Productive Performance and Technology Gaps using a Bayesian Metafrontier Production Function: A cross-country comparison.

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Productive Performance and Technology Gaps using a Bayesian Metafrontier Production Function: A cross-country comparison

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Abstract

Growth theory argues on the role of heterogeneity that can lead to multiple regimes examining countries performance. A meta-production stochastic function under a Bayesian perspective has been developed to estimate technical efficiencies across countries over a time period. The metafrontier model is used to highlight heterogeneity among cluster of countries revealing catch up phenomena. The estimation procedure relies on the solution of an optimization problem and on the concept of the upper orthant order of two multivariate normal random variables. The proposed models are applied in a real dataset consisting of 109 countries for a 20-year period from 1995-2014. The productive performance differential and the associated technology gaps were investigated using two distinct frontiers (OECD vs non-OECD countries). Empirical results reveal that heterogeneity indeed plays a significant and distinctive role in determining technological gaps.

keywords: Technological heterogeneity,Bayesian approach, Metafrontier, Spillovers,
JEL Classifications: C11,C23,C51,D24,O10,

1 Introduction and motivation

Production function modeling is a crucial tool in analyzing entities' productive performance, returns to scale, technical change and productivity growth. During the last decades a great deal of effort has been devoted to model the production relationships while a plethora of studies has been used to analyze economic behavior in many sectors (Fried et al., 2008). Thus, the production function framework has been emulated in empirical studies while its continuing use and the great need for applied research have highlight significant problems to be solved.

One of these problems refers to the fact that several entities under different technological structures (i.e countries, industries, firms, regions) can face dissimilar production possibilities that differ over time. These production possibilities can be attributed firstly to the different way the specific entities transform the available set of inputs to the set of outputs and secondly, to differences due to the environment that they operate. The first one is attributed to the technological status that each entity uses while the second considers that each entity is conditional to the technological group that belongs.

These conditions may inhibit entities to choose the best available technology and is closely related with two concepts; technological hierarchy and heterogeneity. The first term, hierarchy, conceptually refers to a specific regulatory framework while the second one has a more arbitrary meaning (Dosi et al., 2010). Thus, an attractive avenue for further empirical research is to assume that each production entity belongs to each own technological group. However, such this technological isolation (Tsekouras et al., 2016, 2017) can not be meaningfully pursued using classical approaches. Recognition of this significant limitation has motivated many researchers to use/borrow the differential geometry term of envelope and to develop the concept of meta-production function.

The initiation by the development of a theoretically meta-production function (Hayami, 1969; Hayami and Ruttan, 1970) and the refinement and transposition of this concept to a stochastic frontier (SFA) and a data envelopment analysis (DEA) framework (Battese and Rao, 2002; Battese et al., 2004; ODonnell et al., 2008) concluded in the metafrontier production function[1]. The major drawback of Battese et al. (2004) approach is that in the second step of their method the metafrontier production function is calculated using linear programming methods (Huang et al., 2014) and thus does not allow for the existence of statistical properties (Amsler et al., 2017; Huang et al., 2014).

Motivated by this limitation, we propose a Bayesian metaproduction function using an SFA approach to estimate technology gaps. To the best of our knowledge, there is no other attempt for calculating technology gaps while the incorporation of a SFA approach is more suitable for panel data (Tsionas, 2002) but still rare in applied research (Tsionas, 2002; Griffin and Steel, 2007; Tabak and Tecles, 2010). In addition, the Bayesian SFA provides a more realistic approach (Chen et al., 2015) and leads to more accurate efficiency estimations (Tsionas, 2002; Tabak and Tecles, 2010)) and incorporate model uncertainty (Tabak and Tecles, 2010) and caters for heterogeneity (Tsionas, 2002)

Heterogeneity in the Bayesian context (Van den Broeck et al., 1994) has been studied through the use of hierarchical models (Tsionas, 2002; Huang et al., 2014) and in the inefficiency factor using covariates in the distribution of the non-negative error component (Koop et al., 1997). In advance, (Griffin and Steel, 2004, 2007) provide models of observed heterogeneity using flexible and non-parametric mixtures of inefficiency while Galán et al. (2015) discuss unobserved inefficiency heterogeneity with the inclusion of a random parameter in the inefficiency distribution. On the other hand, heterogeneity stemming from differentials in the characteristics of the production environment has never been explored in the literature in a Bayesian perspective.

[1] In the first stage efficiency estimates are provided for each group while in the second stage the metafrontier production function and the corresponding technology gaps are estimated by polling all the data of the participated groups using an LP problem.

In this study we exploit a dataset consisting of 109 countries for a 20-year period from 1995-2014 and investigate the productive performance differential and the associated technology gaps using a metafrontier Bayesian approach from two distinct frontiers. The first one consists of countries that belong to OECD while the second one to countries that do not belong at OECD. The incorporation of a metaproduction function under a Bayesian perspective permits us to give statistical properties to the first stage estimates for the meta-efficiency scores. Furthermore, allows the incorporation, into the model, of any available, theoretical or based on previous studies, prior information through the prior distributions of the parameters. This prior information is combined with the information contained in the observed data to provide new insights into the nature of the data. This is very important in similar datasets since information maybe is available from previous economic studies. Finally, it is worth mentioning that since a simulated sample from the posterior distribution is always available, even for the unobserved variables, it is straight forward to estimate any quantity of interest.

Our empirical results reveal that heterogeneity indeed plays multi-edged roles in the spillover effects through different channels. Among them, we can distinguish technology choice set, absorptive capacity and capabilities, human capital level and localized technical change. Moreover, the existence of significant technology gaps especially for the non-OECD countries groups reveal the serious obstacles regarding technology spillovers Bardhan and Lapan (1973) and support the idea of non catch-up phenomena. Most importantly, the different trends that each group follows underline a world of divergence during the 20-year period of examination.

The rest of the paper is organized as follows. In Section 2 the stochastic frontier model and the formulation of the metafrontier production function is presented. In Section 3 the frontier model under a Bayesian framework is given in a coherent way by presenting in detail all the necessary steps to apply the MCMC algorithm. In Section 4 the proposed Bayesian metafrontier production model is presented. In the following section the proposed analysis is applied to a data set obtained by the World Bank by using two distinct frontiers (OECD vs non-OECD countries). Finally. some concluding remarks are given in the last section.

2 Stochastic frontier model and formulation of metafrontier production function

Stochastic frontier production functions have been used, extensively, in a large number of empirical studies to account the possible existence of technical inefficiencies in production. Stemming from the seminal paper of Aigner et al. (1977) and Meeusen and van den Broeck (1977) and following Kumbhakar and Lovell (1998), it is assumed that the production technology S models the transformation of a vector of inputs $\mathbf{x}^{'}_{it(j)} = (x_{1it(j)}, x_{2it(j)}, ..., x_{kit(j)}) \in R^k_+$ that each unit i in the group j (for example country i in geographical region or organization j) can employ at time t to produce a vector of output $\mathbf{y}^{'}_{it(j)} = (y_{1it(j)}, y_{2it(j)}, ..., y_{pit(j)}) \in R^p_+$, The technology set S provides a description of all technologically feasible relationships between inputs $\mathbf{x}$ and outputs $\mathbf{y}$ and it is denoted as $S(\mathbf{x}) = \{(\mathbf{x}, \mathbf{y}) : \mathbf{x} \text{ can produce } \mathbf{y}\}$.

Note, that all units (hereafter countries) do not make necessarily the most of the inputs $\mathbf{x}'_{it(j)}$ given the technology embodied in the production function and may produce less than it might due to a degree of inefficiency. One should recognize that this degrees of inefficiency might be effected by the geographical region or the organization j that a country belongs since none country is technologically isolated (Tsekouras et al., 2016, 2017). On the other hand, random shocks, that are assumed to be independent by any technical inefficiency, can increase or decrease the final production of a specific country. These characteristics cause extra heterogeneity in the final production and for that reason a flexible model should be defined to describe the production of the $i-th$ country in the $j-th$ group (out of total J groups) at year t (over the time period of T years). As a consequence, the stochastic production function can be expressed as:

$$Y_{it(j)} = f(\mathbf{x}_{it(j)}, \boldsymbol{\beta}_{(j)}) exp(v_{it(j)} - u_{it(j)}), \;\; t = 1, \ldots, T, \;\; i = 1, \ldots, n_j, j = 1, \ldots, J. \quad (1)$$

(see for example Aigner et al. (1977); Battese and Rao (2002), where $\mathbf{x}_{it(j)}$ is the vector of the values of some functions of the inputs used by the $i-th$ unit in the $t-th$ time period for the $j-th$ group, $\boldsymbol{\beta}_{(j)}$ the $(k+1) \times 1$ parameter vector, $v_{it(j)}$ a normal error term and $u_{it(j)} \geqslant 0$ a measure of technical inefficiency. Usually, the unobservable random errors are independently distributed with $v_{it(j)} \sim N(0, \sigma_v^2)$ and $u_{it(j)}$ is a non negative random variable for each group. The above model is usually referred as Error Component Model (ECM) (Battese and Coelli) due to the fact that the final production of every country is a result of two errors components.

