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M. Filippini and E. Tosetti

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Stocastic Frontier Models for Long Panel Data Sets: Measurement of the "Underlying Energy Efficiency" for the OECD Countries

Massimo Filippini,
ETH Zurich and University of Lugano

Elisa Tosetti,
Brunel University and ETH Zurich

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Abstract

In this paper we propose a general approach for estimating stochastic frontier models, suitable when using long panel data sets. We measure efficiency as a linear combination of a finite number of unobservable common factors, having coefficients that vary across firms, plus a time-invariant component. We adopt recently developed econometric techniques for large, cross sectionally correlated, non-stationary panel data models to estimate the frontier function. Given the long time span of the panel, we investigate whether the variables, including the unobservable common factors, are non-stationary, and, if so, whether they are cointegrated.

To empirically illustrate our approach, we estimate a stochastic frontier model for energy demand, and compute the level of the "underlying energy efficiency" for 24 OECD countries over the period 1980 to 2008. In our specification, we control for variables such as Gross Domestic Product, energy price, climate and technological progress, that are known to impact on energy consumption. We also allow for heterogeneity across countries in the impact of these factors on energy demand.

Our panel unit root tests suggest that energy demand and its key determinants are integrated and that they exhibit a long-run relation. The estimation of efficiency scores points at European countries as the more efficient in consuming energy.

Keywords: Energy demand, panels, common factors, principal components.
JEL Classification: C10, C31, C33.

1 Introduction

The literature on the measurement of productive efficiency of firms using econometric approaches is relatively large and well documented. In the past two decades, empirical studies have been increasingly using panel data sets for the estimation of stochastic frontier models, since they overcome some limitations of models based on cross-sectional data (Murillo-Zamorano (2004), Greene (2008)). A wide range of assumptions on the efficiency component have been proposed, that are needed for measuring efficiency and disentangle it from the random noise (Porcelli (2009)). A number of studies model efficiency as a stochastic variable, often assumed to have a one-sided distribution and independent of the explanatory variables (inputs, input prices, outputs etc.) (e.g. Aigner, Lovell, and Schmidt (1977), Battese and Coelli (1992), and Greene (2005b)). More recent studies try to relax strong distributional assumptions on the efficiency term, by proposing general specifications where the level of productive efficiency can be correlated with the inputs, and is characterised by complicated, time-varying, functions, such as dynamic, partial adjustment processes (e.g., Park, Sickles, and Simar (2003)), factor models (e.g., Ahn, Lee, and Schmidt (2007)), semi-parametric or non-parametric functions (Kneip, Sickles, and Song (2003)). Generally, all these stochastic frontier models have been developed for short panel data sets, i.e. using variables observed over a relatively short period of time, generally lower than 10-15 time periods. On the contrary, only few studies estimate stochastic frontier models using long panels, i.e., data set where the time series dimension (T) and cross-section dimension (N) are relatively large (T and N larger then 20) (e.g., Mastromarco, Serlenga, and Shin (2009), Hsu, Lin, and Yin (2012), and Mastromarco, Serlenga, and Shin (2013)).

Recently, a growing literature on panel time series econometrics has introduced new methods for estimating long, possibly non-stationary panels, also allowing for contemporaneous correlation in the errors (Bai and Ng (2004), Pesaran (2006), Kapetanios and Pesaran (2007), Bai (2009), and Bai and Carrion-i-Silvestre (2013)). In this paper, we draw from this literature to propose a new general approach for estimating stochastic frontier models, suitable for long panel data sets. We assume that our frontier function is a panel data regression model with group effects, group-specific linear trends, and a multifactor structure. Hence, we proxy firm's efficiency by a linear combination of a finite number of unobservable time effects, or common factors, having coefficients that vary across firms, plus a time-invariant component. The advantage of such specification relative to other approaches when modelling efficiency, is that the estimation of efficiency scores does not require strong distributional assumptions on the common factors and their loadings. Moreover, in panel data covering a relatively long time period, the variables, including the unobservable common factors, are potentially non-stationary. It is well know that ignoring non-stationarity of the variables leads to spurious statistical results under the Ordinary Least Squares (Engle and Granger (1987)). Non-stationarity of the time-varying efficiency components may exist if, for example, technical efficiencies measured in various firms do not converge over time (Ahn and Sickles

