Setting nkt as right hand side for
restriction (2) at t+1
             linprog(f, At, bt);
            D2(t-1, k) = 1/ans(1); % CRS Dt at t+1, FGNZ equation 17
            CCD1(t-1,k) = D2(t-1,k)./D1(t-1,k); \frac{1}{2} CCD Malmquist index at t,
FGNZ equation 4
            At(1,2:Acol) = -Yinput(t,1:K); % Assigning negative Y-weights
for lambda at t
            At(2,2:Acol) = Xinput(t,1:K); % Assigning positive X-weights
for lambda at t
             linprog(f, At, bt);
            D4(t-1, k) = 1/ans(1); % CRS Dt+1 at t+1, FGNZ equation 16 at
t+1
```
end

```
 linprog(f, At, bt, Aeq, beq);
           D6(t-1,k) = 1/ans(1); % VRS Dt+1 at t+1, FGNZ equation 16 at
t+1At(1,1) = Yinput(t-1,k); % Setting ymkt as theta-weight at t
```

```
bt(1,2) = Xinput(t-1,k); % Setting nkt as right hand side for
restriction (2) at t
             linprog(f, At, bt);
            D3(t-1, k) = 1/ans(1); % CRS Dt+1 at t, FGNZ equation 17 with
transposed t and t+1
            CCD2(t-1, k) = D4(t-1, k). / D3(t-1, k); % CCD Malmquist index at
t+1, equation 5
            MALM(t-1, k) = sqrt(CCD1(t-1, k) .* CCD2(t-1, k)); % Malmquist
index, FGNZ equation 6
            EFFCH(t-1,k) = D4(t-1,k)./ D1(t-1,k); % Efficiency change, FGNZ
equation 7
            TECHCH(t-1,k) = MALM(t-1,k) . EFFCH(t-1,k); % Technical
change, FGNZ equation 7
            t=t-1; % Restore time count to period t
         end
     end
end
clearvars Acol ans Arow At bt
for k = 1:K,
    OutputGeomean(k,1) = geomean(MALM(1:T-1,k)); % Annual change
geometrical means for MALM
   OutputGeomean(k,2) = geomean(TECHCH(1:T-1,k)); % Annual change
geometrical means for TECHCH
   OutputGeomean(k, 3) = qeomean(EFFCH(1:T-1, k)); % Annual change
geometrical means for EFFCH
    ans1 = \text{cumprod}(\text{MALM}(1:T-1,k));ans2 = cumprod(TECHCH(1:T-1,k));ans3 = cumprod(EFFCH(1:T-1,K));
    OutputCumsum(k,1) = ans1(T-1,1); % Cumulative sums for MALM
    OutputCumsum(k, 2) = ans2(T-1, 1); % Cumulative sums for TECHCH
    OutputCumsum(k, 3) = ans3(T-1, 1); % Cumulative sums for EFFCH
end
[row, col] = size(OutputGeomean);
for k = 1:col,
   OutputGeomean (K+1, k) = geomean (OutputGeomean (1:K, k)); % Geometrical
sample means
    OutputCumsum(K+1, k) = geomean(OutputCumsum(1:K, k)); % Cumulative sample
sums
end
clearvars ans1 ans2 ans3 col k row t; % Clear from Workspace
c<sub>1</sub>c
```
# <span id="page-38-0"></span>**Appendix III: The PWT5 data used by Färe** *et al***. (1994)**

This table contains the input data set denoted X1994PWT5 in the MATLAB code:



This table contains the output data set denoted Y1994PWT5 in the MATLAB code:



# <span id="page-39-0"></span>**Appendix IV: 1979-1988 PWT5 figures and tables**

This appendix provides figures and tables with results from 1979 to 1988 and PWT5.













#### **Average Annual Changes, 1979-1988, PWT5**

## **Cumulated Productivity, 1979-1988, PWT5**



# <span id="page-43-0"></span>**Appendix V: The PWT8 data for 2002-2011**

This table contains the input data set denoted X2014PWT8 in the MATLAB code:



This table contains the output data set denoted Y2014PWT8 in the MATLAB code:



# <span id="page-44-0"></span>**Appendix VI: 2002-2011 PWT8 figures and tables**

This appendix provides figures and tables with results from 2002 to 2011 and PWT8.













## **Average Annual Changes, 2002-2011, PWT8**



# <span id="page-48-0"></span>**Appendix VII: The PWT8 data for 1979-1988**

This table contains the input data set denoted X1994PWT8 in the MATLAB code:



This table contains the output data set denoted Y1994PWT8 in the MATLAB code:



# <span id="page-49-0"></span>**Appendix VIII: 1979-1988 PWT8 figures and tables**

This appendix provides figures and tables with results from 1979 to 1988 and PWT8.













## **Average Annual Changes, 1979-1988, PWT8**