By taking natural logarithm in both sides of equation (1) we have

$$\ln Y_{it(j)} = \ln f(\mathbf{x}_{it(j)}; \boldsymbol{\beta}_{(j)}) + v_{it(j)} - u_{it(j)}, \;\; t = 1, \ldots, T, \;\; i = 1, \ldots, n_j, j = 1, \ldots, J. \quad (2)$$

A frequently used mathematical representation for $f(\mathbf{x}_{it(j)}; \boldsymbol{\beta}_{(j)})$ is

$$f(\mathbf{x}_{it(j)}; \boldsymbol{\beta}_{(j)}) = \exp\left(\mathbf{x}'_{it(j)} \boldsymbol{\beta}_{(j)}\right). \quad (3)$$

Based on the relation (1) and choosing the above function form for $f(\mathbf{x}_{it(j)}; \boldsymbol{\beta}_{(j)})$, Battesse and Coelli (1992) achieved to expressed a country's technical efficiency, belonging to a specific group, by the following expression:

$$TE_{it(j)} = \frac{Y_{it(j)}}{exp(\mathbf{x}'_{it(j)} \boldsymbol{\beta}_{(j)} + v_{it(j)})} \equiv e^{-u_{it(j)}} \quad (4)$$

Countries, as pointed earlier, are not isolated and the same can be said about for the different groups of countries. As a consequence, it is natural one to want to compare countries that do not belong necessarily to the same group. A method that allow us to do that is to define a common underlying metafrontier production function for all the studied groups as Y_{it}^M. This metafrontier production function can operate as a reference point for all countries under a common shared production technology status. The metafrontier production function can be defined as the convex hull of the jointure of all technology sets and act, in differential geometry terms, as the envelope of all individual groups' production functions. The main idea behind the metafrontier production function Hayami (1969) Hayami and Ruttan (1971) stems from the idea of how much each country could produce, comparing not only with the group that belongs, but also with all the other countries, if it had the opportunity to use all the available technology Amsler et al. (2017). Thus, the metafrontier function model is expressed by

$$Y_{it}^{M} \equiv f(\mathbf{x}_{it(j)};\boldsymbol{\beta}^{M}), \tag{5}$$

where $\boldsymbol{\beta}^{M}$ denotes the vector of parameters for the metaproduction function satisfying the condition $\mathbf{x}_{it(j)}^{'}\boldsymbol{\beta}^{M} \geq \mathbf{x}_{it(j)}^{'}\boldsymbol{\beta}_{(j)}$ for all $j = 1,\ldots,J$ Battese et al. (2004).

The introduction of metafrontier analysis (Amsler et al., 2017) as an approach that allows the investigation of the interrelationships between different technologies Battese et al. (2004) can be used in order to explain differences in production opportunities that can be attributed to available resource endowments, economic infrastructure and other characteristics of the physical, social and economic environment in which production takes place ODonnell et al. (2008); Kontolaimou et al. (2012). Moreover, it accounts for structure of national markets, national regulations and policies, cultural profiles and legal and institutional frameworks Halkos and Tzeremes (2011), different ownership types Casu et al. (2013) and different rate of access and acceptance of General Purpose Technologies-GPT (Kounetas et al., 2009).

All these features allow us to estimate the so-called Technology Gap Ratio (TGR), that measures the ratio of the output for the frontier production function for the $i-th$ country in the $j-th$ group at time t relative to the potential output, given the observed input, that is determined by the metafrontier production function given by

$$TGR(x_{it(j)}) = \frac{f(x_{it(j)};\boldsymbol{\beta}_{(j)})}{f(x_{it(j)};\boldsymbol{\beta}^{M})} = \frac{e^{-u_{it}^{M}}}{e^{-u_{it(j)}}} \tag{6}$$

Related to that, ODonnell et al. (2008) extended the Battese et al. (2004) framework for the technical efficiency with respect to the group's frontier, to the estimation of the technical efficiency with respect to the metafrontier production function, defined as $TEMF_{it} = TE_{it(j)} * TGR(x_{it(j)})$.

3 Frontier models – A Bayesian approach

Some previous efforts in the direction of Bayesian modeling the frontier model can be found in Van den Broeck et al. (1994), Griffin and Steel (2004) and Griffin and Steel (2007). In the present section we present in a coherent way the Bayesian approach for parameter estimation by describing in details every single step for applying the Bayesian analysis. Initially the likelihood function is derived and prior distributions are assigned to the parameter of the model. Due to the complex structure of the posterior distribution direct inference is not possible on it, thus a MCMC algorithm is proposed for sampling from it.

3.1 Likelihood function

In the current section, for simplicity reasons, the subscript (j) and the superscript M will be omitted. Based on equation (2) y_{it}^{*}, the natural logarithm of y_{it}, can be expressed as

$$Y_{it}^* = \mathbf{x}_{it}^{'}\boldsymbol{\beta} + v_{it} - u_{it} \tag{7}$$

From equation (7) and assuming that $v_{it} \sim N(0, \sigma_v^2)$ and $u_{it} \sim Exp(\lambda_u)$, it holds that

$$Y_{it}^*|\boldsymbol{\theta}, \boldsymbol{u} \sim N(\mathbf{x}_{it}^{'}\boldsymbol{\beta} - u_{it}, \sigma_v^2)$$

where $\boldsymbol{\theta} = (\boldsymbol{\beta}, \lambda_u, \sigma_v^2)$ are the parameters of the model. As a consequence, the likelihood conditionally on u_{it}'s is given by

$$\begin{aligned} L(Y^*|\boldsymbol{\theta}, \boldsymbol{u}) &\propto \prod_{i=1}^{n}\prod_{t=1}^{T} \frac{1}{\sigma_v} \exp\left(-\frac{1}{2\sigma_v^2}\left(y_{it}^* - \mathbf{x}_{it}^{'}\boldsymbol{\beta} + u_{it}\right)^2\right) \\ &\propto \frac{1}{\sigma_v^{nT}} \exp\left(\sum_{i=1}^{n}\sum_{t=1}^{T} -\frac{1}{2\sigma_v^2}\left(y_{it}^* - \mathbf{x}_{it}^{'}\boldsymbol{\beta} + u_{it}\right)^2\right). \end{aligned}$$

3.2 Assign priors to the parameters - The full posterior distribution

A conjugate prior is assigned to the regression parameters $\boldsymbol{\beta}$

$$\boldsymbol{\beta} \sim N_{k+1}(\boldsymbol{\beta}_{prior}, \boldsymbol{\Sigma}_\beta)$$

where $k+1$ is the dimension of $\boldsymbol{\beta}$ (including the constant term). The point estimate $\boldsymbol{\beta}_{prior}$ - possibly obtained from previous or draft analysis - reflects the researcher's belief on the most likely region of the parameter space. The choice of $\boldsymbol{\Sigma}_\beta$ reflects his/her degree of confidence in this point estimate. A reasonable choice for $\boldsymbol{\Sigma}_\beta$, under the assumption of no multicollinearity, for a moderate degree of confidence on the point estimate could be $\boldsymbol{\Sigma}_\beta = 10^4 \boldsymbol{I}_{k+1}$, where $\boldsymbol{I}_{k+1}$ is the identity matrix of size $k+1$.