(2000)). Some firms may experience sluggish adoption of new technologies, leading to low efficiency firms not catching up or converging to the frontier with high efficiency firms. On the contrary, stationarity may occur when efficiencies observed in laggard firms catch up in the long run, for example thanks technological diffusion (see Cornwell and Wachter (1999) for a discussion). Hence, in this paper we adopt recently developed econometric techniques for large, cross-sectionally correlated, non-stationary panel data models by Pesaran (2006), Bai (2009) and Bai and Carrion-i-Silvestre (2013) to investigate whether the variables, including the unobservable common factors, are non-stationary, and, if so, whether they are cointegrated. Existing literature has used cross-section averages to proxy unobservable common factors in stochastic frontier models with a multifactor structure (Mastromarco, Serlenga, and Shin (2009)). However, as discussed later on (see Section 2), while this approach delivers consistent estimates of the slope coefficients, estimation of the unobservable common factors and their loadings through the cross-section averages is more problematic. Hence, differently from this literature, in this paper, we adopt Bai (2009)'s principal components approach to consistently estimate common factors and attached loadings. Given the possible non-stationarity of data, following Bai and Carrion-i-Silvestre (2013), we estimate common factors and residuals from data expressed in first difference. Hence, we re-cumulate these estimated quantities and use them to construct statistics to test for cointegration. The main contribution of this paper respect to previous studies is to provide an econometric approach for the estimation of cost and production stochastic frontier models using long panels that allow to consistently estimate the unobservable common factors, whether or not they are integrated, under a set of broad regularity conditions.

Our econometric approach can be adopted for estimating a production or a cost frontier function, using data sets at the firm's or country level. In this paper, to empirically illustrate our procedure, we estimate a stochastic frontier model for energy demand using aggregate data for a sample of OECD countries. Following Filippini and Hunt (2011), we control for variables that are known to impact on energy consumption, such as Gross Domestic Product, energy price, climate and technological progress. In the computation of our efficiency score, we follow Farsi, Filippini, and Kuenzle (2005) and Filippini and Hunt (2012) and apply the Mundlak (1978)'s adjustment to sweep out efficiency from time-invariant heterogeneity.

This paper is organised as follows. Section 2 briefly reviews the literature on stochastic frontier modelling using panel data. Section 3 illustrates the main features of our model and summarises the estimation strategy. Section 4 describes the data while Section 5 comments on the empirical results. Finally, Section 6 concludes.

2 Stochastic frontier modelling using panels

In this section we illustrate some econometric approaches to estimate stochastic frontier models using panel data. We discuss these models using an energy demand frontier function introduced by Filippini and Hunt (2011). A country total aggregate energy demand is derived from the demand for several energy services used in an economy, all of which are produced by combining capital, energy and labour (Filippini and Hunt (2011)). Accordingly, suppose that the energy demand in country i at time t, E_{it}, with $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$, follows

$$E_{it} = f(X_{it})\tau_{it}w_{it}, \tag{1}$$

where X_{it} is a set of country-specific characteristics that impact on energy consumption, w_{it} captures the stochastic nature of the frontier, and τ_{it} it is the level of 'underlying energy efficiency'. One standard assumption in the literature is that there exists a log-linear relationship amongst the variables E_{it} and X_{it}, so that

$$e_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + \varepsilon_{it}. \tag{2}$$

where $e_{it} = \ln(E_{it})$, $\mathbf{x}_{it} = \ln(X_{it})$ is a k-dimensional vector, and ε_{it} is a random error. It is then assumed that ε_{it} consists of two components

$$\varepsilon_{it} = v_{it} + u_{it}, \tag{3}$$

where $v_{it} = \ln(w_{it})$ is an idiosyncratic noise, while $u_{it} = \ln(\tau_{it})$ represents the underlying energy level of efficiency, and can be interpreted as an indicator of the inefficient use of energy.[1]

