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Environmental factors in cross-country productivity growth: A conditional Malmquist Index

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Abstract

This paper presents a novel approach to measuring cross-country productivity growth by introducing a revised Malmquist Productivity Index designed to overcome the limitations of traditional methods. The proposed index mitigates the impact of outliers and incorporates key environmental factors, which can influence productivity comparisons across countries. This research: (i) analyzes the productivity growth of 95 countries over two distinct periods, refining the original Malmquist index by combining the order-m methodology with a conditional approach; (ii) compares traditional and conditional Malmquist models to assess the differential effects of environmental variables on productivity estimates; and (iii) introduces a novel decomposition of the Malmquist index, the Environmental Variables Index Factor (EVIF), which quantifies the bias introduced by environmental factors. This study identifies that the exclusion of environmental variables systematically biases all components of the Malmquist index, including efficiency change and technological change. The findings indicate that the conditional model produces unbiased cross-country productivity estimates, particularly during periods of significant volatility in environmental factors.

Keywords: Environmental variables, Malmquist indices, Order-m, Outliers, Productivity

JEL classification: C14, D24, O47

Environmental Factors in Cross-Country Productivity Growth: A Conditional Malmquist Index *

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Abstract

This paper presents a novel approach to measuring cross-country productivity growth by introducing a revised Malmquist Productivity Index designed to overcome the limitations of traditional methods. The proposed index mitigates the impact of outliers and incorporates key environmental factors, which can influence productivity comparisons across countries. This research: (i) analyzes the productivity growth of 95 countries over two distinct periods, refining the original Malmquist index by combining the order-m methodology with a conditional approach; (ii) compares traditional and conditional Malmquist models to assess the differential effects of environmental variables on productivity estimates; and (iii) introduces a novel decomposition of the Malmquist index, the Environmental Variables Index Factor (EVIF), which quantifies the bias introduced by environmental factors. This study identifies that the exclusion of environmental variables systematically biases all components of the Malmquist index, including efficiency change and technological change. The findings indicate that the conditional model produces unbiased cross-country productivity estimates, particularly during periods of significant volatility in environmental factors.

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1. Introduction

The Malmquist Productivity Index (MPI) is a widely used method for measuring cross-country productivity growth. Originally introduced by Sten Malmquist (1953) to analyze consumption patterns, it was later adapted and named by Caves et al. (1982) to assess productivity changes over time. Färe et al. (1992) through the application of Data Envelopment Analysis (DEA), proposed a decomposition of the index into technological change and efficiency change.[1] The MPI framework is particularly useful for assessing performance across a wide variety of Decision Making Units (DMUs). Building on the influential contributions of Färe et al. (1994), this study applies the MPI to further examine productivity dynamics between countries.

Despite some of the advantages of the MPI, such as the possibility to decompose productivity change not only into technological and efficiency change, but also into additional components, it is not free from some shortcomings.[2] Among them, the MPI's reliance on deterministic production frontiers makes it vulnerable to the influence of outliers. Exceptional performance by a single country can set an unrealistic benchmark, potentially misclassifying other countries as inefficient, not due to actual inefficiencies, but because of skewed comparisons (Cazals et al., 2002). As a result, previous studies may have misestimated countries' productivity growth due to the influence of outliers, leading to inaccurate cross-country comparisons.

Most studies on economic growth using the Malmquist index have traditionally focused on labor and capital stock as inputs, with real GDP as the sole output, effectively excluding inflation from GDP calculations (Badunenko and Romero-Ávila, 2013; Henderson et al., 2007; Mastromarco and Simar, 2015). However, only considering the effect of inflation on GDP fails to fully capture its broader impact on productivity. Inflation, for instance, is known to reduce investment and hinder growth (Fischer, 1993). Beyond inflation, other factors such as climate conditions also play a crucial role in shaping economic growth. Temperature variations between countries can affect productivity by influencing both labor and capital stock (Henseler and Schumacher, 2019). Additionally, national output tends to decrease with rising temperatures in some countries (Hsiang, 2010). Past studies using the Malmquist index have generally assumed uniform climatic and inflationary conditions across nations. Comparing countries with varying inflation rates and temperature conditions can be problematic, as some may be more impacted by these factors than others. These differing environmental conditions make it difficult to draw meaningful comparisons, potentially leading to ineffective policy recommendations. For these reasons, our study proposes adjusting for these variables, ensuring that countries with similar inflation and temperature conditions are compared, thereby improving the accuracy of productivity assessments and enabling more informed policy decisions.

Our study aims to make a threefold contribution. Firstly, considering a large sample of

[1]For a historical overview of the Malmquist Productivity Index and its decomposition, see Grosskopf (2003). For broader discussions on productivity change measurement, including non-frontier approaches, refer to the surveys by Del Gatto et al. (2011) and Martin and Riley (2024).

[2]This has led to some authors to propose, at least, not only bipartite, but tripartite (Kumar and Russell, 2002), quadripartite (Henderson and Russell, 2005) and quinquepartite (Badunenko and Romero-Ávila, 2013) decompositions (at least) of productivity change.

95 countries, we measure their productivity change by extending the original Malmquist decomposition (Färe et al., 1992) combining the order-m methodology (Cazals et al., 2002), which minimizes the impact of outliers, and incorporating contextual environmental factors using the conditional approach outlined in Simar and Wilson (2007). This novel combined methodology provides a more comprehensive analysis by addressing both outlier bias and environmental heterogeneity, two challenges that have not been explored in sufficient detail in previous studies. Secondly, we examine the effects of inflation and temperature on productivity growth by comparing the results of the order-m Malmquist index (which accounts only for outliers) with the conditional order-m Malmquist index (which accounts for both outliers and environmental factors) to determine whether there are statistically significant differences in productivity measurement. Thirdly, we introduce a novel component to the Malmquist decomposition: the Environmental Variables Index Factor (EVIF). This metric is specifically designed to detect and quantify the degree to which the exclusion of environmental factors distorts productivity assessments. By determining whether productivity growth is overestimated or underestimated without these factors, the EVIF provides a more accurate view of actual growth. This insight is especially useful for policymakers, helping them assess whether these distortions are substantial enough to warrant policy adjustments.

Our findings highlight that the exclusion of key environmental factors leads to substantial distortions in cross-country comparisons across all components of the Malmquist index. These results are particularly important in light of recent events, such as the inflation surge between 2021 and 2023 after the COVID-19, and the intensifying effects of climate change, which might underlie the increasing frequency of natural disasters worldwide. Our analysis highlights how quickly environmental factors can reshape productivity dynamics. If such variables are overlooked in productivity assessments, policymakers risk enacting strategies that do not reflect actual economic conditions, potentially hindering growth and jeopardizing long-term stability.

The remainder of this paper is structured as follows: section 2 reviews recent advances in productivity measurement. Next, we present the theoretical framework for our conditional order-m model and introduce the Environmental Variables Index Factor (EVIF) in section 3. We provide a detailed description of the data in section 4, followed by the empirical analysis in section 5. Finally, we conclude with a discussion of the findings in section 6 and offer suggestions for future research and conclusions in section 7.

2. Background

Since the early 1990s, Malmquist indices have been widely applied to cross-country productivity growth, particularly after Färe et al. (1994) presented a three-way decomposition of the Malmquist index in efficiency change (improvements in the use of resources relative to the best practices), technological change (shifts in the production frontier), and scale efficiency change (changes in productivity based on the size or scale of operations). Later on, Kumar and Russell (2002) introduced capital accumulation as an additional component of the Malmquist index, while Henderson and Russell (2005) incorporated human capital into the model. These studies, while methodologically innovative, present limitations that call for closer examination. A major issue with earlier productivity growth studies lies in their reliance on deterministic production-frontier methods, which are particularly sensitive to outliers (Cazals et al., 2002). Additionally, these analyses often assume that countries operate under similar technological conditions, have equal access to resources, and face comparable environmental factors, assumptions that are rarely realistic and lead to biased conclusions about productivity growth (Dyson et al., 2001).

To address the outlier sensitivity problem, researchers have developed robust Malmquist indices based on the methodology of Cazals et al. (2002). Among these are the order-m Malmquist indices (De Jorge Moreno and Sanz-Triguero, 2011; Pilyavsky and Staat, 2008; Tzeremes, 2020; Wheelock and Wilson, 2007), which, along with the order-α developed by Aragon et al. (2005) and applied to Malmquist indices by Tzeremes and Tzeremes (2021), have been shown to significantly reduce the influence of outliers on productivity measurements. While these methods effectively reduce the influence of outliers, they still rely on the assumption that countries operate in homogeneous environments. As a result, they fail to account for critical external factors such as macroeconomic events or climate conditions that can significantly affect productivity growth and are specific of each country.

In this regard, inflation is widely recognized as one of the most critical determinants of economic growth, with a broad consensus supporting a negative relationship between the two variables (Ghosh and Phillips, 1998). However, traditional Malmquist indices applied to growth models tend to overlook the impact of inflation on productivity growth, allowing for comparisons between countries with vastly different inflationary environments. Although prior studies consistently find a negative relationship between inflation and growth, these results largely depend on country-specific characteristics, further highlighting the heterogeneous effects of inflation on growth (Akinsola and Odhiambo, 2017). Similarly, studies examining cross-country productivity often compare countries with very different climates, assuming that climate has no impact on productivity. However, previous research has demonstrated the negative effects of climate on economic growth. For example, Henseler and Schumacher (2019) identified temperature as the dominant driver of weather-related economic impacts. Prior research suggest that higher temperatures not only reduce the level of output but also slow long-term growth rates, providing strong empirical evidence for the adverse effects of temperature on economic growth and its underlying factors of production (Dell et al., 2012). Other authors, however, suggest that the relationship between temperature and productivity is non-linear, peaking at an annual average temperature of 13°C and declining rapidly at higher temperatures (Burke et al., 2015). Given the substantial influence of inflation and temperature on productivity growth, we designed a new Malmquist index that accounts for these variables by employing the conditional approach introduced by Daraio and Simar (2005, 2007). This conditional Malmquist model allows for countries to be compared with others that experienced similar environmental conditions specifically, comparable inflation and temperature levels. Additionally, our model integrates robust measures based on Cazals et al. (2002) to mitigate the bias introduced by outliers and extreme values in the dataset.

This dual focus on environmental factors and outliers aims to address a crucial gap in the literature. While many studies have advanced productivity growth analysis, those that consider outliers often fail to account for environmental factors, and conversely, methods centered on environmental variables tend to neglect the effect of outliers. For instance, Johnson and Ruggiero (2014) introduced a Malmquist model incorporating external environmental factors under Constant Returns to Scale (CRS). Building on this, Brennan et al. (2014) and Blackburn et al. (2014) extended the model to Variable Returns to Scale (VRS). More recently, Aparicio et al. (2024) integrated quality of government as an environmental variable, refining the decomposition from Ray and Desli (1997). Additionally, alternative decompositions such as the Global Malmquist Index (GMI), combined with the Benefit-of-the-Doubt (BoD) method (Camanho et al., 2023), have been explored, with D'Inverno et al. (2024) adapting these models to include environmental variables. While these studies account for specific environmental conditions, their reliance on deterministic frontiers leaves them vulnerable to outlier distortion, highlighting the importance of our dual approach.