For the inverse of the variance of v_{it}, σ_v^{-2}, and the parameter λ_u for the exponential distribution of u_{it} conjugate priors are assigned. More specifically,

$$\begin{aligned} \sigma_v^{-2} &\sim Gamma(\alpha_v, \gamma_v) \\ \lambda_u &\sim Gamma(\alpha_u, \gamma_u). \end{aligned}$$

with means α_v/γ_v, α_u/γ_u and variances α_v/γ_v^2, α_u/γ_u^2 respectively that reflect available information from previous studies. Otherwise, non informative priors such as $Gamma(2,1/2)$ or $Gamma(2,1)$ are used for σ_v^{-2} and λ_u as well.

Thus, the full posterior distribution for the regression model is given by

$$\begin{aligned}
\pi(\boldsymbol{\theta},\boldsymbol{u}|data) =& L(Y^*|\boldsymbol{\theta},\boldsymbol{u})\pi(\boldsymbol{u}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}) \\
=& L(Y^*|\boldsymbol{\theta},\boldsymbol{u})\pi(\boldsymbol{u}|\boldsymbol{\lambda_u})\pi(\boldsymbol{\lambda_u})\pi(\sigma_v^2)\pi(\boldsymbol{\beta}) \\
=& \frac{1}{\sigma_v^{nT}}\exp\left(\sum_{i=1}^{n}\sum_{t=1}^{T}-\frac{1}{2\sigma_v^2}\left(y_{it}^*-\mathbf{x}_{it}^{'}\boldsymbol{\beta}+u_{it}\right)^2\right)\cdot \\
& \lambda_u^{\alpha_u-1}\exp\left(-\gamma_u\lambda_u\right)\cdot \\
& \left(\frac{1}{\sigma_v^2}\right)^{\alpha_v-1}\exp\left(-\gamma_v\frac{1}{\sigma_v^2}\right)\cdot \\
& \exp\left(-\frac{1}{2}(\boldsymbol{\beta}-\boldsymbol{\beta}_{prior})'\boldsymbol{\Sigma}_{\beta}^{-1}(\boldsymbol{\beta}-\boldsymbol{\beta}_{prior})\right)\cdot \\
& \prod_{i=1}^{n}\prod_{t=1}^{T}\lambda_u\exp(-\lambda_u u_{it})I(u_{it}>0)
\end{aligned}$$

which can be expressed as

$$\begin{aligned}
\pi(\boldsymbol{\theta},\boldsymbol{u}|data) = \left(\frac{1}{\sigma_v^2}\right)^{\frac{nT}{2}+\alpha_v-1}&\exp\left(-\frac{1}{\sigma_v^2}\left(\gamma_v+\frac{1}{2}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(y_{it}^*-\mathbf{x}_{it}^{'}\boldsymbol{\beta}+u_{it}\right)^2\right)\right)\cdot \\
&\exp\left(-\frac{1}{2}(\boldsymbol{\beta}-\boldsymbol{\beta}_{prior})'\boldsymbol{\Sigma}_{\beta}^{-1}(\boldsymbol{\beta}-\boldsymbol{\beta}_{prior})\right)\cdot \\
&\lambda_u^{nT+\alpha_u-1}\exp\left(-\lambda_u\left(\gamma_u+\sum_{i=1}^{n}\sum_{t=1}^{T}u_{it}\right)\right)\prod_{i=1}^{n}\prod_{t=1}^{T}I(u_{it}>0).
\end{aligned}$$

3.3 The MCMC algorithm

Due to the complicated structure of the posterior distribution, direct inference is infeasible. Thus, MCMC methods are adopted. From the full posterior distribution it is obvious that a data augmentation procedure for the unobserved u_{it} should be followed as an initial step in each iteration of the MCMC algorithm. The MCMC algorithm can be described by the following steps:

Step 1. For each i and t sample from the full conditional posterior distribution of u_{it}

$$u_{it}|\boldsymbol{\beta},\lambda_u,\sigma_v,data \sim N_+\left(-y_{it}+\mathbf{x}_{it}^{'}\boldsymbol{\beta}-\lambda_u\sigma_v^2,\sigma_v^2\right)$$

using the current values of $\boldsymbol{\beta},\lambda_u,\sigma_v$

Step 2. For each $\ell\in 0,1,\ldots,k$ sample from the full conditional posterior distribution of β_ℓ

$$\beta_\ell|\boldsymbol{\beta}_{(-\ell)},\sigma_v,\lambda_u,\boldsymbol{u},data \sim N\left(\mu_{\beta_\ell},\sigma_{\beta_\ell}^2\right)$$

where

$$\mu_{\beta_\ell} = \frac{\sigma_v^2 \mu_\ell + \sigma_\ell^2 \sum_{i=1}^{n}\sum_{t=1}^{T} x_{it(\ell)} \left(y_{it} + u_{ui} - x_{it(-\ell)}^{'} \boldsymbol{\beta}_{(-\ell)} \right)}{\sigma_v^2 + \sigma_\ell^2 \sum_{i=1}^{n}\sum_{t=1}^{T} x_{it(\ell)}^2}$$

$$\sigma_{\beta_\ell}^2 = \frac{\sigma_v^2 \sigma_\ell^2}{\sigma_v^2 + \sigma_\ell^2 \sum_{i=1}^{n}\sum_{t=1}^{T} x_{it(\ell)}^2}$$

and $\boldsymbol{\beta}_{(-\ell)}$ is the coefficient vector of $\boldsymbol{\beta}$ without β_ℓ, σ_ℓ^2 is the ℓth diagonal element of $\boldsymbol{\Sigma^2}$, μ_ℓ is the ℓth element of the mean vector of $\boldsymbol{\beta}_{prior}$ and $x_{it(\ell)}$ is the the ℓth element of x_{it}

Step 3. Sample from the full conditional posterior distribution of σ_v^2

$$\sigma_v^2 | \boldsymbol{\beta}, \lambda_u, \boldsymbol{u}, data \sim InvGamma \left(\frac{nT}{2} + \alpha_v - 2, \gamma_v + \frac{1}{2} \sum_{i=1}^{n}\sum_{t=1}^{T} \left(y_{it} - \mathbf{x}_{it}^{'} \boldsymbol{\beta} + u_{it} \right)^2 \right)$$

Step 4. Sample from the full conditional posterior distribution of λ_u

$$\lambda_u | \boldsymbol{\beta}, \sigma_v, \boldsymbol{u}, data \sim Gamma \left(nT + \alpha_u, \gamma_u + \sum_{i=1}^{n}\sum_{t=1}^{T} u_{it} \right)$$

4 Estimating the parameters of the metafrontier production function

In the classical, deterministic approach the metafrontier model is determined by choosing a specific function (of the same of form of each frontier) such that the predicted value for the metafrontier is larger than or equal to the predicted value from the stochastic frontier for all entities and groups.The best metafrontier is identified by minimizing the sum of absolute deviations or the sum of squares of the deviations . The first criterion assigns the same weight to all the observations in the sample while the latter assigns larger weights to the deviations associated with observations that have larger technology gap ratios. Both these approaches are similar and for that reason the identification of metafrontier model is only presented under the minimization of the sum of squares of deviations.

4.1 Minimum Sum of Squares of Deviations

In the classical approach given the estimates $\hat{\boldsymbol{\beta}}_{(j)}$ for the parameters of the cluster stochastic frontiers, $\boldsymbol{\beta}_{(j)}, j = 1, 2, \ldots J$, the $\boldsymbol{\beta}^M$-parameters can be computed by solving the optimization problem:

$$\begin{aligned} min\ S = min \sum_{t=1}^{T} \sum_{t=1}^{N} \left(\mathbf{x}_{it}^{'} \boldsymbol{\beta}^{M} - \mathbf{x}_{it}^{'} \hat{\boldsymbol{\beta}}_{(j)} \right)^2 \\ s.t.\ \ \mathbf{x}_{it}^{'} \boldsymbol{\beta}^{M} \geq \mathbf{x}_{it}^{'} \hat{\boldsymbol{\beta}}_{(j)} \end{aligned} \tag{8}$$

where $\mathbf{x}_{it}^{'} \hat{\boldsymbol{\beta}}_{(j)}$ is defined with correctly associate $\hat{\boldsymbol{\beta}}_{(j)}$ with $\mathbf{x}_{it}^{'}$ for the jth cluster.