A number of alternative assumptions on u_{it} have been suggested in the literature, needed to identify the inefficiency component and disentangle it from the idiosyncratic noise. One of the most popular assumptions is that u_{it} is a one side non-negative IID disturbance term, often taken to be distributed as a half-normal or a truncated normal (Aigner, Lovell, and Schmidt (1977)). A further widely used specification for the inefficiency component is that it is made up of three firm-specific terms, a time-invariant firm effect, a linear and a quadratic time trend (Cornwell, Schmidt, and Sickles (1990)). Battese and Coelli (1992) assume that u_{it} varies over time as a linear function of a set of explanatory variables. Greene (2005b) and Greene (2005a) propose to add to model (2) a random individual effect that accounts for all time-invariant, unobserved socio-economic and environmental characteristics, and interpret the residual term, u_{it}, assumed to be half normal or truncated normal, as inefficiency component. This model, known as *true random effects*, is therefore able to differentiate

[1] In the production and cost frontier function framework, u_{it} represents the level of technical efficiency and cost efficiency, respectively.

unobserved heterogeneity from time-varying inefficiency. However, this model excludes from the inefficiency estimates the persistent component, i.e. that part of inefficiency that remains constant over time. The true random effects model may also suffer from endogeneity problems, due to the potential correlation between the group effects and the regressors. To deal with these issues, Farsi, Filippini, and Kuenzle (2005) and Filippini and Hunt (2012) propose to incorporate the Mundlak (1978)'s adjustment within the random effects frontier framework. Under this approach, the random effects model is augmented with the group means of time-varying regressors. By doing this, time-invariant unobserved factors are captured by the Mundlak (1978)'s adjustment rather than by the inefficiency term, thus alleviating the bias in inefficiency estimates.

An alternative approach is taken by Ahn, Lee, and Schmidt (2007). The authors assume that firms' inefficiencies in (3) consist of a linear combination of m unobserved components, or factors, that vary over time and that are common to all units (or pervasive):

$$u_{it} = \gamma_{i1} f_{1t} + \gamma_{i2} f_{2t} + ... + \gamma_{im} f_{mt} = \sum_{j=1}^{m} \gamma_{ij} f_{jt}. \tag{4}$$

In the above, $f_{1t}, ..., f_{mt}$ are the so-called unobserved common factors, or inefficiency components, that are common to all countries, with m assumed to be small relative to N. The coefficients $\gamma_{i1}, ..., \gamma_{im}$ are known as factor loadings, and represent the sensitivity of cross-section units to movements in the factors. The above set up is very general, and renders a variety of regression models used in stochastic frontier analysis as special cases. For example, by setting $m = 3$, $f_{1t} = 1$, $f_{2t} = t$ and $f_{3t} = t^2$, this specification reduces to the Cornwell, Schmidt, and Sickles (1990) model, while the familiar fixed or random effects models correspond to the case where $m = 1$ and $f_{1t} = 1$. Ahn, Lee, and Schmidt (2007) suggest a Generalised Method of Moments estimator of (2)-(3) with efficiencies (4), valid when N is large and T is fixed. We observe that, while the authors incorporate time dummies in their model, they do not include group effects. A similar framework is also adopted by Kneip, Sickles, and Song (2003), who propose a semiparametric estimation method based on smoothing spline techniques. The authors use this approach to explore the efficiency of banking industry.

A number of recent studies have adopted the above specification for stochastic frontier models, in the context of *long panel data sets*. Mastromarco, Serlenga, and Shin (2009) take a factor-based approach to model productivity differentials across 24 OECD countries over the period 1970-2005. The authors applies the Pesaran (2006)'s Common Correlated Effects (CCE) method and propose to directly estimate the efficiency components by using the cross-section averages of the dependent variable and regressors as proxies for the unobservable common effects. A similar methodology is adopted by Mastromarco, Serlenga, and Shin (2013), who assume that the time-varying technical inefficiency consists of three components, a time-invariant individual effects, a time trend, and a *single* common factor structure. The authors estimate technical efficiency using a data set of the 18 EU countries over 1970-2004. A regression model with unobservable common factors is also adopted by Hsu, Lin, and Yin (2012) with data on 311 commercial banks from a set of OECD countries, and covering the period 1996-2009. The authors assume that the factor structure represents the technological progress, while setting u_{it} in (3) as IID half normal. Hence, they adopt a CCE approach with the aim to filter out the technological components. It is important to note that all existing studies on stochastic frontier models using long panels, ignore potential non-stationarity of the variables. However, it is well know that ignoring non-stationarity of the variables may lead to spurious statistical results. The existence of a long-run relationships should be tested to reduce the risk of finding spurious conclusions.