3. Methodology

3.1. Malmquist index decomposition

In this section, we revisit the original Malmquist index proposed by Färe et al. (1992) which evaluates productivity and can be decomposed into two main components: efficiency change and technological change. The efficiency change component reflects improvements in efficiency relative to the best-performing units from time t to time $t+1$, while the technological change component captures shifts in production technology during the same period. The output oriented Malmquist productivity index decomposition can be defined as:

$$
\begin{aligned}
M_o(y^{t+1}, x^{t+1}, y^t, x^t) &= \left[\left(\frac{D_o^t(y^{t+1}, x^{t+1})}{D_o^t(y^t, x^t)} \right) \times \left(\frac{D_o^{t+1}(y^{t+1}, x^{t+1})}{D_o^{t+1}(y^t, x^t)} \right) \right]^{1/2} = \\
&= \underbrace{\left(\frac{D_o^{t+1}(y^{t+1}, x^{t+1})}{D_o^t(y^t, x^t)} \right)}_{\text{Efficiency Change}} \times \left[\underbrace{\left(\frac{D_o^t(y^{t+1}, x^{t+1})}{D_o^{t+1}(y^{t+1}, x^{t+1})} \right) \times \left(\frac{D_o^t(y^t, x^t)}{D_o^{t+1}(y^t, x^t)} \right)}_{\text{Technological Change}} \right]^{1/2} .
\end{aligned} \tag{1}
$$

Where $M_o(y^{t+1}, x^{t+1}, y^t, x^t)$ is the Malmquist productivity index that tracks the changes from t to $t+1$ of the DMU under analysis. $D_o^t(y^t, x^t)$ is the output distance function of the DMU under analysis at t in relation to the technology at t. $D_o^{t+1}(y^{t+1}, x^{t+1})$ is the output distance function of the DMU under analysis at $t+1$ in relation to the technology at $t+1$. $D_o^t(y^{t+1}, x^{t+1})$ is the output distance function of the DMU under analysis at $t+1$ in relation to the technology at t. $D_o^{t+1}(y^t, x^t)$ is the output distance function of the DMU under analysis at t in relation to the technology at $t+1$.

The output distance functions (Shephard, 1970) defined in equation (1) can be expressed for a given DMU at time t as:

$$D_o^t(y^t, x^t) = \inf\left\{\theta : \left(\frac{y^t}{\theta}, x^t\right) \in S^t\right\}. \tag{2}$$

If we substitute t by $t+1$ in equation (2) we obtain the expression for $D_o^{t+1}(y^{t+1}, x^{t+1})$. We also need to define the other two distance functions with respect to two different time periods:

$$D_o^t(y^{t+1}, x^{t+1}) = \inf\left\{\theta : \left(\frac{y^{t+1}}{\theta}, x^{t+1}\right) \in S^t\right\}. \tag{3}$$

Again, if we substitute t by $t+1$ in equation (3) we obtain the expression for $D_o^{t+1}(y^t, x^t)$. The production possibility set S^t can then be defined as:

$$S^t = \{(x^t, y^t) \mid x^t \text{ produces } y^t\}. \tag{4}$$

Where the production technology S^t represents the process of transforming inputs, $x^t \in \mathbb{R}_+^I$, into outputs, $y^t \in \mathbb{R}_+^R$. By replacing t with $t+1$ in equation (4), we derive the production possibility set for the period $t+1$. The distance function, $D_o^t(y^t, x^t)$ will take a value which is less than or equal to one if the output vector, y^t, is an element of the feasible production set, S^t. Similarly, $D_o^{t+1}(y^{t+1}, x^{t+1})$ will take a value which is less than or equal to one if the output vector, y^{t+1}, is an element of the feasible production set, S^{t+1}. However, $D_o^{t+1}(y^t, x^t)$ can have values greater than one if the production (y^t, x^t) occurs outside the set of feasible production S^{t+1}. $D_o^t(y^{t+1}, x^{t+1})$ can also have values greater than one if the production (y^{t+1}, x^{t+1}) occurs outside the set of feasible production S^t.

The output distance functions, $D_o^t(y^t, x^t)$, $D_o^{t+1}(y^{t+1}, x^{t+1})$, $D_o^{t+1}(y^t, x^t)$ and, $D_o^t(y^{t+1}, x^{t+1})$ (Shephard, 1970) used to construct the Malmquist index are reciprocal to the Farrell (1957) coefficient. This coefficient can be calculated by solving the DEA output-oriented model (Charnes et al., 1978) for a country j', where $j' = 1, \ldots, J$,

$$\begin{aligned}
&(D_o^t(y_{j'}^t, x_{j'}^t))^{-1} = \max \beta_{j'} \\
&\text{subject to:} \\
&x_{j'i}^t - \sum_{j=1}^{J} \lambda_j^t \cdot x_{j,i}^t \geq 0 \quad i = 1, \ldots, I \\
&-\beta_{j'} \cdot y_{j'r}^t + \sum_{j=1}^{J} \lambda_j^t \cdot y_{j,r}^t \geq 0 \quad r = 1, \ldots, R \\
&\lambda_j^t \geq 0 \quad j = 1, \ldots, J.
\end{aligned}
\qquad
\begin{aligned}
&(D_o^t(y_{j'}^{t+1}, x_{j'}^{t+1}))^{-1} = \max \beta_{j'} \\
&\text{subject to:} \\
&x_{j'i}^{t+1} - \sum_{j=1}^{J} \lambda_j^t \cdot x_{j,i}^t \geq 0 \quad i = 1, \ldots, I \\
&-\beta_{j'} \cdot y_{j'r}^{t+1} + \sum_{j=1}^{J} \lambda_j^t \cdot y_{j,r}^t \geq 0 \quad r = 1, \ldots, R \\
&\lambda_j^t \geq 0 \quad j = 1, \ldots, J.
\end{aligned}
\tag{5}$$

Note that by replacing t with $t+1$, it is possible to compute both $D_o^{t+1}(y_{j'}^{t+1}, x_{j'}^{t+1})$ and $D_o^{t+1}(y_{j'}^{t}, x_{j'}^{t})$. The vector of the observed inputs corresponding to unit j is $x_j = (x_{j,1}, x_{j,2}, \ldots, x_{j,I}) \in \mathbb{R}_+^I$, forming part of the sample containing J units; $y_j = (y_{j,1}, y_{j,2}, \ldots, y_{j,R}) \in \mathbb{R}_+^R$ is the vector of the observed outputs corresponding to unit j, forming part of the sample containing J units; and $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_J)$ is the activity vector used to construct the linear segments of the frontier.

The coefficient $\beta_{j'}$ (or its inverse, the distance functions) indicates the technical efficiency level of each of the units evaluated. If $\beta_{j'} = 1$, the unit under evaluation is efficient. That is, no other peer has been found that yields the same output vector with a smaller consumption of inputs. Otherwise, $\beta_{j'} > 1$ indicating the presence of technical inefficiency. As $D_o^{t+1}(y^t, x^t)$ and $D_o^{t}(y^{t+1}, x^{t+1})$ mix observations from both time periods, $\beta_{j'}$ can also have values lower than 1 when estimating these distance functions.

We adopted the assumption of constant returns to scale (CRS) in line with the original decomposition (Färe et al., 1992), a common approach when estimating Malmquist indices. This assumption avoids cases where the constraint sets become infeasible for certain DMUs, which can happen when the technology and the assessed unit (in our case, country) are from different time periods. Such issues typically arise under Variable Returns to Scale (VRS) (Burgess and Wilson, 1995).

3.2. Unconditional order-m Malmquist index

The deterministic nature of the frontiers estimated in the original model implies that any data distortion in observing the DMUs could significantly skew the efficiency scores for some or all of the other DMUs, leading to errors in productivity assessment. These drawbacks can be mitigated by adopting the robust order-m approach (Cazals et al., 2002).

The original model assesses the efficiency of each DMU relative to the entire dataset. In contrast, the order-m methodology improves robustness to outliers and measurement errors by drawing B random subsamples, each containing m DMUs. This randomization ensures some subsamples include outliers while others do not, yielding a more stable efficiency estimate. For each subsample, the method calculates the distance function of a particular DMU, and the B resulting scores are averaged to derive a robust efficiency score. As m approaches J (the total number of DMUs), these estimates converge to those of the original model (Cazals et al., 2002).

Following Tzeremes (2020), we adapt the four distance functions from the original model, as specified in equations (2) and (3), to reflect the new production possibility sets of order-m. These sets, denoted as S_m^t for period t and S_m^{t+1} for period $t+1$, are constructed from only m randomly selected DMUs, rather than including all J units from the original dataset. We can express the new distance functions as:

$$D^t_{o,m}(y^t, x^t) = \inf\left\{\theta : \left(\frac{y^t}{\theta}, x^t\right) \in S^t_m\right\}, \tag{6}$$

$$D^t_{o,m}(y^{t+1}, x^{t+1}) = \inf\left\{\theta : \left(\frac{y^{t+1}}{\theta}, x^{t+1}\right) \in S^t_m\right\}. \tag{7}$$

By substituting t by $t+1$ we can express $D^{t+1}_{o,m}(y^{t+1}, x^{t+1})$ and $D^{t+1}_{o,m}(y^t, x^t)$. The robust version of the distance function is obtained by averaging the scores of the distance functions over B bootstrap replicates. It is given by:

$$\hat{D}^t_{o,m}(y^t, x^t) = \frac{1}{B}\sum_{b=1}^{B} D^{t,b}_{o,m}(y^t, x^t), \tag{8}$$

$$\hat{D}^t_{o,m}(y^{t+1}, x^{t+1}) = \frac{1}{B}\sum_{b=1}^{B} D^{t,b}_{o,m}(y^{t+1}, x^{t+1}). \tag{9}$$

By replacing t with $t+1$, we can express both $\hat{D}^{t+1}_{o,m}(y^{t+1}, x^{t+1})$ and $\hat{D}^{t+1}_{o,m}(y^t, x^t)$. It is important to note that, when evaluating the distance functions $D^t_{o,m}(y^t, x^t)$ and $D^{t+1}_{o,m}(y^{t+1}, x^{t+1})$, which benchmark a given DMU against m DMUs from the same time period, the random selection process for each bootstrap iteration b ($b = 1, \ldots, B$) may or may not include the DMU under evaluation in the subsample of size m. If the DMU under analysis performs better than the average of the other m DMUs and is not included in the reference set, it will receive a super-efficient score ($\beta_{j'} < 1$ or $D^t_{o,m}(y^t, x^t) > 1$, $D^{t+1}_{o,m}(y^{t+1}, x^{t+1}) > 1$). However, when evaluating $D^t_{o,m}(y^{t+1}, x^{t+1})$ and $D^{t+1}_{o,m}(y^t, x^t)$, the DMU under analysis will, by construction, never be included in the m-subsample because the reference technology S^t_m or S^{t+1}_m is formed by DMUs from a different period. Therefore, if the DMU outperforms the average of the other m DMUs, it will achieve a super-efficient score.

It is essential to fix the parameter m, which determines the number of DMUs selected in each bootstrap replicate b. A common approach for selecting m is to plot the percentage of super-efficient units as a function of m and choose the value of m at the point where the curve shows an inflection (Daraio and Simar, 2007).