In the Bayesian framework $\hat{\boldsymbol{\beta}}_{(j)}$ are not given as point estimates but can be described by their posterior distribution obtained by the procedure described in the previous section. As a result a similar procedure can not be adopted without any further modification. Since $\hat{\boldsymbol{\beta}}_{(j)}$ are given as random variables one should also provide/obtain, in a Bayesian framework, the "best" $\boldsymbol{\beta}^M$ in terms of its distribution.

A natural extension of the optimization problem (8) can be stated in terms of the expected value as follows

$$\begin{aligned} min\ S = min \sum_{t=1}^{T} \sum_{t=1}^{N} \left(E(\mathbf{x}_{it}^{'} \boldsymbol{\beta}^{M}) - E(\mathbf{x}_{it}^{'} \hat{\boldsymbol{\beta}}_{(j)}) \right)^2 \\ s.t.\ \ E(\mathbf{x}_{it}^{'} \boldsymbol{\beta}^{M}) \geq E(\mathbf{x}_{it}^{'} \hat{\boldsymbol{\beta}}_{(j)}). \end{aligned} \tag{9}$$

The condition $E(\mathbf{x}_{it}^{'} \boldsymbol{\beta}^{M}) \geq E(\mathbf{x}_{it}^{'} \hat{\boldsymbol{\beta}}_{(j)})$, which expresses the fact the metafrontier should be larger than or equal to the predicted value from the stochastic frontier for all entities and groups, in the aforementioned optimization problem (9) can be expressed as

$$\mathbf{x}_{it}^{'} E(\boldsymbol{\beta}^{M}) \geq \mathbf{x}_{it}^{'} E(\hat{\boldsymbol{\beta}}_{(j)}).$$

The $E(\hat{\boldsymbol{\beta}}_{(j)})$ appearing in the right hand of the above inequality can be replaced by $\tilde{\boldsymbol{\beta}}_{(j)}$, the posterior mean of $\boldsymbol{\beta}_{(j)}$. As a consequence, the optimization problem (9) can be approximated by

$$\begin{aligned} min\ S = min \sum_{t=1}^{T} \sum_{t=1}^{N} \left(\mathbf{x}_{it}^{'} E(\boldsymbol{\beta}^{M}) - \mathbf{x}_{it}^{'} \tilde{\boldsymbol{\beta}}_{(j)} \right)^2 \\ s.t.\ \ \mathbf{x}_{it}^{'} E(\boldsymbol{\beta}^{M}) \geq \mathbf{x}_{it}^{'} \tilde{\boldsymbol{\beta}}_{(j)}. \end{aligned} \tag{10}$$

This optimization problem can be solved following exactly the same steps as in the optimization problem (8).

The solution $\boldsymbol{\mu}_{\beta^M}$ of the optimization problem (10) provide us only with the mean value of $\boldsymbol{\beta}^M$. In order to fully describe the distribution of $\boldsymbol{\beta}^M$ a specific family of distributions should be adopted.

A natural, first choice for the distribution of $\boldsymbol{\beta}^M$ is a multivariate normal distribution. As a result to obtain the distribution of $\boldsymbol{\beta}^M$ one should also provide the variance-covariance matrix of $\boldsymbol{\beta}^*$. An appropriate choice for the variance-covariance matrix of $\boldsymbol{\beta}^M$ can be made by requiring $\boldsymbol{\Sigma} - \boldsymbol{\Sigma}_{(j)}$ to be positive semi-definite for all $1 \leq j \leq J$.

The above property, along with the property $\boldsymbol{\mu}_{\hat{\beta}_{(j)}} \leq \boldsymbol{\mu}_{\beta^M}$, implies that $\hat{\boldsymbol{\beta}}_{(j)} \leq_{icx} \boldsymbol{\beta}^M$ for every $j = 1, 2 \ldots, C$. The symbol $\leq_{icx}$ states that the random variable $\boldsymbol{\beta}_{(j)}, j = 1, 2 \ldots, C$ is smaller than the random variable $\boldsymbol{\beta}^M$ with respect to the increasing convex order (see Müller, 2001, Theorem 7). The increasing convex order implies that

$$E(f(\boldsymbol{\beta}_{(j)})) \leq E(f(\boldsymbol{\mu}_{\beta^M}))$$

for every increasing convex function in $f : \mathbb{R}^n \to \mathbb{R}$.

A natural choice for $\boldsymbol{\Sigma}$, which although may not be the optimum, is given by $\boldsymbol{\Sigma} = \sum_{j=1}^{C} \boldsymbol{\Sigma}_{(j)}$ (see Horn and Johnson, 2012, Observation 7.1.3)

Remark 1. *Optimization problem (8) can be viewed as a special case of optimization problem (10) in the case where $\hat{\boldsymbol{\beta}}_{(j)}$ and $\boldsymbol{\beta}^M$ are degenerate random variables.*

5 Dataset and Variables

To illustrate the methodology a database drawn from World Bank was used that consists of the GDP (Y) in million dollars (in 2010 current prices), the capital (K), the labour (L) and the energy (E), measured in Ktoe, for several countries. For some countries the data were long-standing and up to date but unfortunately for others, the data were of more recent origin or were severely unreliable.

Thus, the complete available dataset consists of data over the period 1995-2014 for 109 countries, 35 members of OECD and 74 non-OECD countries, creating a balanced panel of 2180 observations. The chosen time period not only covers a sufficiently long period but also allows us to examine countries productive performance over a large number of countries during different economic cycles covering periods of expansion (growth) and contraction (recession).

In this study the labor force was captured by the total hours worked by employees. The physical capital was estimated from gross fixed capital formation in million dollars (in 2010 current prices) using the perpetual inventory method with a depreciation rate of 10%, following, for example, King and Levine (1994). All variables were scaled with respect to the values of USA in 1995, year which was selected as the reference year. The time evolution of the four scaled variables across countries in a log-scale are presented in Figures 1 and 2. The central line presents the median while the far out lines present the max and min values for each year. The inner lines, defining the dark grey region, present the first and the third quartiles while the remaining lines, defining the light gray, present the upper 2.5% and 97.5% percentile points for each year.

From the plots it is obvious that there is a clear increase in the GPD and in the gross fixed capital formation and that the OECD countries present in general a better performance in these characteristics revealing a heterogeneous behavior comparing with non-OECD. It is worth pointing out the convergence of the economy of China to that of USA (both define the upper lines in their group) by managing to fill the gap in 2014 that it was clear in 1995. On the other hand the labor force and the energy use present a more stable behaviour through the study period. The non-OECD countries present a larger heterogeneity in their labor force than the OECD countries. The OECD coun-

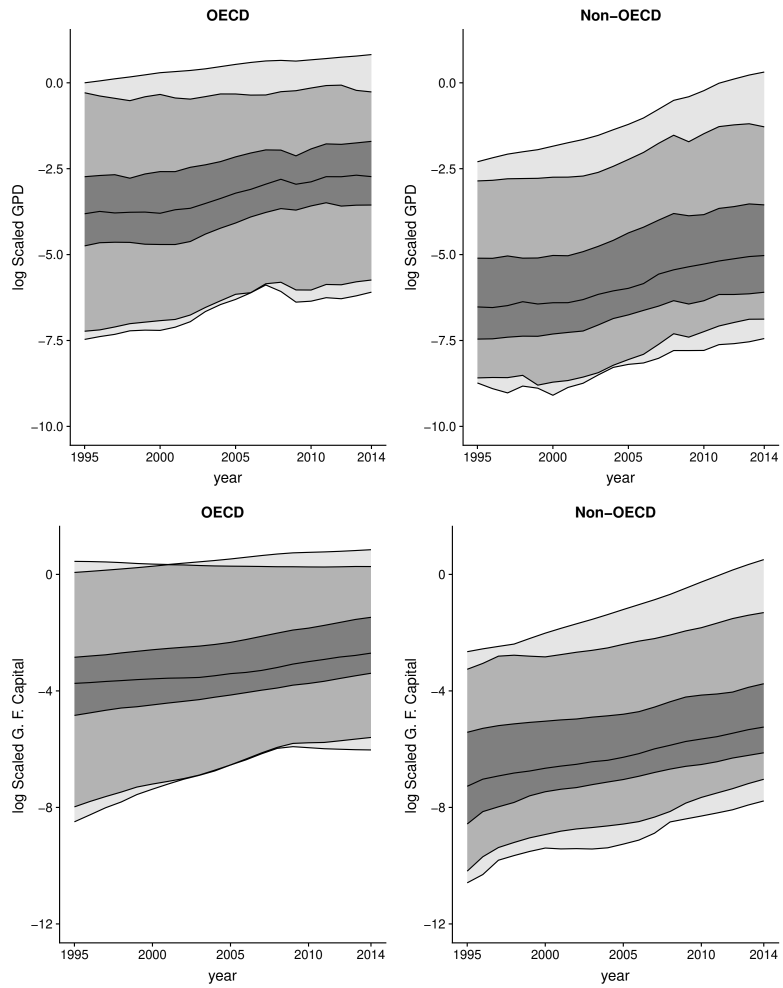

Figure 1: The time evolution of GPD (upper plots) and the gross fixed capital formation for the OECD (left plots) and the non-OECD (right plots) countries. The central line presents the median while the far out lines present the max and min values for each year. The inner lines, defining the dark gray region, present the first and the third quartiles while the remaining lines, defining the light gray, present the upper 2.5% and 97.5% percentile points for each year.