The CCE has been widely used for estimating stochastic frontier modelling under the common factor approach. Indeed, this method is easy to apply, and it yields valid inferences on the slope coefficients under general conditions, including when the unobservable common factors follow unit root processes and are possibly cointegrated (Kapetanios, Pesaran, and Yagamata (2011)). One important assumption under this approach is that the regressors in (2) depend on the unobservable common factors via the following model:

$$\mathbf{x}_{it} = \mathbf{\Gamma}_i' \mathbf{f}_t + \boldsymbol{\nu}_{it}, \tag{5}$$

where $\mathbf{\Gamma}_i$ are $m \times k$ factor loading matrices with fixed components, and $\boldsymbol{\nu}_{it}$ are the distributed independently of $\mathbf{f}_t$. The CCE method approximates the unobservable factors by cross-section averages of the dependent and explanatory variables, namely, in our application, $\bar{e}_t = (1/N) \sum_{i=1}^{N} e_{it}$, and $\bar{\mathbf{x}}_t = (1/N) \sum_{i=1}^{N} \mathbf{x}_{it}$. Hence, Ordinary Least Squares (OLS) can be applied to the following auxiliary regression where the cross-section averages are included among the observed regressors:

$$e_{it} = \alpha + \boldsymbol{\beta}' \mathbf{x}_{it} + \theta_i \bar{e}_t + \boldsymbol{\vartheta}_i' \bar{\mathbf{x}}_t + u_{it}, \tag{6}$$

Pesaran (2006) shows that estimation of the slope coefficients $\boldsymbol{\beta}$ is consistent under a set of general assumptions. However, consistent estimation of the unobservable common factors and their loadings through the cross-section averages is more problematic. In fact, the relationship between the loadings of the unobservable common factors,γ_{ij}, and the loadings attached to the cross-section averages, θ_i and ϑ_{ij} in the auxiliary regression (6), is not straightforward. In the presence of a single common factor (i.e., when $m = 1$), the factor loadings can be recovered from θ_i and ϑ_{ij} (see Mastromarco, Serlenga, and Shin (2013)). However, when $m > 1$, the relationship is much more complicated, and the factor loadings cannot be not easily recovered from the loadings attached to the cross-section averages. For stochastic frontier modelling we are mostly interested in a method that delivers simple, consistent estimation of common factors and their loadings in (4), and that is valid for any finite m.

From the above discussion it is evident that there exists a large variety of assumptions and methods proposed in the literature to model productive efficiency. The common factor specification (4), firstly proposed by Ahn, Lee, and Schmidt (2007) in the context of stochastic frontier modelling seems the most general approach, as it encompasses many other specifications as special cases. However, the CCE often adopted in empirical work does not seem the most appropriate method for estimating technical inefficiency under this framework.

We next present our framework, which is a generalisation of Ahn, Lee, and Schmidt (2007) approach to deal with the case of long panels.

3 The framework

Consider the following model

$$e_{it} = d_i t + \boldsymbol{\beta}' \mathbf{x}_{it} + u_{it} + v_{it}, \quad i = 1, 2, ..., N; t = 1, 2, ..., T, \tag{7}$$

where $d_i t$ are country-specific time trends that account for differences across countries in technological factors, and $\mathbf{x}_{it}$ is a $k \times 1$ vector of observed individual specific regressors. In this paper, we use the following general specification for technical efficiency

$$u_{it} = \alpha_i + \sum_{j=1}^{m} \gamma_{ij} f_{jt} = \alpha_i + \boldsymbol{\gamma}_i' \mathbf{f}_t. \tag{8}$$

Hence, efficiency is given by the sum of a time-invariant component, α_i, plus a linear combination of m unobservable time effects, having coefficients that vary across countries. Following recent literature on panel data with cross-sectionally dependent errors, we allow the unobservable common factors and/or factor loadings to be correlated with the included regressors, $\mathbf{x}_{it}$. Differently from this literature, under our approach the common factors are not regarded as a nuisance element, but rather important components of firms'/countries' efficiency that need to be consistently estimated. To this end, we will adopt the interactive-effects estimator by Bai (2009). This is the solution of the following set of non-linear equations:

$$\hat{\boldsymbol{\beta}} = \left(\sum_{i=1}^{N} \mathbf{X}_i' \mathbf{M}_{\hat{F}} \mathbf{X}_i \right)^{-1} \sum_{i=1}^{N} \mathbf{X}_i' \mathbf{M}_{\hat{F}} \mathbf{e}_i, \tag{9}$$

$$\frac{1}{NT} \left[\sum_{i=1}^{N} \left(\mathbf{e}_i - \mathbf{X}_i \hat{\boldsymbol{\beta}} \right) \left(\mathbf{e}_i - \mathbf{X}_i \hat{\boldsymbol{\beta}} \right)' \right] \hat{\mathbf{F}} = \hat{\mathbf{F}} \hat{\mathbf{V}}, \tag{10}$$

where $\mathbf{X}_i = (\mathbf{x}_{i1}, \mathbf{x}_{i2}, ..., \mathbf{x}_{iT})'$, $\mathbf{M}_{\hat{F}} = \mathbf{I}_T - \hat{\mathbf{F}}\left(\hat{\mathbf{F}}'\hat{\mathbf{F}}\right)^{-1}\hat{\mathbf{F}}'$, and $\hat{\mathbf{V}}$ is a diagonal matrix with the $\hat{m}$ largest eigenvalues of the matrix in the square brackets, arranged in decreasing order.

In practise, this method alternates principal components analysis applied to OLS residuals and least squares estimation several times, until convergence. Given that the panel covers a long time span, we allow e_{it} and $\mathbf{x}_{it}$ to be non-stationary, and investigate whether there exists a cointegration relation among our variables. This will be achieved by testing whether the unobservable common factors, $\mathbf{f}_t$, and/or idiosyncractic component, v_{it}, are non-stationary, in the context of model (7)-(8), by adopting the cointegration test for panels with I(1) regressors proposed by Bai and Carrion-i-Silvestre (2013). This approach consists of carrying the following steps:

1. Transform all variables in equation (7) into their first-differences, to make them stationary, and then express them in deviations from their temporal mean, to get rid of group-specific trends. Let

$$\mathbf{e}_i^* = \mathbf{M}\Delta\mathbf{e}_i, \quad \mathbf{X}_i^* = \mathbf{M}\Delta\mathbf{X}_i,$$

   where $\Delta\mathbf{e}_i = (\Delta e_{i2}, \Delta e_{i3}, ..., \Delta e_{iT})'$, $\Delta\mathbf{X}_i = (\Delta\mathbf{x}_{i2}, \Delta\mathbf{x}_{i3}, ..., \Delta\mathbf{x}_{iT})'$ and $\mathbf{M} = \mathbf{I}_{T-1} - T^{-1}\mathbf{1}_{T-1}\mathbf{1}'_{T-1}$, be the dependent variable and regressors first-differenced and demeaned

2. Apply the Bai (2009)'s interactive-effects estimator outlined in equations (9)-(10) to the transformed variables, to obtain $\hat{\boldsymbol{\beta}}$, $\hat{\boldsymbol{\gamma}}$, and $\hat{\mathbf{F}}^* = \mathbf{M}\Delta\mathbf{F}$. Define $\hat{z}_{it} = \mathbf{e}_{it}^* - \hat{\boldsymbol{\beta}}'\mathbf{x}_{it}^* - \hat{\boldsymbol{\gamma}}_i'\hat{\mathbf{f}}_t^*$

3. Estimate the common factors, $\mathbf{f}_t$, and idiosyncractic component, v_{it}, by re-cumulating $\hat{\mathbf{f}}_t^*$ and $\hat{z}_{it}$, as follows:

$$\hat{\mathbf{f}}_t = \sum_{s=2}^{t}\hat{\mathbf{f}}_s^*, \hat{v}_{it} = \sum_{s=2}^{t}\hat{z}_{is}, \quad t = 2, 3, ..., T \tag{11}$$