Based on the definitions above-specified, the order-m version of the output oriented Malmquist productivity index by Färe et al. (1992) can be defined as follows:

$$\hat{M}_{o,m}(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\left(\frac{\hat{D}^t_{o,m}(y^{t+1}, x^{t+1})}{\hat{D}^t_{o,m}(y^t, x^t)}\right) \times \left(\frac{\hat{D}^{t+1}_{o,m}(y^{t+1}, x^{t+1})}{\hat{D}^{t+1}_{o,m}(y^t, x^t)}\right)\right]^{1/2} =$$
$$= \underbrace{\left(\frac{\hat{D}^{t+1}_{o,m}(y^{t+1}, x^{t+1})}{\hat{D}^t_{o,m}(y^t, x^t)}\right)}_{\text{Robust Efficiency Change}} \times \left[\underbrace{\left(\frac{\hat{D}^t_{o,m}(y^{t+1}, x^{t+1})}{\hat{D}^{t+1}_{o,m}(y^{t+1}, x^{t+1})}\right) \times \left(\frac{\hat{D}^t_{o,m}(y^t, x^t)}{\hat{D}^{t+1}_{o,m}(y^t, x^t)}\right)}_{\text{Robust Technological Change}}\right]^{1/2}. \tag{10}$$

Where $\hat{M}_{o,m}(y^{t+1}, x^{t+1}, y^t, x^t)$ is the order-m Malmquist index that tracks the changes from t to $t+1$ of a given DMU. $\hat{D}^t_{o,m}(y^t, x^t)$ is the robust order-m output distance function of a given DMU at t in relation to the technology S^t_m. $\hat{D}^{t+1}_{o,m}(y^{t+1}, x^{t+1})$ is the robust order-m output distance function of a given DMU at $t+1$ in relation to the technology S^{t+1}_m. $\hat{D}^t_{o,m}(y^{t+1}, x^{t+1})$ is the robust order-m output distance function of a given DMU at $t+1$ in relation to the technology S^t_m. $\hat{D}^{t+1}_{o,m}(y^t, x^t)$ is the robust order-m output distance function of a given DMU at t in relation to the technology S^{t+1}_m.

3.3. Conditional order-m Malmquist index

The original Malmquist index, introduced by Färe et al. (1992), and its order-m version, focus exclusively on inputs and outputs, overlooking the influence of environmental factors. These factors, which are neither inputs nor outputs and lie outside the control of the decision-making units, can have a substantial impact on both production processes and efficiency levels.

To better understand the effect of environmental variables on productivity estimation, the concept of separability, introduced by Simar and Wilson (2007), becomes particularly relevant. Separability suggests that while environmental variables may influence the efficiency of DMUs (i.e., how close they are to the production frontier), these variables do not affect the underlying technology or the shape of the production frontier itself. If the separability condition holds, it implies that the production possibility sets of order-m, S^t_m or S^{t+1}_m, remain the same for all possible environmental conditions $z \in Z$. In other words, the environmental variables Z do not affect the structure or boundary of the production possibility set, and thus can be excluded from efficiency calculations without introducing bias.

In contrast, under non-separability, environmental variables Z can influence both the efficiency distribution and the production possibilities of the units. This means that the shape and boundary of the production set may change depending on the environmental conditions. Under non-separability, distance functions become difficult to interpret because they no longer measure the distance to a consistent production frontier. DMUs facing different environmental conditions are operating against distinct production frontiers. When separability does not hold, failing to account for environmental variables can lead to biased results.

Daraio et al. (2018) developed a test to determine the separability condition. The test assesses separability by comparing the means of conditional estimates with those of unconditional estimates, rejecting the null hypothesis of separability if a 'large' difference is identified. To ensure independence in the comparison of means, the test requires the original sample to be split into two sub-samples. To improve the reliability of the test, the results can be cross-validated using a new method developed by Simar and Wilson (2020). This technique utilizes a bootstrap approach, repeating the initial test multiple times with different sample splits.

When the separability test indicates that environmental variables affect the production frontier (i.e. separability is rejected), we develop our model building on the work of Cazals et al. (2002) and Daraio and Simar (2005, 2007). These researchers introduced a method to integrate the environmental variables Z into the analysis to obtain 'conditional' measures of efficiency avoiding the need for separability. Specifically, unlike the order-m Malmquist model, where all observations have an equal probability of being included in the subsample m, the probability of each DMU being selected depends on its environmental variables z.

For each bootstrap replicate b, m units are selected based on their similarity to the environmental variables z of the unit being evaluated. These selected units form the reference set used to calculate the distance function. To achieve this, we smooth the environmental variables Z by estimating a kernel function centered at the vector z corresponding to the unit being evaluated. The probability of selection is then determined by the kernel density function, evaluated at Z.

Our selection of variables for Z includes only continuous variables, making the approaches of Bădin et al. (2010) and Peter Hall and Li (2004) appropriate. However, note that these methods are not applicable to discrete variables.

We modify the four distance functions specified in equations (6) and (7). These modified functions will now measure efficiency relative to a frontier formed by a subset of m DMUs, which are influenced by similar environmental variables as the unit under analysis. Specifically, the production possibility sets are $S^t_{m|z}$ for time t and $S^{t+1}_{m|z}$ for time $t+1$:

$$D^t_{o,m|z}(y^t, x^t \mid z^t) = \inf\left\{\theta : \left(\frac{y^t}{\theta}, x^t\right) \in S^t_{m|z}\right\}, \tag{11}$$

$$D^t_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1}) = \inf\left\{\theta : \left(\frac{y^{t+1}}{\theta}, x^{t+1}\right) \in S^t_{m|z}\right\} \tag{12}$$

By substituting t by $t+1$ we can express $D^{t+1}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$ and $D^{t+1}_{o,m|z}(y^t, x^t \mid z^t)$. The robust and conditional version of the distance function can be expressed as the average distance function over b bootstrap replicates:

$$\hat{D}^t_{o,m|z}(y^t, x^t \mid z^t) = \frac{1}{B}\sum_{b=1}^{B} D^{t,b}_{o,m|z}(y^t, x^t \mid z^t), \tag{13}$$

$$\hat{D}^t_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1}) = \frac{1}{B}\sum_{b=1}^{B} D^{t,b}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1}). \tag{14}$$

By replacing t with $t+1$, we can express $\hat{D}^{t+1}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$ and $\hat{D}^{t+1}_{o,m|z}(y^t, x^t \mid z^t)$. The conditional distance functions $D^t_{o,m|z}(y^t, x^t \mid z^t)$ and $D^{t+1}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$ benchmark the DMU under evaluation against m other DMUs with similar environmental conditions from the respective time period. As in the robust case, during each bootstrap iteration b, the DMU being evaluated may or may not be included in the subsample of size m. If the DMU outperforms the average of the other m DMUs but is not part of the reference set, it will be assigned a super-efficient score, indicated by $\beta_{j'} < 1$, $D^t_{o,m|z}(y^t, x^t \mid z^t) > 1$ or $D^{t+1}_{o,m|z}(y^{t+1}, x^{t+1}) > 1$.

However, when assessing $D^t_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$ and $D^{t+1}_{o,m|z}(y^t, x^t \mid z^t)$, the DMU under evaluation is never included in the m-sized subsample. This is because the reference technology $S^t_{m|z}$ or $S^{t+1}_{m|z}$ is constructed using DMUs from a different period, chosen based on their similarity to the environmental conditions of the DMU being evaluated. Therefore, if the DMU outperforms the average of the other m DMUs, it will achieve a super-efficient score. For example, in $D^t_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$, the environmental variables z^{t+1} of a given DMU are used to identify m DMUs from period t with similar environmental conditions.

According to the definitions specified above, the conditional order-m Malmquist productivity index can be defined as:

$$\hat{M}_{o,m|z}\left((y^{t+1}, x^{t+1} \mid z^{t+1}), (y^t, x^t \mid z^t)\right) = \left[\left(\frac{\hat{D}^t_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})}{\hat{D}^t_{o,m|z}(y^t, x^t \mid z^t)}\right) \times \left(\frac{\hat{D}^{t+1}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})}{\hat{D}^{t+1}_{o,m|z}(y^t, x^t \mid z^t)}\right)\right]^{1/2} =$$
$$= \underbrace{\left(\frac{\hat{D}^{t+1}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})}{\hat{D}^t_{o,m|z}(y^t, x^t \mid z^t)}\right)}_{\text{Robust and Conditional Efficiency Change}} \times \left[\underbrace{\left(\frac{\hat{D}^t_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})}{\hat{D}^{t+1}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})}\right) \times \left(\frac{\hat{D}^t_{o,m|z}(y^t, x^t \mid z^t)}{\hat{D}^{t+1}_{o,m|z}(y^t, x^t \mid z^t)}\right)}_{\text{Robust and Conditional Technological Change}}\right]^{1/2}. \tag{15}$$

Where $\hat{M}_{o,mlz}\left((y^{t+1}, x^{t+1} \mid z^{t+1}), (y^t, x^t \mid z^t)\right)$ is the conditional order-m Malmquist index that tracks the changes from t to $t+1$ of a given DMU. $\hat{D}^t_{o,m|z}(y^t, x^t \mid z^t)$ is the conditional order-m output distance function of a given DMU at t in relation to the technology $S^t_{m|z}$. $\hat{D}^{t+1}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$ is the conditional order-m output distance function of a given DMU at $t+1$ in relation to the technology $S^{t+1}_{m|z}$. $\hat{D}^t_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$ is the conditional order-m output distance function of a given DMU at $t+1$ in relation to the technology $S^t_{m|z}$. $\hat{D}^{t+1}_{o,m|z}(y^t, x^t \mid z^t)$ is the conditional order-m output distance function of a given DMU at t in relation to the technology $S^{t+1}_{m|z}$.

3.4. Environmental Variables Index Factor (EVIF)

Traditional Malmquist productivity indices are susceptible to bias when environmental variables significantly affect the production frontier and the distribution of efficiencies. However, the extent of this bias and its implications for productivity measurement remain unclear. The primary objective of the Environmental Variables Index Factor (EVIF) is to determine whether omitting environmental factors leads to overestimated or underestimated productivity estimates, and by how much. It serves as a diagnostic tool that not only identifies whether environmental factors are influencing productivity calculations but also quantifies the extent of that influence.

The EVIF is derived combining distance functions from both models: the unconditional and conditional order-m. It acts as a bridge between the two, if we multiply the conditional model ($\hat{M}_{o,mlz}$), defined in equation (15), by the EVIF, we obtain the unconditional model ($\hat{M}_{o,m}$). Thus, it allows us to isolate the influence of environmental variables and accurately measure their impact on productivity change. The EVIF is given by:

$$\hat{M}_{o,m}(y^{t+1}, x^{t+1}, y^t, x^t) = \hat{M}_{o,m|z}\left((y^{t+1}, x^{t+1} \mid z^{t+1}), (y^t, x^t \mid z^t)\right) \times EVIF =$$
$$= \hat{M}_{o,m|z}\left((y^{t+1}, x^{t+1} \mid z^{t+1}), (y^t, x^t \mid z^t)\right) \times \left(\frac{\frac{\hat{D}^t_{o,m|z}(y^t,x^t|z^t)}{\hat{D}^t_{o,m}(y^t,x^t)}}{\frac{\hat{D}^t_{o,m|z}(y^{t+1},x^{t+1}|z^{t+1})}{\hat{D}^t_{o,m}(y^{t+1},x^{t+1})}} \right) \times \left(\frac{\frac{\hat{D}^{t+1}_{o,m|z}(y^t,x^t|z^t)}{\hat{D}^{t+1}_{o,m}(y^t,x^t)}}{\frac{\hat{D}^{t+1}_{o,m|z}(y^{t+1},x^{t+1}|z^{t+1})}{\hat{D}^{t+1}_{o,m}(y^{t+1},x^{t+1})}} \right)^{1/2}. \tag{16}$$

When the EVIF for a given DMU exceeds 1, it indicates that the exclusion of environmental variables has led to an overestimation of the unit's productivity. The higher the EVIF, the more pronounced the environmental influence, and consequently, the greater the degree of overestimation. Conversely, if the EVIF is less than 1, it suggests that excluding environmental variables has caused an underestimation of productivity. A lower EVIF score signals a more substantial underestimation, highlighting the increasing bias from disregarding environmental factors. Finally, an EVIF equal to 1 implies that the omission of environmental variables has no impact on the measurement of productivity. In this case, the unconditional order-m Malmquist index provides an accurate assessment of productivity changes, free from any bias related to environmental conditions.