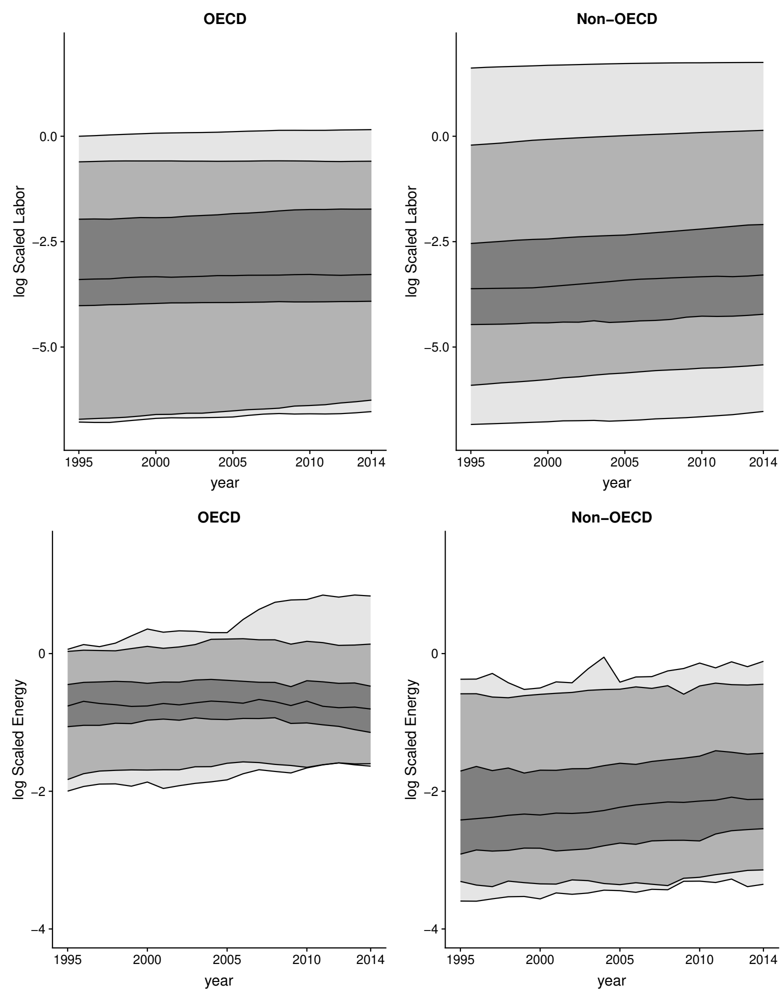

Figure 2: The time evolution of labor force (upper plots) and energy use for the OECD (left plots) and the non-OECD (right plots) countries. The central line presents the median while the far out lines present the max and min values for each year. The inner lines, defining the dark gray region, present the first and the third quartiles while the remaining lines, defining the light gray, present the upper 2.5% and 97.5% percentile points for each year.

tries seems to consume a significant larger amount of energy since their third quartile is almost at the same level with the 97.5% percentile points of the non-OECD countries.

In the rest of this section, the Bayesian stochastic frontier model along with the proposed metafrontier stochastic model are presented. Table 1 summarizes the sample statistics of the countries data including the inputs and outputs for each group.

5.1 Frontier models for the two distinct group of countries

The empirical specification of the GDP in million dollars (in 2010 current prices) function for each group of countries (OECD and non-OECD) was defined as followed

$$\ln Y_{it(j)} = \beta_{0(j)} + \beta_{1(j)} K_{it(j)} + \beta_{2(j)} L_{it(j)} + \beta_{3(j)} E_{it(j)} + \beta_{4(j)} t + v_{it(j)} - u_{it(j)}, \quad (11)$$

for $t = 0, \ldots, 19$, $i = 1, \ldots, n_j, j = 1, 2$, where $Y_{it(j)}$ denotes the scaled, as described earlier, GDP in million dollars (in 2010 current prices) of the $i-th$ country in the $j-th$ group ($j = 1$ refers to OECD countries and $j = 2$ to non-OECD) at year t (year 1995 was set as $t = 0$) and $K_{it(j)}$, $L_{it(j)}$ and $E_{it(j)}$ the corresponding scaled gross fixed capital formation (K), labor (L) and energy (E) respectively. A time trend was also included in the model, in order to obtain some temporal changes. The $\boldsymbol{\beta}_{(j)}$ present the parameter vectors for the two groups while the unobservable random errors are assumed independent, normally distributed with $v_{it(j)} \sim N(0, \sigma^2_{v_{(j)}})$ and $u_{it(j)}$ are assumed to follow an exponential distribution with parameter $\lambda_{u(j)}$.

Since we wanted to tested our proposed method using as little as possible prior information the non-informative priors $Gamma(2, 1/2)$ were chosen for σ_v^{-2} and λ_u. For the regression parameters the following again non-informative prior $\boldsymbol{\beta} \sim N_{k+1}(\mathbf{0}, 10^4 I)$ was assigned.

For each group, the proposed MCMC algorithm was ran for a total of 200,000 iterations and the first 60,000 iterations discarded as burn-in. The trace plots (left) and kernel-smoothed estimates of the marginal posterior distributions (right) of some of the model's parameters are presented in Figure 3. The plots present the marginal posterior distributions of the model's parameters $\beta_{0(j)}$, $\beta_{1(j)}$ and $\beta_{2(j)}$ for $j = 1$ (OECD countries). In addition, some descriptive statistics for their posterior distributions (for both groups) are presented in Table 1.

Our results indicate that all the participated variables are statistically significant with positive signs, a reasonable case concerning the nature of the variables, for both individual frontier. However, small differences can be observed concerning the magnitude of the participated variables. For example, the gross fixed capital formation seems to have larger impact on GPD in the OECD countries (mean = 0.29602) comparing to the non-OCED (mean = 0.24284). The opposite conclusion holds for the labor force. Regarding the unobservable random errors $v_{it(j)}$ it seems that OECD countries present a slightly larger variation compare to the non-OECD countries. Finally, the posterior distribution parameters $\lambda_{u(j)}$, j=1,2 of the exponential distributions of $u_{it(j)}$, which are related with the technical efficiency relative to the stochastic frontier for the $j-th$ group, i.e. captures the level of the inefficiency of each country, and ensures that each country efficiency lies on or below the frontier model, seems to take larger values for the OECD countries. This also indicates a larger heterogeneity among the OECD countries comparing with the variation observed among the non-OECD countries.

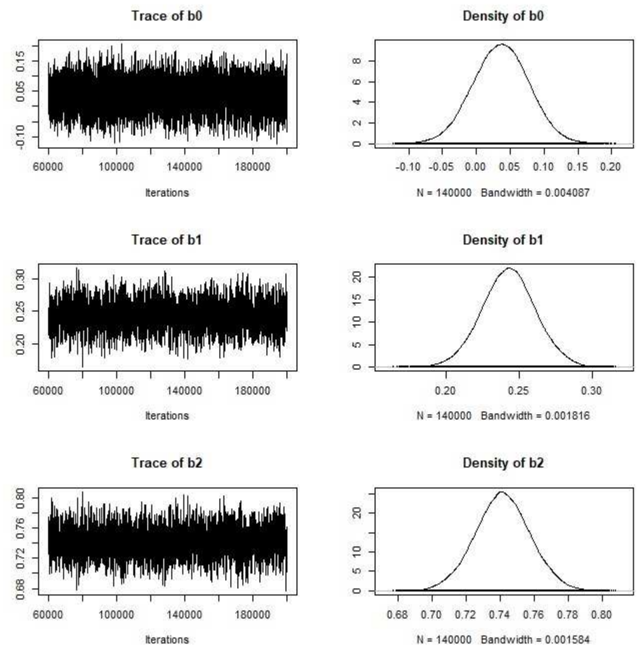

Figure 3: The trace (left plots) and kernel-smoothed estimates of the marginal posterior distributions (right plots) of the model's parameters $\beta_{0(j)}$, $\beta_{1(j)}$ and $\beta_{2(j)}$ for $j = 1$ (OECD countries).

Table 1: Descriptive statistics for the posterior distributions of the parameters of the frontier models (OECD countries - upper half, non-OECD countries - lower half).

		Mean	SD	2.5%	Q1	Median	Q3	97.5%
OECD	$\beta_{0(1)}$	-0.20550	0.047246	-0.29713	-0.23760	-0.20592	-0.17380	-0.11232
	$\beta_{1(1)}$	0.29602	0.009495	0.27740	0.28961	0.29611	0.30246	0.31440
	$\beta_{2(1)}$	0.66387	0.009329	0.64578	0.65753	0.66386	0.67015	0.68203
	$\beta_{3(1)}$	0.23878	0.015776	0.20800	0.22809	0.23883	0.24951	0.26943
	$\beta_{4(1)}$	0.01337	0.001634	0.01017	0.01227	0.01338	0.01448	0.01657
	$\sigma^2_{v_{(1)}}$	0.09053	0.005190	0.08062	0.08696	0.09045	0.09403	0.10083
	$\lambda_{u(1)}$	8.58404	1.416350	6.47614	7.57914	8.35415	9.34479	12.00389
non-OECD	$\beta_{0(2)}$	0.03631	0.041242	-0.044666	0.008486	0.03653	0.06416	0.11662
	$\beta_{1(2)}$	0.24284	0.018576	0.206094	0.230523	0.24288	0.25508	0.27968
	$\beta_{2(2)}$	0.74136	0.016173	0.709327	0.730637	0.74131	0.75206	0.77329
	$\beta_{3(2)}$	0.17777	0.026575	0.125734	0.159862	0.17776	0.19564	0.22983
	$\beta_{4(2)}$	0.01198	0.001893	0.008264	0.010707	0.01199	0.01326	0.01569
	$\sigma^2_{v_{(2)}}$	0.04720	0.004800	0.038276	0.043869	0.04701	0.05037	0.05705
	$\lambda_{u(2)}$	7.51293	1.140784	5.789874	6.717939	7.34238	8.11120	10.26581

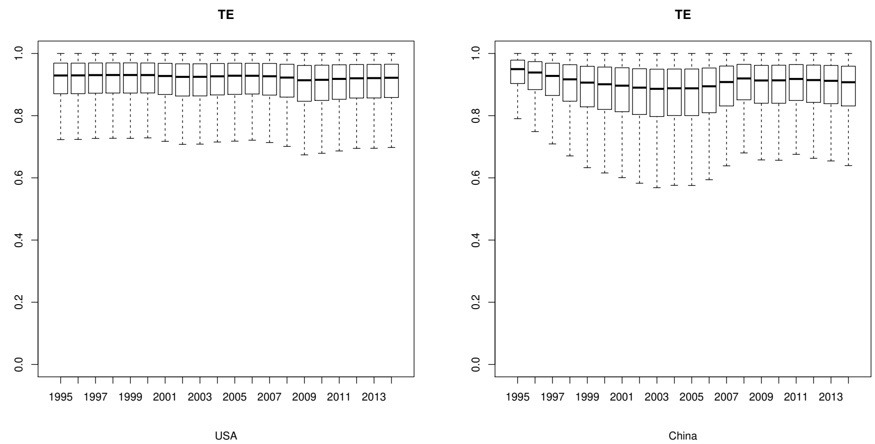

Figure 4: The boxplots of the posterior distributions of the technical efficiencies for the two leading economies of each group, namely the USA (left plot) and China (right plot) for all the years in the study.

5.1.1 Technical efficiencies results for the estimated frontiers

Since for each iteration of the MCMC algorithm u_{it}s are sampled from their full conditional posterior distribution for each i, t and j one can obtain the descriptive statistics or the kernel-smoothed estimates of their posterior distributions, or equivalently for the Technical Efficiencies defined as

$$TE_{it(j)} = e^{-u_{it(j)}}.$$

The boxplots of the posterior distributions are presented in Figure 4 of the technical efficiencies for the two leading economies of each group, namely the USA (OECD country) and China (non-OECD country) for all the years in the study. The USA seems to present a relative stable performance close to the group frontier presenting a small decrease just after 2008. On the other hand, China presents a more unstable behavior. Initially, the technical efficiency of China seems to decline and to reach its minimum around 2003 before it starts to slowly increase and stabilize after 2008. Comparing the level of the inefficiency of these two countries with respect to their frontier one can say that both economies perform relative close to their frontier model with USA to be the country that constantly performs better with respect to other countries in their group.

Regarding the time evolution of the technical efficiencies of all countries in each group one can focus on the median of the posterior distributions in each year for each country. The kernel-smoothed estimates of the distribution of the medians of the technical efficiencies of all countries in each group for each determined by their posterior distributions are presented in Figure 5 (left panel for the OECD countries and right panel for the non-OECD countries). For the OECD countries the plots reveal in general more or less a unimodal behavior for the median technical efficiencies (there are some cases in which a bimodal behavior is presented but in most of these cases the

Table 2: The top and the last five countries' efficiency scores under the technology frontier for each group (left panels) and the metatechnology frontier (right panel) based the mean value of the median of the posterior distributions in each year for each country.

	OECD countries	TE	non-OECD countries	TE	Global technology	TE_{MF}
Champions	Ireland	0.9462	Nigeria	0.9606	Italy	0.9088
	United Kingdom	0.9455	Cuba	0.9499	Ireland	0.9029
	Norway	0.9449	Sudan	0.9497	United Kingdom	0.9018
	Luxembourg	0.9449	Saudi Arabia	0.9458	Switzerland	0.9017
	Canada	0.9350	Uruguay	0.9432	Denmark	0.8962
Laggards	Estonia	0.8521	Malaysia	0.8749	Singapore	0.7079
	Slovak Republic	0.8201	Mongolia	0.8703	Malaysia	0.6954
	Japan	0.7892	Nepal	0.8670	Korea, Rep.	0.6919
	Czech Republic	0.7846	Ukraine	0.8152	Ukraine	0.6727
	Korea, Rep.	0.7414	Thailand	0.7965	Thailand	0.6359

second, smaller, mode presents actually a single, outlier country). For the non-OECD countries there are several years, for example 1996, 2009 and the last two 2013 and 2014, that a clear bimodal behavior is observed.

Apart from that, the plots reveal a significant dispersion in 2005 and 2010 for the OECD countries. The measurements of 2005 can be interpret as creating an additive outlier behavior which has no latter affects. On the other hand, the measurements regarding 2010 seems to reflect an innovative outlier behavior in that year that seems to affect the subsequent years.

In order to observe in detail the changes that occur in the top and bottom ranked countries regarding their performance the mean value of the 20 posterior medians (one of each year) was calculated for each country. Although the median of the technical efficiency scores is only an indicative measure of the countries' performance, their mean value can still provide an overall index of the performance of each country.

The first two panels in Table 2 show the top and last 5 countries under the technology frontier for each group. Ireland, United Kingdom, Norway, Luxemburg and Canada consist the top five countries for the OECD frontier while Estonia, Japan, Slovak Republic, Czech Republic and Korea Republic consist the last five countries group. Regarding the non-OECD technological frontier, Saudi Arabia, Sudan, Cuba, Uruguay and Nigeria consist the champions group while Malaysia, Mongolia,Nepal, Ukraine and Thailand perform worst. The data concerning the metatechnology frontier presented in the right panel of Table 2 are discussed in the following subsection.