4. Data

This study analyzes the productivity growth of 95 countries during two time periods: 1971–1973 and 2006–2008, using a basic production model that incorporates three key macroeconomic variables: labor, capital, and real GDP. The model follows the seminal framework from Färe et al. (1994), with data sourced from the Penn World Table (PWT) version 10.01.

The input variables in our model include labor, which is measured by the number of workers (EMP), representing the total employed population in each country, and capital, which is captured by the capital stock adjusted for purchasing power parities (PPP), denoted as CN. Further details regarding the calculation of CN can be found in Feenstra et al. (2015). The output variable is the expenditure-side real GDP at PPP (RGDPE), which allows for cross-country comparisons by accounting for price level differences. These input and output variables, derived from the PWT data, are widely supported in the literature on productivity studies, as noted by Badunenko and Romero-Ávila (2013), Henderson et al. (2007), and Mastromarco and Simar (2015).

As indicated in previous sections, and in addition to the production variables, we include two environmental factors, Z, specifically inflation and temperature, which are hypothesized to bias cross-country productivity growth. Inflation data is sourced from the World Bank and calculated using the GDP deflator, while temperature data is obtained from the CRU TS dataset (Climatic Research Unit Gridded Time Series), a globally recognized climate resource that provides quality-controlled temperature data from thousands of stations worldwide. Table 1 presents the descriptive statistics for the key input, output, and environmental variables used in the analysis.

We analyze two distinct periods, each marked by different external shocks to our environmental variables Z. The first period, spanning from 1971 to 1973, includes the time before and after the 1973 oil embargo. In response to the Yom Kippur War, the Organization of Arab Petroleum Exporting Countries (OAPEC) imposed substantial oil production cuts, leading to a sharp increase in global inflation (Blinder and Rudd, 2013). In our dataset, the average inflation rate during this period rose from 6.32% to 21.84%. The second period of interest covers the years 2006 to 2008, during the global financial crisis. This period was marked by rising aggregate demand and increasing commodity prices, which created inflationary pressures, especially in emerging and developing economies, as outlined by Habermeier et al. (2009). In our dataset, the average inflation rate increased from 7.84% to 9.70%. By comparing these two periods, one marked by dramatic inflationary shocks (1971–1973) and the other by more moderate changes (2006–2008), we aim to determine whether the impacts in Z observed in earlier decades align with those in more recent times. Through this comparison, we can explore how varying intensities of environmental change affect productivity growth across different countries and periods.

Table 1: Descriptive statistics of input, output, and environmental variables

Variable name	Units	Year	Mean	Std Dev	Median	Min	Max
Inputs (x)							
Number of workers	Persons (in millions)	1971	12.95	44.31	2.80	0.05	375.93
		1973	13.65	46.71	2.94	0.06	395.44
		2006	26.66	91.91	5.65	0.13	767.21
		2008	27.33	92.74	5.74	0.13	774.46
Stock of capital	Currency (in mil. 2017US$)	1971	695,952	2,445,764	63,575	659	22,033,434
		1973	749,336	2,610,893	69,379	775	23,606,832
		2006	2,659,016	7,174,132	497,167	11,302	57,539,900
		2008	3,134,349	7,956,787	695,972	14,813	59,952,004
Outputs (y)							
Real GDP	Currency (in mil. 2017US$)	1971	206,617	620,186	42,111	753	5,488,999
		1973	233,639	692,815	45,236	1,146	6,121,103
		2006	771,927	2,068,207	204,621	6,502	16,448,620
		2008	843,619	2,167,223	224,581	6,155	16,515,918
Environmental variables (z)							
Inflation	%	1971	6.32	6.81	5.90	-9.48	31.69
		1973	21.84	46.13	12.72	0.21	414.81
		2006	7.84	9.70	5.88	-2.02	84.68
		2008	9.70	7.55	8.22	-1.38	33.75
Temperature	Degrees Celsius	1971	18.89	7.77	21.86	-4.98	28.64
		1973	19.20	7.92	22.06	-4.25	29.11
		2006	19.93	7.67	22.83	-2.72	29.29
		2008	19.75	7.68	22.62	-4.48	28.96

5. Results

Our analysis reveals that excluding key environmental factors such as inflation and temperature skews productivity assessments within all components of the Malmquist index, impacting both efficiency and technological change in each period. These results suggests that these variables play a consistent role in shaping productivity metrics, highlighting their importance for accurately capturing productivity dynamics over time and across varying economic conditions.

The first step in our analysis was to assess whether inflation and temperature significantly affect the production frontier, and thus productivity, supporting the use of a conditional approach. To do this, we applied the separability test proposed by Simar and Wilson (2020) (see details in subsection 3.3). The test results, presented in Table 2, show p-values below 0.05, allowing us to formally reject the separability assumption, thereby justifying the relevance of adopting a conditional approach.

Table 2: Separability test results (H_0: separability holds)

Year	p-value	Test statistic
1971	0.013 **	1.0403
1973	0.019 **	1.0918
2006	0.034 **	0.4973
2008	0.014 **	0.6612

Significance levels: *** p-value < 0.001; ** p-value < 0.05;

Having established the influence of environmental factors on productivity, the next step is determining the appropriate value of m, which represents the number of selected DMUs in each replicate b for performing the order-m analysis (see details in subsection 3.2). A common approach, as suggested by Daraio and Simar (2007), is to plot the percentage of super-efficient units against m and choose the value of m at the curve's inflection point. The results of these plots, which guide the choice of m, are presented in Figure A1. For the period 1971 to 1973, we selected $m = 20$ units, while for the period 2006 to 2008, $m = 40$ DMUs were chosen. Additionally, we tested the models with $m = 30$ and $m = 20$, finding no significant differences.

Next, we computed the four distance functions required for estimating the unconditional order-m productivity, as well as the corresponding four distance functions for the conditional model (see section 3). The results are shown in Table A1, where we present efficiency changes, technological changes, and the Malmquist Productivity Index (MPI) for both periods.

To analyze the differences between the unconditional and conditional models, we compared the distributions of Efficiency Change (EC), Technological Change (TC), and the Malmquist Productivity Index (MPI) for the two periods. The results, presented in Figure 1 for 1971–1973 and Figure 2 for 2006–2008, reveal clear visual differences between the distributions. Unconditional order-m scores are represented in green, while conditional order-m scores are shown in orange.

To assess whether these visual differences are statistically significant, we applied the test proposed by Simar and Zelenyuk (2006), an adaptation of the Li (1996) test. This method compares the distributions of Farrell-type efficiency scores across different groups of DMUs and has been effectively applied in previous studies on productivity and efficiency (Chowdhury et al., 2011; Pastor and Tortosa-Ausina, 2008). The results from the Simar and Zelenyuk (2006) test, illustrated in Table 3 for the period 1971-1973 and in Table 4 for the period 2006-2008, confirm the statistical significance of the observed visual differences, with p-values for all three components falling below 0.05. The significant differences in productivity distributions between the unconditional and conditional models suggest that omitting environmental factors such as inflation and temperature can lead to biased productivity estimates when the separability condition does not hold. In such cases, the unconditional model, which does not account for these factors, may either under or overestimate productivity levels, especially in countries experiencing significant external economic shocks. This is particularly relevant when inflationary pressures and temperature fluctuations had profound economic impacts.

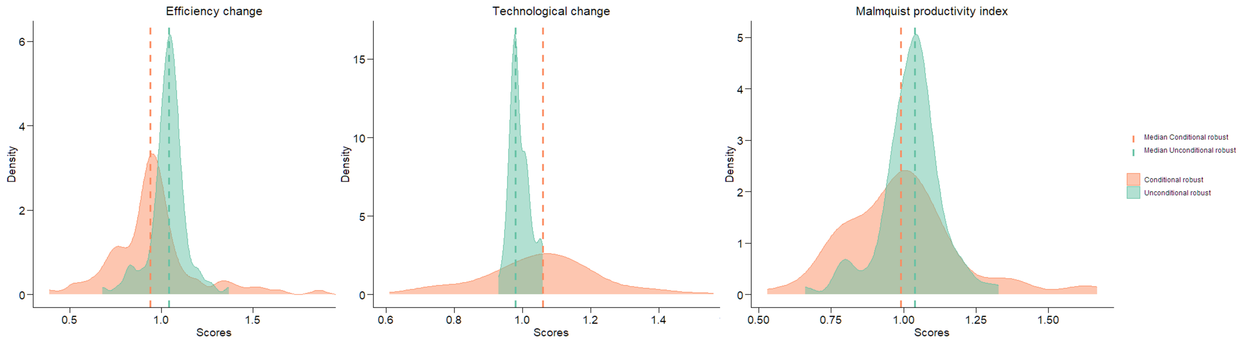
6. Discussion

The unconditional model allows productivity growth comparisons across countries with significantly different economic environments. For example, countries experiencing very high inflation rates in 1971, like Uruguay, Argentina, or Brazil (inflation $>$ 20-25%), can be compared with those that had much lower inflation rates ($<$ 5%) in the same year, including Guatemala, Ethiopia, or Luxembourg. Similarly, very cold countries on average such as Canada, Norway, or Finland can be compared with warmer countries such as the United Arab Emirates or Qatar. The conditional model, on the other hand, assesses productivity growth within a more controlled context, comparing each country with others that exhibit similar inflation and temperature levels. This approach ensures that productivity growth is evaluated against peers similarly influenced by these environmental factors, allowing for more context-sensitive comparisons.

We begin by examining the differences in the Efficiency Change (EC) component computed using both models. The EC component measures how a country's efficiency evolves over time relative to the best-performing countries. An EC score greater than 1 indicates that the country has improved its efficiency in $t+1$ compared to t, relative to the top performers, whereas a score less than 1 suggests a decline in efficiency over the same period. The unconditional model for 1971–1973 reveals that countries with a positive EC had a mean inflation change of 8% and 18°C, while those with a negative EC experienced a substantially higher inflation of 36% and warmer temperatures of 22°C on average. This results suggest that countries with lower inflation levels and colder temperatures tend to inflate the median EC scores, disproportionately favoring them over nations facing more challenging economic or environmental conditions.

The conditional model reveals contrasting results: countries experiencing an average inflation change of 23% report a positive EC, while those with an 11% inflation change experience a negative EC. Both groups of countries, those with positive and negative efficiency change, have a similar average temperature of 19°C. These findings suggest that countries not facing severe inflation and warmer temperatures are more likely to maintain or improve their efficiency when benchmarked against nations with harsher environments. Yet, when compared to peers facing similar conditions, we observe that their true efficiency change declines. Our results align with existing literature indicating a negative correlation between inflation and growth, particularly in developed nations (Akinsola and Odhiambo, 2017). However, the specific inflation threshold that is conducive to negative growth remains a subject of debate. Sarel (1996) argues that inflation exceeding 8% has a significantly adverse effect on growth, whereas Gylfason and Herbertsson

Figure 1: Distribution scores for the 1971-1973 period



(2001) finds that inflation becomes detrimental when it exceeds 10% to 20%. Additionally, previous studies have established that rising temperatures are associated with decreased productivity (Dell et al., 2012; Hsiang, 2010), which may help explain why countries with cooler climates experience a positive change in efficiency compared to their warmer counterparts.

Using more recent data from 2006–2008, and under less severe environmental conditions (where inflation was significantly lower across all sample periods compared to 1971–1973), we reassess the models to confirm their robustness. The results align with those from 1971–1973, the unconditional model shows that countries with EC scores > 1 had lower average inflation than those with EC scores < 1. Meanwhile, the conditional model reveals that, under comparable inflation and climate conditions, countries with higher inflation experienced improvements in the efficiency change component.

Table 3: Simar and Zelenyuk (2006) test results 1971-1973 period (H_0: equality of distributions)

Component	p-value	Test statistic
Efficiency change	0.000 ***	15.3543
Technological change	0.000 ***	21.6276
Malmquist productivity index	0.000 ***	4.5452

Significance levels: *** p-value < 0.001; ** p-value < 0.05;

The Technological Change (TC) component of the Malmquist index reflects shifts in the production frontier over time. A positive TC indicates technological progress while a negative TC suggests that countries experienced technological regression in $t+1$ relative to t. The results from the unconditional order-m model for the period 1971 to 1973 indicate that Australia, the United States, the Netherlands, and France achieved the highest levels of technological progress. These findings are consistent with those of Färe et al. (1994) and Yörük and Zaim (2005), who also reported technological advancements for these nations in different time periods. Repeating the analysis with the conditional model reveals that all four countries demonstrated further increases in their technological change scores compared to those from the unconditional model. These findings suggest that these nations experienced even greater technological progress when controlling for inflation and temperature.

The 2006 to 2008 sample reveals a contrasting trend. Under the conditional model, most countries in our sample, including Australia, the United States, and France, experienced technological regression. This trend is aligned with the economic context of the period. Although 2006 did not mark the start of the global financial crisis, 2008 saw its escalation, especially with the collapse of major financial institutions such as Lehman Brothers in September. Economic downturns often result in sectoral imbalances, requiring workers to transition from declining sectors (e.g., construction and finance during 2008) to growing or stable ones. This reallocation can temporarily reduce productivity due to skill mismatches between workers from shrinking industries and the demands of expanding sectors (Valletta and Cleary, 2008).

We now shift our focus to analyzing productivity growth across countries using the Malmquist Productivity Index (MPI), which can be decomposed into the two previously examined components: Efficiency Change (EC) and Technological Change (TC). A positive MPI score indicates productivity growth, while a negative MPI suggests a decline in productivity in $t+1$ relative to t. Our findings reveal that, between 1971 and 1973, most countries in our sample experienced productivity increases. Specifically, under the unconditional model, 67% of the countries showed positive growth; however, this figure dropped to 48% under the conditional model. We evaluate the extent of overestimation or underestimation in productivity growth when using the unconditional model. To do this, we employ the Environmental Variables Index Factor (EVIF) to assess how excluding key environmental variables, such as inflation and temperature, introduces bias into productivity growth estimates. Our results indicate that the unconditional model tended to overestimate productivity for 60% of the sample, as these countries had an EVIF score greater than 1.

Table 4: Simar and Zelenyuk (2006) test results 2006-2008 period (H_0: equality of distributions)

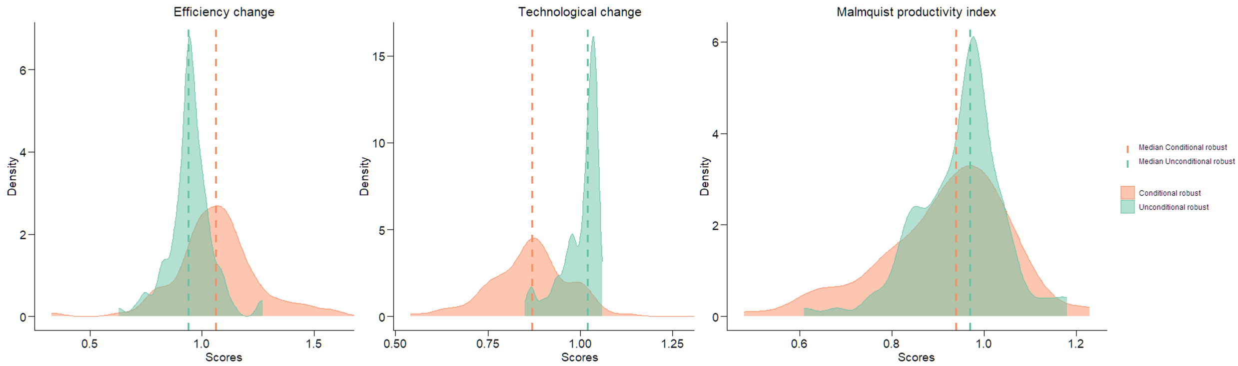
Component	p-value	Test statistic
Efficiency change	0.000 ***	11.7627
Technological change	0.000 ***	26.1081
Malmquist productivity index	0.030 **	1.8756

Significance levels: *** p-value $<$ 0.001; ** p-value $<$ 0.05;

For the 2006-2008 sample, only 24% of the countries showed productivity growth under the unconditional model, though this increased to 32% with the conditional model. During this period, 49% of the countries exhibited an EVIF greater than 1, again indicating overestimation of true productivity levels. The productivity decline of most countries observed between 2006 and 2008 can be attributed to widespread technological regress and a reduction in efficiency change across most countries due to the start of the global financial crisis in 2008.

We compare Myanmar and Sweden, which exhibit opposite scores on the Environmental Variables Index Factor (EVIF), to highlight how accounting for environmental factors affects the measurement of productivity growth. Using the conditional model, which controls for factors like inflation and temperature, Myanmar ranks highest in productivity growth among its peers with similar environmental conditions. However, its position drops to 66th when evaluated

Figure 2: Distribution scores for the 2006-2008 period



using the unconditional model, which compares countries across diverse environments. An EVIF score of 0.59 indicates that Myanmar's productivity is significantly underestimated when environmental factors are excluded. Myanmar achieved GDP growth from 1971 to 1973 despite a shift from 2% deflation to 10% inflation. Controlling for inflation and temperature reveals that Myanmar outperformed all other countries facing similar environmental conditions.

Between 1971 and 1973, Sweden experienced a 2% productivity growth when compared to peers from diverse economic environments. However, when Sweden is assessed alongside peers with similar inflation rates and temperature levels in a conditional model, it actually faced a 2% decline in productivity. This discrepancy indicates that Sweden's productivity growth is overestimated when environmental variables are not considered, as evidenced by its EVIF score exceeding one.

These results show that benchmarking productivity against similar economies helps governments set realistic goals rooted in actual economic conditions. For example, Sweden's EVIF above 1 suggests productivity overestimation, which could mislead policymakers into setting unattainable targets. Conversely, Myanmar's EVIF below 1 indicates underestimation of true productivity, risking overlooked growth opportunities. The EVIF thus alerts governments to check if productivity assessments reflect true conditions, helping to avoid policy decisions based on skewed or biased data.

7. Conclusions

Using data from the Penn World Table for 95 countries over two periods (1971-1973 and 2006-2008), we analyzed productivity growth through a production model incorporating labor, capital, and real GDP. Our findings demonstrate that the conditional Malmquist model, which accounts for environmental factors such as inflation and temperature, provides a more precise measure of productivity growth than the traditional model. This approach reveals statistically significant differences in efficiency change, technological change, and Malmquist productivity scores between the conditional and unconditional models, across both periods.

We introduce the Environmental Variables Index Factor (EVIF) as a new component within the Malmquist decomposition. The EVIF quantifies the impact of environmental factors on productivity estimates, enabling policymakers to detect potential overestimation or underestimation of productivity. This tool provides a more reliable foundation for long-term productivity projections.

Future research could explore models with Variable Returns to Scale (VRS) and further decompose the Malmquist index to assess the interplay between environmental factors, technological progress, and efficiency. Additionally, the absence of data from 2019 to 2022 in the Penn World Table presents a future opportunity to expand the analysis, particularly in light of significant global events like the COVID-19 pandemic and the inflationary shocks of 2021. By addressing these gaps, future research can provide valuable insights into recent dynamics of productivity growth.

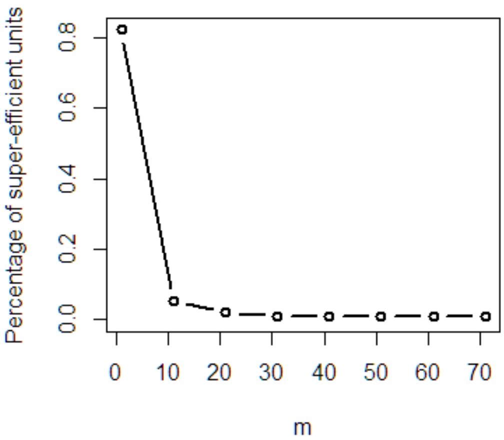
Declaration of competing interest

None.

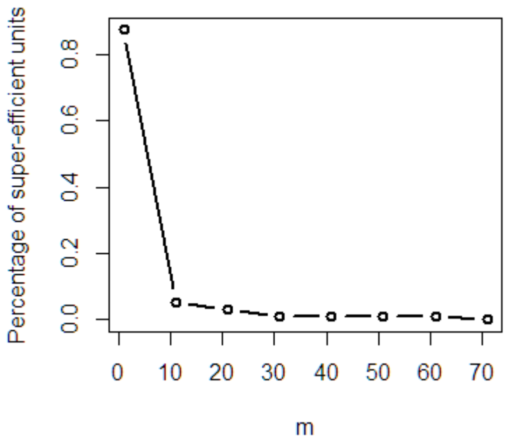
Appendix

A1. Figures

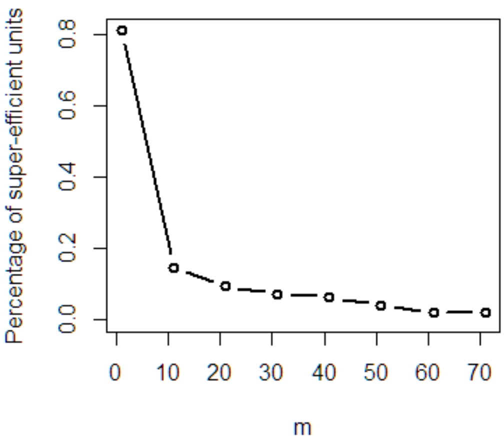
Figure A1: Choice of m based on Daraio and Simar (2007)