5.2 Metafrontier model

As presented earlier a multivariate normal distribution is a natural choice for $\boldsymbol{\beta}^M$, the parameter vector for the metafrontier model. Following the steps described in Section 4.1 one can obtain the following mean $\boldsymbol{\mu}_{\beta^M}$ and variance-covariance matrix $\boldsymbol{\Sigma}$ of $\boldsymbol{\beta}^M$:

$$\boldsymbol{\mu}_{\beta^M} = (0.15025, 0.28825, 0.69309, 0.26532, 0.01253)$$

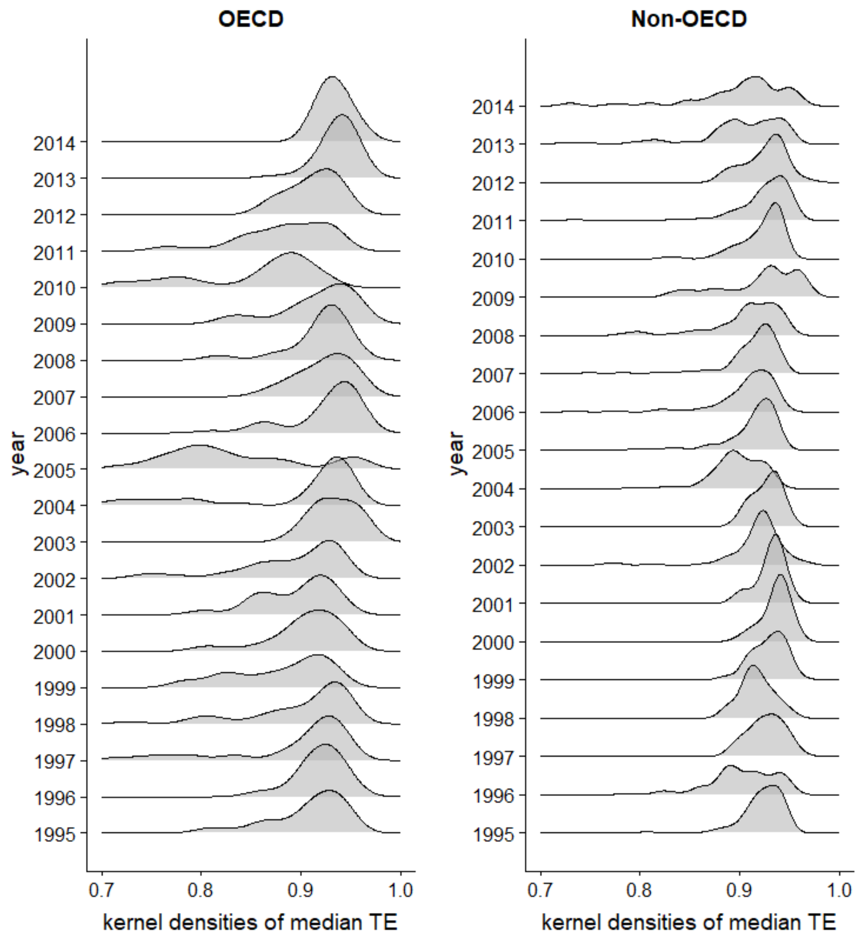

Figure 5: The kernel-smoothed estimates of the distribution of the medians of the technical efficiencies of all countries in each group for each determined by their posterior distributions (left panel for the OECD countries and right panel for the non-OECD countries).

$$\boldsymbol{\Sigma} = 10^{-5} \cdot \begin{pmatrix} 393.3035 & 37.0860 & -3.4969 & 79.7091 & -7.3321 \\ 37.0860 & 43.5219 & -35.2888 & 43.2678 & 1.7793 \\ -3.4969 & -35.2888 & 34.8619 & -38.8513 & -1.9585 \\ 79.7091 & 43.2678 & -38.8513 & 95.5108 & 1.8227 \\ 7.3321 & 1.7793 & -1.9585 & 1.8227 & 0.6252 \end{pmatrix}$$

Figure 6 presents the time evolution of the technical efficiency with respect to the metafrontier (TEMF) of all countries. More specifically, the time evolution of TEMF is demonstrated by the kernel-smoothed estimates of the distribution of the medians of the technical efficiency with respect to the metafrontier of all countries determined by their posterior distributions. The light blue curves present the OECD countries and the grey curves the non-OECD countries. The distributions of the medians of the TEFM indicates a different picture compared with the technical efficiency with respect to the group frontier.

Both groups experience important dispersions and present significant heterogeneity resulting to multimodal, left skewed distributions reflecting significant differences not only between the two groups but also within groups. The latter differences reflect the large dispersion of the technology gap ratios (TGR) , due to country-specific environments that is usually used to identify technological differentials with respect to the global meta-technology Battese et al. (2004); ODonnell et al. (2008), (Tsekouras et al., 2016, 2017).

In Figure 7 is presented the chronological change of the TGR for the OECD (left plot) and the non-OECD (right plot) countries. The central line presents the median while the far out lines present the max and min values for each year. The inner lines, defining the dark gray region, present the first and the third quartiles while the remaining lines, defining the light gray, present the upper 2.5% and 97.5% percentile points for each year. One of the interesting things to note in these plots is the relative large dispersion of the TGR in each group which explains, as mentioned earlier, the significant differences of the TEFM within the two groups (see Figure 6).

Additional features of the plots in Figure 7 that are worth mentioning are the different level of the TGR values in the two groups and the completely different trend of TGR which highlights especially in the last years the significant different values of the TGR between the two groups. the different trends denote a diverging rather a converging behaviour of the two groups which in its turn indicates the increasing technology gap between the two groups.

The aforementioned characteristics are responsible for the distribution of the TEMF, as shown in Figure 6, which reveal the out-performance of the OECD countries compared with the non-OECD countries, with small exceptions in years 1999 and 2005, allowing us to study the impact of pure technical spillover effects generated at World level, affecting country performance that co-exist at the global technology level (Tsekouras et al., 2016, 2017) even if, at least theoretically, all countries share the possibility of technological interaction with each other. However, the extent of knowledge assimilation and performance enhancement heavily relies on the absorptive capacity and appropriability conditions Nelson (2009) of each national economy. This is illustrated to the non-OECD countries which seem, in general, not to be able to exploit at the same degree the technological opportunities by adopting efficiently the external sources of