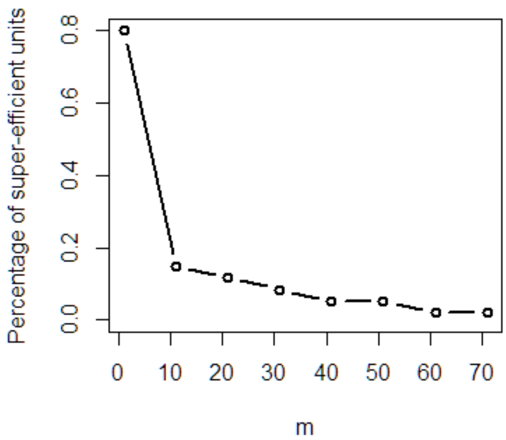
(a) Choice of m for the year: 1971



(b) Choice of m for the year: 1973



(c) Choice of m for the year: 2006



(d) Choice of m for the year: 2008

A2. Tables

Table A1: Results of unconditional and conditional models

Unit	Country	Period	Unconditional order-m							Conditional order-m							
			e00	e11	e10	e01	EC	TC	MQ	e00_c	e11_c	e10_c	e01_c	EC_c	TC_c	MQ_c	EVIF
1	Algeria	71-73	0.49	0.58	0.58	0.48	1.16	1.02	1.19	0.28	0.62	0.62	0.51	2.19	0.75	1.63	0.73
		06-08	0.57	0.53	0.55	0.55	0.93	1.04	0.97	0.60	0.53	0.60	0.93	0.88	0.85	0.75	1.29
2	Argentina	71-73	0.54	0.56	0.55	0.56	1.03	0.98	1.01	1.00	0.87	1.00	0.80	0.87	1.20	1.04	0.97
		06-08	0.62	0.60	0.61	0.61	0.96	1.02	0.98	0.80	1.00	0.83	0.93	1.24	0.84	1.05	0.94
3	Australia	71-73	0.62	0.61	0.65	0.58	0.99	1.06	1.05	1.03	0.74	0.80	0.75	0.72	1.22	0.87	1.20
		06-08	0.61	0.59	0.60	0.59	0.96	1.03	0.99	0.96	1.00	0.98	1.01	1.04	0.97	1.00	0.99
4	Austria	71-73	0.59	0.62	0.63	0.61	1.06	0.99	1.05	1.00	0.95	1.04	0.94	0.95	1.08	1.02	1.02
		06-08	0.67	0.64	0.65	0.64	0.95	1.04	0.98	0.80	0.85	0.74	0.92	1.06	0.87	0.92	1.07
5	Bahrain	71-73	0.92	0.96	0.98	0.90	1.05	1.02	1.07	1.00	0.66	0.38	0.63	0.66	0.95	0.62	1.71
		06-08	0.64	0.69	0.72	0.61	1.08	1.04	1.12	0.52	0.98	0.59	1.06	1.87	0.54	1.02	1.11
6	Bangladesh	71-73	1.08	0.91	0.86	1.14	0.84	0.95	0.80	0.99	0.92	1.09	1.07	0.93	1.05	0.98	0.82
		06-08	0.51	0.51	0.48	0.55	1.00	0.94	0.94	0.50	0.55	0.48	0.56	1.11	0.88	0.98	0.96
7	Barbados	71-73	1.36	1.29	1.31	1.36	0.95	1.01	0.96	1.15	1.03	0.82	1.12	0.89	0.91	0.81	1.18
		06-08	1.02	0.76	0.77	1.01	0.74	1.01	0.75	0.99	1.00	0.75	1.35	1.01	0.74	0.75	1.00
8	Belgium	71-73	0.55	0.61	0.63	0.53	1.11	1.03	1.14	0.85	0.81	0.93	0.74	0.95	1.15	1.09	1.04
		06-08	0.68	0.64	0.66	0.66	0.95	1.03	0.98	0.76	0.86	0.78	0.89	1.13	0.88	1.00	0.98
9	Bolivia	71-73	0.34	0.36	0.35	0.36	1.06	0.97	1.02	0.38	0.34	0.73	0.33	0.89	1.56	1.39	0.74
		06-08	0.68	0.74	0.72	0.71	1.09	0.96	1.04	0.67	0.74	0.73	0.67	1.10	0.99	1.09	0.96
10	Botswana	71-73	0.33	0.35	0.34	0.34	1.05	0.97	1.02	0.34	0.32	0.32	0.31	0.94	1.04	0.98	1.04
		06-08	0.73	0.54	0.56	0.72	0.74	1.02	0.76	0.89	0.83	0.67	0.99	0.94	0.85	0.80	0.95
11	Brazil	71-73	0.54	0.58	0.58	0.54	1.07	1.00	1.07	0.39	0.50	0.46	0.48	1.30	0.86	1.12	0.96
		06-08	0.54	0.51	0.52	0.53	0.94	1.02	0.97	0.52	0.71	0.50	0.71	1.36	0.72	0.98	0.99
12	Burkina	71-73	0.75	0.82	0.77	0.81	1.09	0.93	1.02	0.77	0.85	0.80	0.84	1.10	0.93	1.02	1.00
	Faso	06-08	0.66	0.66	0.60	0.75	1.00	0.90	0.89	0.59	0.66	0.56	1.14	1.13	0.66	0.75	1.20
13	Cameroon	71-73	0.44	0.47	0.46	0.45	1.07	0.98	1.05	0.43	0.44	0.47	0.41	1.01	1.06	1.07	0.98
		06-08	0.62	0.60	0.57	0.65	0.98	0.95	0.92	0.61	0.66	0.57	0.73	1.09	0.85	0.92	1.00
14	Canada	71-73	0.70	0.71	0.76	0.67	1.02	1.05	1.07	1.00	1.00	1.06	0.95	1.00	1.06	1.06	1.01
		06-08	0.69	0.63	0.66	0.66	0.92	1.05	0.96	1.00	1.00	0.99	1.07	1.00	0.96	0.96	1.00
15	Chad	71-73	0.62	0.50	0.48	0.66	0.81	0.95	0.77	0.69	0.49	0.51	0.64	0.71	1.07	0.76	1.02
		06-08	0.76	0.83	0.73	0.88	1.09	0.87	0.95	0.72	0.80	0.68	0.85	1.12	0.85	0.95	1.00
16	Chile	71-73	0.67	0.60	0.58	0.68	0.89	0.98	0.88	1.00	1.00	0.89	1.15	1.00	0.88	0.88	1.00
		06-08	0.68	0.59	0.62	0.65	0.87	1.04	0.91	0.92	0.93	0.84	1.10	1.02	0.87	0.88	1.03
17	China	71-73	0.71	0.69	0.66	0.75	0.96	0.96	0.93	1.00	1.19	0.97	1.31	1.19	0.79	0.94	0.98
		06-08	0.55	0.50	0.50	0.57	0.91	0.98	0.89	0.96	0.92	0.83	1.06	0.96	0.90	0.87	1.03
18	Colombia	71-73	0.31	0.38	0.38	0.31	1.20	1.01	1.22	0.23	0.30	0.18	0.27	1.32	0.71	0.93	1.31
		06-08	0.49	0.51	0.52	0.48	1.05	1.02	1.06	0.48	0.70	0.51	0.66	1.45	0.73	1.06	1.00
19	Congo	71-73	0.37	0.36	0.35	0.38	0.98	0.98	0.95	0.36	0.33	0.34	0.34	0.92	1.04	0.96	0.99
		06-08	0.71	0.49	0.49	0.74	0.70	0.97	0.68	0.70	0.45	0.47	0.71	0.64	1.01	0.65	1.05
20	Costa Rica	71-73	0.74	0.77	0.75	0.76	1.04	0.98	1.02	0.89	0.67	0.51	0.67	0.75	1.01	0.75	1.35
		06-08	0.70	0.66	0.67	0.70	0.94	1.01	0.95	0.67	0.82	0.65	0.77	1.22	0.83	1.01	0.94
21	Côte	71-73	1.20	1.17	1.16	1.24	0.98	0.98	0.96	1.06	1.12	1.09	1.17	1.06	0.94	0.99	0.97
	d'Ivoire	06-08	1.19	1.06	0.98	1.33	0.89	0.91	0.81	1.06	1.00	0.93	1.33	0.95	0.86	0.81	1.00
22	Congo	71-73	0.59	0.59	0.57	0.61	0.99	0.96	0.96	0.59	0.54	0.48	0.57	0.91	0.96	0.87	1.09
		06-08	0.19	0.24	0.22	0.20	1.26	0.94	1.18	0.19	0.25	0.21	0.19	1.36	0.91	1.23	0.96
23	Denmark	71-73	0.56	0.58	0.59	0.56	1.04	1.01	1.05	0.90	0.82	0.89	0.81	0.91	1.10	1.00	1.04
		06-08	0.64	0.60	0.63	0.62	0.94	1.04	0.98	0.79	0.78	0.73	0.91	0.99	0.90	0.89	1.10
24	Dominican	71-73	0.60	0.61	0.60	0.62	1.02	0.98	0.99	0.72	0.54	0.61	0.55	0.74	1.22	0.91	1.10