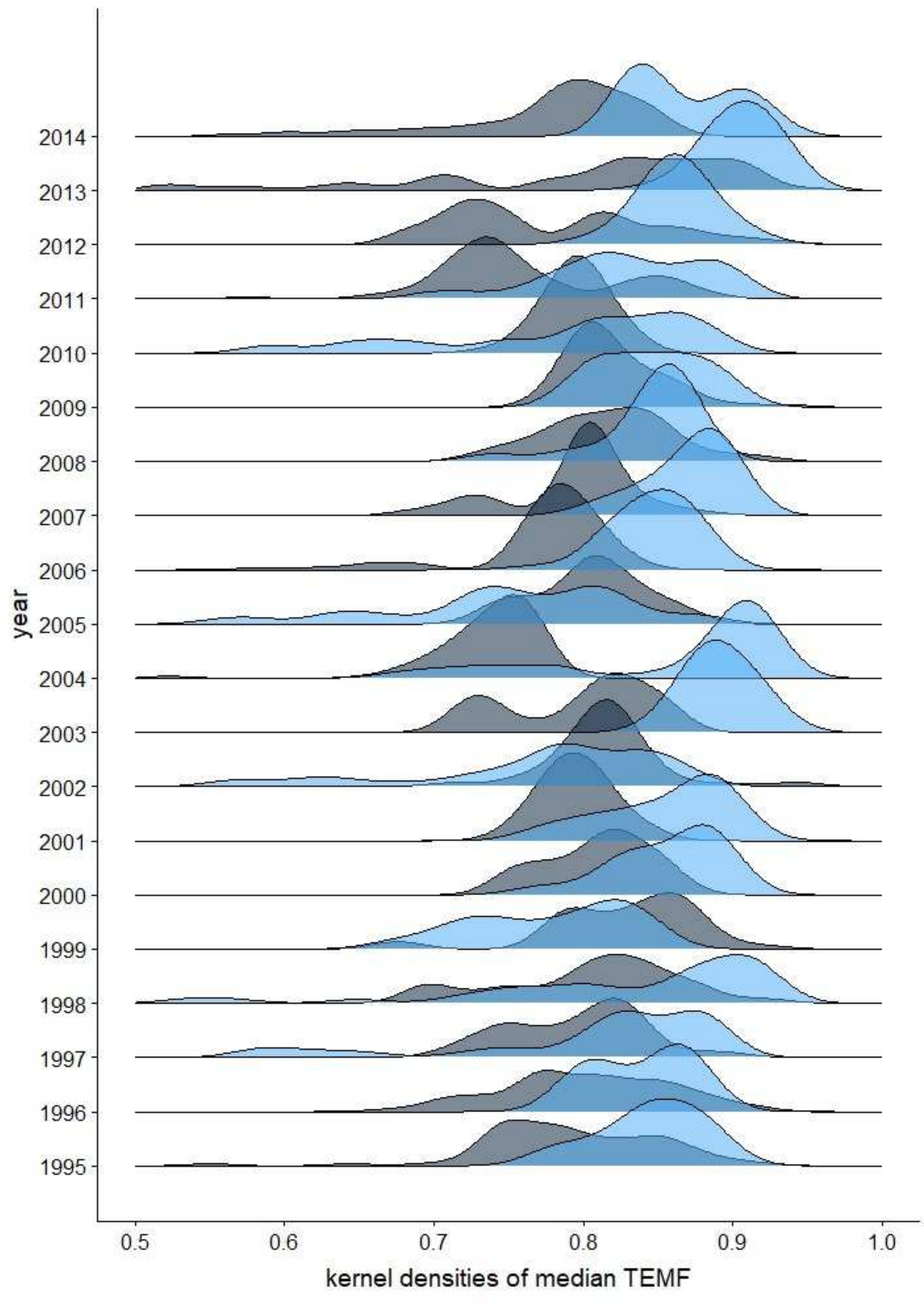

Figure 6: The kernel-smoothed estimates of the distribution of the medians of the technical efficiency with respect to to the metafrontier of all countries in each group determined by their posterior distributions (light blue curves for the OECD countries and gray curves for the non-OECD countries).

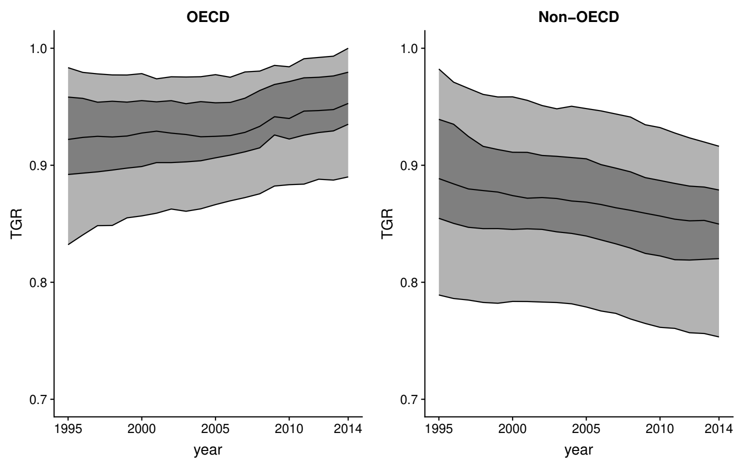

Figure 7: The chronological change of the technology gap ratio (TGR) for the OECD (left plot) and the non-OECD (right plot) countries. The central line presents the median while the far out lines present the max and min values for each year. The inner lines, defining the dark gray region, present the first and the third quartiles while the remaining lines, defining the light gray, present the upper 2.5% and 97.5% percentile points for each year.

opportunities Reichstein and Salter (2006) revealing non significant incoming spillover effects Tsekouras et al. (2016).

The out-performance of the OECD countries compared with the non-OECD countries and the increasing technology gap between the two groups is clearly demonstrated in the boxplots of the posterior distributions of the TEMF for the two leading economies of each group, namely the USA and China for all the years in the study presented in Figure 8. It is interesting to note that even if the two countries are very close to their group frontier (see Figure 4), presenting non significant or small changes, especially China, their posterior distributions of the TEMF reveal other characteristics. Firstly, the posterior distribution of the TEMF of China takes significant smaller values compared with them of USA. Secondly, there is a clear different trend between the values of the TEMF between the two countries even if the decreasing trend of China seems to be slower after 2009. These findings reflects the weakness of China to take full advantage of the strong characteristics of its economy, as for example its large labor force (see the upper/maximum line of the upper right in Figure 2) which actual present the labor force if China.

Finally,in order to have a more detailed picture we turn our attention at Table 2. As we can notice countries as Ireland, United Kingdom, Switzerland, Denmark and Italy consists the champions group while Malaysia, Korea Republic, Ukraine, Singapore and Thailand constitutes the laggards group.

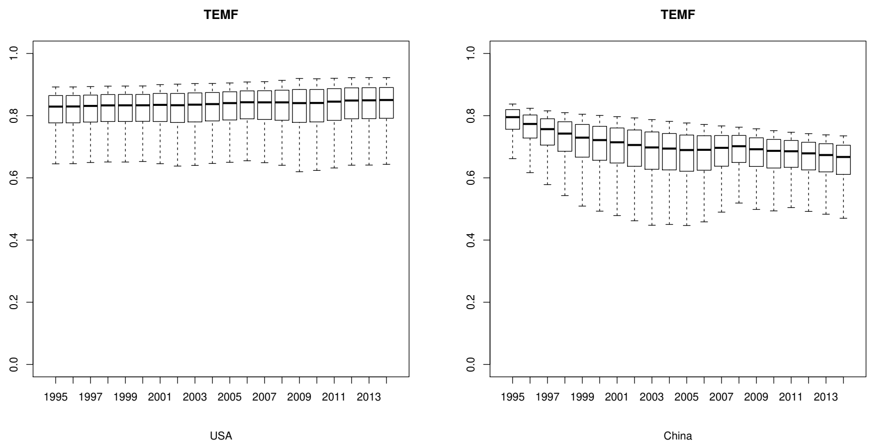

Figure 8: The boxplots of the posterior distributions of the technical efficiencies with respect to to the metafrontier for the two leading economies of each group, namely the USA (left plot) and China (right plot) for all the years in the study.

6 Concluding remarks

Heterogeneity exerts a multifaceted impact on countries' performance and growth and it is closely related with their technology gap and spillover effects. The quantification of the technology gap is achieved through the adoption of a metafrontier framework. This approach has been applied broadly to DEA and SFA model across several disciplines to account for. However, the literature argues on statistical properties of the metafrontier production function based on the second stage of linear programming of calculation.

This study is the first that propose a metatechnology production function under a Bayesian perspective to compare efficiencies of two distinct groups (OECD vs non-OECD countries). This aspect represents an essential contribution, since the literature lack evidence on Bayesian measures of technology gaps and on countries' productive efficiency differentials. Moreover, the focus on technology gaps is crucial since it considers as an indicator of the technological level of each country but also reveal the degree of technological complexity of learning, the level of innovation and openness and the absorptive capabilities of the national economies. For the purpose of our empirical study we concentrate our efforts on a dataset consisting of 109 countries for a 20-year period from 1995-2014.

Empirical results reveal that the efficiency scores for OECD countries form a more or less unimodal pattern comparing with a bimodal behavior of the non-OECD countries group. Regarding the meta-efficiency performance we can denote the different behavior of the two groups with the distinct performance for their scores. In addition the majority of the best performers belong to the OECD countries group. In addition, the two examined groups has distinct and clear different performance regarding their technology gap. The different diachronical trends elevate the role of technological heterogeneity and make clear countries' idiosyncrasies and specificities. Furthermore, our specific finding underline the role of unsimilar competitiveness level, openness of their economies, innovation performance and specific idiosyncrasies regarding the institutional, economic and technological environment that each country operates.

We emphasize that we have merely show a model specification that can be extended in other more complex models such as translog. Although, this extensions may not be so straightforward as it may require further research due to slow convergence of the MCMCM algorithm due to the severe multicolinearity of the explanatory variables in such models. Finally, further research is required to test if the choice of $\mathbf{\Sigma}$ is indeed the optimal one and also to exploit its stochastic properties in order to compute credible regions for the metafrontier parameters.

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