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Unit	Country	Period	Unconditional order-*m*							Conditional order-*m*							
			e00	e11	e10	e01	EC	TC	MQ	e00_c	e11_c	e10_c	e01_c	EC_c	TC_c	MQ_c	EVIF
	Republic	06-08	0.59	0.52	0.53	0.57	0.89	1.03	0.91	0.58	0.70	0.53	0.79	1.23	0.74	0.91	1.00
25	Ecuador	71-73	0.44	0.45	0.43	0.46	1.02	0.96	0.98	1.00	0.51	0.58	0.53	0.51	1.46	0.75	1.30
		06-08	0.41	0.42	0.43	0.40	1.03	1.01	1.04	0.48	0.51	0.49	0.54	1.06	0.92	0.98	1.07
26	Egypt	71-73	1.99	2.06	1.97	2.07	1.04	0.96	0.99	1.21	1.63	2.41	1.59	1.35	1.06	1.43	0.70
		06-08	1.06	1.07	1.05	1.09	1.00	0.98	0.98	1.02	1.02	1.01	1.30	0.99	0.88	0.88	1.12
27	Ethiopia	71-73	0.69	0.72	0.69	0.73	1.05	0.94	0.99	0.42	0.60	0.45	0.56	1.43	0.75	1.08	0.92
		06-08	0.35	0.44	0.38	0.41	1.27	0.86	1.08	0.35	0.51	0.33	0.37	1.46	0.78	1.13	0.96
28	Finland	71-73	0.43	0.45	0.48	0.42	1.06	1.04	1.10	0.73	0.70	0.77	0.67	0.96	1.10	1.05	1.05
		06-08	0.60	0.60	0.63	0.58	1.00	1.04	1.04	0.78	0.86	0.80	0.88	1.10	0.91	1.00	1.04
29	France	71-73	0.55	0.59	0.63	0.53	1.07	1.06	1.13	0.87	0.80	0.95	0.75	0.92	1.17	1.08	1.05
		06-08	0.63	0.59	0.62	0.61	0.94	1.05	0.98	0.71	0.78	0.73	0.84	1.10	0.89	0.98	1.00
30	Gabon	71-73	0.63	0.64	0.63	0.64	1.03	0.98	1.00	0.57	0.52	0.46	0.55	0.92	0.96	0.88	1.14
		06-08	0.46	0.45	0.46	0.45	0.97	1.02	0.99	0.42	0.34	0.39	0.82	0.81	0.77	0.62	1.59
31	Germany	71-73	0.44	0.47	0.48	0.43	1.08	1.02	1.10	0.69	0.68	0.77	0.61	0.99	1.13	1.12	0.98
		06-08	0.63	0.59	0.62	0.59	0.94	1.05	0.99	0.75	0.85	0.70	0.89	1.14	0.83	0.95	1.04
32	Ghana	71-73	0.33	0.32	0.32	0.34	0.98	0.98	0.96	0.31	0.25	0.20	0.26	0.83	0.96	0.79	1.21
		06-08	0.37	0.36	0.36	0.38	0.99	0.98	0.97	1.00	0.33	0.36	0.51	0.33	1.46	0.48	2.00
33	Greece	71-73	0.42	0.45	0.47	0.41	1.08	1.03	1.11	0.80	0.71	0.92	0.65	0.89	1.26	1.12	0.99
		06-08	0.53	0.51	0.53	0.51	0.96	1.04	1.00	0.64	0.70	0.73	0.70	1.09	0.98	1.07	0.94
34	Guatemala	71-73	0.65	0.68	0.65	0.66	1.04	0.97	1.02	0.81	0.62	0.56	0.61	0.76	1.10	0.84	1.21
		06-08	0.52	0.51	0.51	0.52	0.98	1.00	0.97	0.52	0.59	0.50	0.70	1.14	0.79	0.90	1.08
35	Haiti	71-73	0.24	0.25	0.24	0.25	1.02	0.98	1.00	0.25	0.23	0.20	0.23	0.90	0.99	0.89	1.12
		06-08	0.18	0.19	0.18	0.19	1.01	0.98	0.99	0.18	0.18	0.18	0.18	0.99	1.00	0.99	1.00
36	Honduras	71-73	0.52	0.57	0.56	0.53	1.09	0.98	1.07	0.69	0.52	0.55	0.48	0.75	1.23	0.92	1.16
		06-08	0.51	0.45	0.45	0.52	0.90	0.98	0.88	0.49	0.55	0.44	0.65	1.11	0.78	0.86	1.02
37	Hungary	71-73	0.36	0.40	0.38	0.37	1.11	0.96	1.06	0.81	0.74	0.87	0.70	0.92	1.16	1.07	0.99
		06-08	0.66	0.55	0.57	0.65	0.82	1.03	0.85	0.88	0.82	0.76	0.98	0.93	0.91	0.85	1.00
38	Iceland	71-73	0.56	0.58	0.61	0.54	1.03	1.05	1.08	0.87	0.84	1.07	0.80	0.96	1.18	1.14	0.95
		06-08	0.62	0.64	0.66	0.59	1.03	1.04	1.07	0.77	0.81	0.86	0.78	1.06	1.02	1.08	1.00
39	India	71-73	0.33	0.36	0.35	0.33	1.09	0.98	1.07	0.32	0.33	0.30	0.31	1.01	0.98	0.99	1.08
		06-08	0.46	0.43	0.42	0.48	0.93	0.97	0.90	0.45	0.47	0.41	0.54	1.03	0.86	0.89	1.02
40	Indonesia	71-73	0.34	0.41	0.40	0.35	1.20	0.97	1.17	0.36	0.38	0.40	0.33	1.06	1.07	1.14	1.02
		06-08	0.51	0.43	0.43	0.52	0.84	0.99	0.83	0.51	0.38	0.41	0.49	0.75	1.06	0.80	1.04
41	Iran	71-73	0.33	0.42	0.42	0.33	1.28	1.00	1.28	0.55	0.66	1.05	0.51	1.19	1.31	1.57	0.82
		06-08	0.59	0.55	0.58	0.56	0.93	1.05	0.98	0.79	0.90	0.89	1.01	1.15	0.87	1.00	0.98
42	Iraq	71-73	1.10	1.17	1.13	1.12	1.07	0.98	1.04	0.99	1.06	1.05	1.06	1.08	0.96	1.04	1.00
		06-08	1.11	1.13	1.14	1.12	1.02	1.00	1.02	1.00	1.00	1.09	1.09	1.00	1.00	1.00	1.02
43	Ireland	71-73	0.58	0.64	0.64	0.58	1.10	1.00	1.10	0.98	1.00	0.97	0.97	1.01	0.99	1.01	1.09
		06-08	0.76	0.67	0.69	0.74	0.88	1.03	0.91	0.88	0.94	0.82	0.97	1.06	0.89	0.95	0.96
44	Israel	71-73	0.57	0.60	0.62	0.57	1.05	1.02	1.07	0.93	0.97	0.54	0.91	1.04	0.75	0.78	1.37
		06-08	0.64	0.59	0.62	0.61	0.93	1.05	0.97	0.97	0.90	0.92	0.95	0.93	1.02	0.95	1.03
45	Italy	71-73	0.50	0.52	0.54	0.49	1.04	1.03	1.07	0.89	0.79	0.95	0.73	0.90	1.20	1.08	0.99
		06-08	0.59	0.57	0.61	0.57	0.98	1.04	1.02	0.72	0.81	0.75	0.79	1.14	0.92	1.04	0.98
46	Jamaica	71-73	0.40	0.43	0.43	0.41	1.07	0.99	1.06	0.40	0.33	0.24	0.33	0.81	0.95	0.77	1.39
		06-08	0.40	0.31	0.32	0.40	0.76	1.02	0.78	0.39	0.34	0.29	0.53	0.86	0.80	0.69	1.13
47	Japan	71-73	0.51	0.52	0.53	0.50	1.03	1.01	1.04	0.92	0.78	0.81	0.78	0.85	1.11	0.94	1.11
		06-08	0.52	0.48	0.50	0.50	0.93	1.03	0.96	0.59	0.69	0.58	0.72	1.17	0.83	0.97	0.99
48	Kenya	71-73	0.42	0.42	0.41	0.43	0.99	0.97	0.96	0.73	0.38	0.39	0.40	0.52	1.37	0.72	1.34
		06-08	0.64	0.61	0.57	0.70	0.95	0.93	0.88	0.59	0.56	0.56	0.84	0.95	0.84	0.80	1.11
49	Kuwait	71-73	1.97	1.80	1.85	1.96	0.91	1.01	0.93	0.98	1.36	0.75	1.46	1.38	0.61	0.84	1.10
		06-08	1.24	1.38	1.42	1.21	1.11	1.03	1.14	1.03	1.00	1.20	0.96	0.97	1.13	1.10	1.04

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Unit	Country	Period	Unconditional order-m							Conditional order-m							
			e00	e11	e10	e01	EC	TC	MQ	e00_c	e11_c	e10_c	e01_c	EC_c	TC_c	MQ_c	EVIF
50	Luxembourg	71-73	0.74	0.83	0.87	0.71	1.11	1.05	1.17	1.00	1.03	1.29	0.92	1.03	1.16	1.20	0.97
		06-08	0.91	0.86	0.90	0.89	0.95	1.04	0.98	1.01	1.00	1.03	1.06	0.99	0.99	0.98	1.00
51	Madagascar	71-73	0.73	0.70	0.67	0.77	0.95	0.96	0.91	0.66	0.61	0.81	0.65	0.92	1.16	1.07	0.86
		06-08	0.52	0.51	0.46	0.59	0.98	0.89	0.87	0.54	0.57	0.50	0.56	1.07	0.91	0.97	0.90
52	Malaysia	71-73	0.33	0.39	0.39	0.33	1.20	1.00	1.19	0.49	0.31	0.23	0.27	0.62	1.17	0.73	1.63
		06-08	0.66	0.66	0.68	0.64	1.01	1.03	1.04	0.63	0.99	0.63	0.92	1.59	0.66	1.04	1.00
53	Mali	71-73	1.22	1.00	0.94	1.27	0.82	0.95	0.78	1.03	1.03	0.88	1.37	1.00	0.80	0.80	0.98
		06-08	1.00	1.07	0.94	1.16	1.07	0.87	0.93	0.91	1.00	0.85	1.10	1.09	0.84	0.92	1.01
54	Malta	71-73	0.48	0.51	0.50	0.49	1.07	0.97	1.04	0.77	0.64	0.67	0.60	0.83	1.16	0.96	1.08
		06-08	0.77	0.71	0.74	0.74	0.92	1.04	0.96	1.00	1.00	1.03	1.05	1.00	0.99	0.99	0.97
55	Mauritius	71-73	1.01	1.07	1.05	1.04	1.06	0.98	1.04	0.98	0.97	0.83	0.95	0.99	0.94	0.93	1.11
		06-08	0.76	0.64	0.65	0.75	0.83	1.02	0.85	0.79	0.89	0.72	1.00	1.12	0.80	0.90	0.95
56	Mexico	71-73	0.60	0.62	0.64	0.60	1.04	1.01	1.05	0.95	0.82	0.74	0.79	0.87	1.04	0.90	1.17
		06-08	0.62	0.59	0.61	0.60	0.96	1.03	0.99	0.76	0.84	0.76	0.85	1.11	0.90	1.00	0.99
57	Morocco	71-73	0.98	1.00	0.97	1.02	1.02	0.96	0.98	1.00	1.00	1.03	1.01	0.99	1.01	1.00	0.98
		06-08	0.51	0.43	0.44	0.51	0.84	1.00	0.85	0.62	0.65	0.53	0.86	1.06	0.76	0.80	1.06
58	Myanmar	71-73	1.41	1.46	1.40	1.47	1.04	0.96	0.99	0.84	1.26	2.18	1.17	1.50	1.11	1.67	0.59
		06-08	1.23	1.14	1.03	1.45	0.93	0.87	0.81	1.02	1.01	1.02	1.65	0.99	0.79	0.78	1.04
59	Netherlands	71-73	0.56	0.60	0.65	0.54	1.07	1.06	1.14	0.85	0.81	0.95	0.73	0.95	1.17	1.11	1.02
		06-08	0.69	0.65	0.68	0.66	0.94	1.04	0.98	0.84	0.91	0.78	0.95	1.08	0.87	0.94	1.04
60	New	71-73	0.65	0.71	0.71	0.65	1.10	1.00	1.09	1.00	1.05	1.24	0.97	1.05	1.10	1.16	0.94
	Zealand	06-08	0.70	0.66	0.70	0.69	0.94	1.04	0.98	0.94	1.00	0.92	1.03	1.06	0.92	0.97	1.01
61	Niger	71-73	0.24	0.20	0.19	0.25	0.83	0.97	0.81	0.31	0.17	0.17	0.22	0.57	1.17	0.67	1.21
		06-08	0.33	0.34	0.32	0.36	1.04	0.92	0.96	0.30	0.36	0.31	0.35	1.19	0.86	1.03	0.94
62	Nigeria	71-73	0.23	0.25	0.25	0.24	1.10	0.99	1.08	0.29	0.20	0.25	0.19	0.69	1.36	0.94	1.15
		06-08	0.30	0.28	0.29	0.29	0.94	1.02	0.96	0.29	0.38	0.28	0.30	1.35	0.84	1.13	0.85
63	Norway	71-73	0.56	0.59	0.60	0.56	1.04	1.01	1.05	0.91	0.85	0.92	0.83	0.94	1.08	1.02	1.03
		06-08	0.80	0.78	0.82	0.77	0.98	1.04	1.02	1.00	1.00	1.06	1.01	1.00	1.02	1.02	1.00
64	Oman	71-73	0.96	0.65	0.63	1.00	0.68	0.96	0.66	0.47	0.44	0.36	0.72	0.94	0.73	0.68	0.96
		06-08	0.99	0.95	0.99	0.96	0.96	1.04	1.00	0.86	1.00	0.86	0.96	1.16	0.88	1.02	0.98
65	Pakistan	71-73	0.66	0.68	0.65	0.68	1.02	0.97	0.99	0.67	0.62	0.71	0.63	0.92	1.10	1.02	0.97
		06-08	0.97	0.92	0.89	1.03	0.95	0.96	0.90	0.99	0.90	0.88	1.24	0.91	0.88	0.80	1.13
66	Panama	71-73	0.77	0.69	0.68	0.79	0.90	0.98	0.88	0.84	0.58	0.58	0.68	0.69	1.11	0.76	1.16
		06-08	0.90	0.74	0.75	0.89	0.82	1.02	0.83	0.89	0.99	0.73	1.20	1.11	0.74	0.82	1.02
67	Paraguay	71-73	0.60	0.62	0.62	0.61	1.05	0.99	1.03	0.59	0.57	0.52	0.56	0.97	0.98	0.95	1.09
		06-08	0.44	0.45	0.45	0.43	1.03	1.00	1.03	0.43	0.53	0.44	0.54	1.24	0.81	1.00	1.03
68	Peru	71-73	0.79	0.83	0.81	0.81	1.06	0.98	1.03	0.85	0.83	0.79	0.81	0.98	1.00	0.98	1.05
		06-08	0.55	0.59	0.59	0.55	1.08	0.99	1.07	0.62	0.97	0.69	0.72	1.56	0.79	1.22	0.88
69	Philippines	71-73	0.38	0.52	0.51	0.39	1.37	0.98	1.33	0.29	0.47	0.40	0.35	1.64	0.84	1.37	0.97
		06-08	0.54	0.51	0.51	0.55	0.95	0.98	0.93	0.54	0.65	0.51	0.70	1.21	0.77	0.94	1.00
70	Portugal	71-73	0.52	0.58	0.55	0.53	1.11	0.97	1.07	0.94	0.89	0.98	0.83	0.94	1.12	1.06	1.02
		06-08	0.45	0.42	0.43	0.43	0.93	1.03	0.96	0.71	0.64	0.65	0.67	0.90	1.04	0.94	1.03
71	Qatar	71-73	2.86	2.71	2.75	2.85	0.95	1.01	0.96	1.00	1.86	1.72	1.97	1.86	0.69	1.28	0.75
		06-08	1.32	1.31	1.38	1.28	0.99	1.04	1.04	1.04	1.00	1.12	2.44	0.96	0.69	0.66	1.56
72	Republic of	71-73	0.27	0.34	0.33	0.28	1.25	0.99	1.23	0.57	0.63	0.66	0.54	1.12	1.05	1.18	1.05
	Korea	06-08	0.54	0.51	0.53	0.53	0.95	1.03	0.98	0.70	0.74	0.65	0.82	1.05	0.87	0.91	1.07
73	Rwanda	71-73	2.85	2.84	2.75	3.10	1.00	0.94	0.94	1.02	1.57	1.89	1.61	1.55	0.87	1.35	0.70
		06-08	0.85	0.84	0.71	1.01	0.98	0.85	0.83	1.00	0.79	0.85	1.98	0.79	0.74	0.58	1.43
74	Saudi	71-73	1.49	1.59	1.57	1.50	1.07	0.99	1.06	1.04	1.26	0.99	1.17	1.20	0.84	1.01	1.04
	Arabia	06-08	0.98	1.12	1.17	0.96	1.14	1.04	1.18	0.86	0.98	1.01	1.49	1.14	0.77	0.88	1.34
75	Senegal	71-73	0.39	0.37	0.36	0.39	0.96	0.98	0.94	0.44	0.32	0.34	0.34	0.73	1.18	0.86	1.09

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			Unconditional order-m							Conditional order-m							
Unit	Country	Period	e00	e11	e10	e01	EC	TC	MQ	e00_c	e11_c	e10_c	e01_c	EC_c	TC_c	MQ_c	EVIF
		06-08	0.48	0.45	0.44	0.50	0.94	0.96	0.91	0.50	0.58	0.45	0.60	1.16	0.80	0.93	0.97
76	Singapore	71-73	0.51	0.51	0.51	0.50	1.00	1.01	1.01	0.49	0.40	0.30	0.40	0.81	0.95	0.77	1.31
		06-08	0.80	0.71	0.74	0.75	0.89	1.06	0.93	0.68	1.00	0.64	1.10	1.46	0.63	0.92	1.01
77	South Africa	71-73	0.58	0.66	0.65	0.60	1.12	0.98	1.10	0.98	0.96	1.20	0.88	0.98	1.18	1.16	0.95
		06-08	0.84	0.70	0.71	0.82	0.83	1.03	0.85	1.00	0.98	0.88	1.20	0.98	0.86	0.85	1.00
78	Spain	71-73	0.52	0.55	0.56	0.53	1.06	1.00	1.06	0.93	0.83	0.87	0.80	0.89	1.10	0.98	1.08
		06-08	0.55	0.52	0.54	0.53	0.94	1.05	0.98	0.73	0.74	0.69	0.75	1.01	0.96	0.97	1.02
79	Sri Lanka	71-73	0.70	0.70	0.69	0.71	1.00	0.98	0.98	0.80	0.63	0.55	0.66	0.78	1.03	0.81	1.22
		06-08	0.86	0.75	0.74	0.89	0.87	0.98	0.86	0.87	0.69	0.74	0.94	0.79	1.00	0.79	1.08
80	Sudan	71-73	0.72	0.62	0.61	0.75	0.86	0.97	0.84	0.74	0.58	0.54	0.70	0.77	1.00	0.78	1.09
		06-08	0.95	0.60	0.58	0.99	0.63	0.96	0.61	0.94	0.75	0.59	1.14	0.79	0.81	0.64	0.94
81	Sweden	71-73	0.57	0.58	0.59	0.58	1.01	1.01	1.02	0.95	0.90	0.93	0.90	0.94	1.04	0.98	1.03
		06-08	0.69	0.65	0.67	0.65	0.94	1.04	0.98	0.96	0.94	0.86	1.04	0.98	0.92	0.91	1.08
82	Switzerland	71-73	0.76	0.76	0.79	0.73	1.00	1.04	1.04	1.00	0.96	1.04	0.97	0.96	1.05	1.01	1.02
		06-08	0.66	0.66	0.69	0.64	1.00	1.04	1.04	0.78	0.91	0.86	0.87	1.17	0.92	1.07	0.96
83	Syrian Arab	71-73	0.50	0.52	0.51	0.50	1.04	0.98	1.02	0.69	0.67	0.99	0.64	0.96	1.27	1.22	0.84
	Republic	06-08	0.56	0.57	0.58	0.55	1.02	1.01	1.04	0.66	0.82	0.66	0.74	1.24	0.85	1.06	0.98
84	Thailand	71-73	0.41	0.42	0.41	0.42	1.03	0.98	1.01	0.49	0.38	0.32	0.38	0.77	1.05	0.81	1.25
		06-08	0.50	0.47	0.47	0.49	0.94	1.01	0.95	0.49	0.63	0.46	0.66	1.28	0.73	0.94	1.01
85	Trinidad	71-73	0.87	0.98	0.99	0.88	1.13	1.00	1.13	0.75	0.76	0.58	0.71	1.01	0.90	0.91	1.24
	and Tobago	06-08	0.91	0.83	0.85	0.89	0.91	1.02	0.93	0.88	0.70	0.72	1.21	0.79	0.87	0.69	1.36
86	Tunisia	71-73	0.63	0.69	0.67	0.65	1.09	0.97	1.06	0.70	0.68	0.67	0.65	0.97	1.03	1.00	1.06
		06-08	0.53	0.47	0.48	0.53	0.88	1.02	0.90	0.65	0.66	0.60	0.74	1.01	0.90	0.91	0.99
87	Turkey	71-73	0.54	0.54	0.55	0.53	1.01	1.01	1.01	0.82	0.92	0.81	0.93	1.12	0.88	0.99	1.02
		06-08	0.76	0.62	0.65	0.74	0.81	1.04	0.85	1.00	0.96	0.85	1.15	0.96	0.88	0.84	1.01
88	Tanzania	71-73	0.43	0.43	0.42	0.45	1.00	0.97	0.97	0.43	0.40	0.44	0.40	0.92	1.08	1.00	0.98
		06-08	0.41	0.37	0.35	0.44	0.89	0.94	0.84	0.43	0.34	0.33	0.48	0.80	0.93	0.74	1.13
89	UAE	71-73	6.12	4.67	5.14	6.12	0.76	1.05	0.80	4.46	1.74	3.72	5.18	0.39	1.36	0.53	1.51
		06-08	1.17	0.92	0.96	1.14	0.79	1.03	0.82	0.94	0.79	0.78	1.63	0.84	0.75	0.63	1.29
90	United	71-73	0.52	0.56	0.59	0.51	1.08	1.03	1.11	0.85	0.85	0.97	0.75	0.99	1.14	1.13	0.98
	Kingdom	06-08	0.71	0.63	0.66	0.69	0.88	1.04	0.92	0.93	0.89	0.81	1.03	0.96	0.91	0.87	1.06
91	United	71-73	0.76	0.75	0.78	0.70	0.99	1.06	1.05	1.01	0.97	1.07	0.91	0.96	1.10	1.06	0.99
	States	06-08	0.76	0.72	0.75	0.73	0.94	1.04	0.98	0.87	0.94	0.86	0.92	1.09	0.93	1.01	0.97
92	Uruguay	71-73	0.61	0.60	0.58	0.60	0.99	0.99	0.98	1.00	1.00	1.01	0.89	1.00	1.07	1.07	0.91
		06-08	0.48	0.47	0.48	0.47	0.99	1.02	1.01	0.59	0.72	0.61	0.66	1.22	0.87	1.06	0.96
93	Venezuela	71-73	0.56	0.57	0.56	0.54	1.02	1.01	1.02	0.51	0.42	0.36	0.45	0.81	0.98	0.80	1.28
		06-08	0.57	0.54	0.56	0.55	0.95	1.03	0.98	0.52	0.56	0.49	0.46	1.06	1.01	1.07	0.91
94	Zambia	71-73	0.54	0.62	0.61	0.56	1.15	0.98	1.12	0.93	0.58	0.64	0.53	0.62	1.40	0.87	1.29
		06-08	0.39	0.40	0.39	0.40	1.04	0.97	1.01	0.37	0.39	0.38	0.38	1.06	0.98	1.04	0.97
95	Zimbabwe	71-73	0.95	1.08	1.05	0.97	1.14	0.97	1.11	0.95	0.97	1.42	0.87	1.03	1.26	1.30	0.86
		06-08	0.35	0.32	0.29	0.37	0.91	0.93	0.85	0.37	0.48	0.32	0.64	1.32	0.61	0.81	1.05

e00: $\hat{D}^t_{o,m}(y^t, x^t)$; e11: $\hat{D}^{t+1}_{o,m}(y^{t+1}, x^{t+1})$; e10: $\hat{D}^t_{o,m}(y^{t+1}, x^{t+1})$; e01: $\hat{D}^{t+1}_{o,m}(y^t, x^t)$; e00_c: $\hat{D}^t_{o,m|z}(y^t, x^t \mid z^t)$; e11_c: $\hat{D}^{t+1}_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$; e10_c: $\hat{D}^t_{o,m|z}(y^{t+1}, x^{t+1} \mid z^{t+1})$; e01_c: $\hat{D}^{t+1}_{o,m|z}(y^t, x^t \mid z^t)$; EC: unconditional efficiency change; TC: unconditional technological change; MQ: unconditional Malmquist productivity index; EC_c: conditional efficiency change; TC_c: conditional technological change; MQ_c: conditional Malmquist productivity index; EVIF: Environmental Variables Index Factor.

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