4. Construct test statistics based on $\hat{\mathbf{f}}_t$ and $\hat{v}_{it}$ to test the null hypothesis of no cointegration. The idiosyncratic component can be tested for non-stationarity using the modified Sargan-Bhargava (MSB) statistic:

$$MSB_{v,i} = \frac{T^{-2}\sum_{t=2}^{T}\hat{v}_{i,t-1}^2}{\hat{\sigma}_i^2}, \tag{12}$$

   where $\hat{\sigma}_i^2$ is an estimate of the long-run variance of $\hat{v}_{it}$

$$\hat{\sigma}_i^2 = \frac{\hat{\sigma}_{i,p}^2}{\left[1 - \hat{\phi}_i(1)\right]^2} = (T-p)^{-1}\sum_{t=2}^{T}\hat{v}_{i,t-1}^2,$$

with $\hat{\sigma}_{i,p}^2 = (T-p-1)^{-1}\sum_{t=p+2}^{T}\hat{\epsilon}_{it}^2$, $\hat{\phi}_i(1) = \sum_{j=1}^{p}\hat{\phi}_{ij}$, and $\hat{\epsilon}_{it}$, ϕ_{ij} are obtained from the OLS estimation of $\Delta\hat{v}_{it} = \phi_{i0}\Delta\hat{v}_{it} + \sum_{j=1}^{p}\phi_{ij}\Delta\hat{v}_{i,t-j} + \epsilon_{it}$. Hence, the individual statistics (12) can be combined using the standardized sample average of individual statistics which is $N(0,1)$ distributed (see Bai and Carrion-i-Silvestre (2013) for details). Similarly, if $m = 1$ (i.e., if there is a single common factor), we can construct a MSB unit root test statistic for $\hat{f}_t$

$$MSB_{\hat{f}} = \frac{T^{-2}\sum_{t=2}^{T}\hat{f}_t^2}{\hat{\sigma}_f^2} \tag{13}$$

where the long-run variance, $\hat{\sigma}_f^2$, can be estimated as described above. When the number of common factors is $m > 1$, $\mathbf{f}_t$ can be tested for non-stationarity using the modified Q statistics, (see Bai and Ng (2004) for details on the procedure).

In step 2, correlation of the regressors with common factors and factor loadings can be controlled by adding in the regression k_1 leads and k_2 lags of $\mathbf{x}_{it}^*$, k_1 and k_2 being two finite scalars. Alternatively, instead of using interactive-effects estimator (9)-(10), we suggest to use the CCE approach to estimate $\boldsymbol{\beta}$, obtain $u_{it}^* = e_{it}^* - \hat{\boldsymbol{\beta}}'\mathbf{x}_{it}^*$ and then apply the principal components analysis to extract $\mathbf{g}_t = \Delta\mathbf{f}_t$ and associated loadings from u_{it}^*. This computationally easier approach avoids including leads and lags of $\Delta\mathbf{x}_{it}$ to control for potential endogeneity of the regressors and will be adopted in this paper when estimating efficiency scores.

Estimation of the efficiency component, u_{it}, using specification (8) involves estimation of the group coefficients. This is achieved using the following formula:

$$\hat{\alpha}_i = \bar{e}_i - \hat{\boldsymbol{\beta}}'\bar{\mathbf{x}}_i - \hat{\boldsymbol{\gamma}}_i'\bar{\hat{\mathbf{f}}} - \hat{d}_i\bar{t}, \tag{14}$$

where

$$\hat{d}_i = \bar{e}_i^* - \hat{\boldsymbol{\beta}}'\bar{\mathbf{x}}_i^* - \hat{\boldsymbol{\gamma}}_i'\bar{\hat{\mathbf{f}}}^*. \tag{15}$$

Once u_{it} is estimated, following Ahn, Lee, and Schmidt (2007) and Mastromarco, Serlenga, and Shin (2009), we can compute a set of energy efficiency scores for each country as follow:

$$\hat{\tau}_{it} = \exp\left[-\left(\hat{u}_{it} - \min_i(\hat{u}_{it})\right)\right], \bar{\hat{\tau}}_i = \exp\left\{-N^{-1}\sum_{i=1}^{N}\left[\hat{u}_{it} - \min_i(\hat{u}_{it})\right]\right\} \tag{16}$$

which, in the case of specification (8), is

$$\hat{\tau}_{it} = \exp\left\{-\left[\hat{\alpha}_i + \hat{\boldsymbol{\gamma}}_i'\hat{\mathbf{f}}_t - \min_i\left(\hat{\alpha}_i + \hat{\boldsymbol{\gamma}}_i'\hat{\mathbf{f}}_t\right)\right]\right\}, \bar{\hat{\tau}}_i = \exp\left\{-N^{-1}\sum_{i=1}^{N}\left[\hat{\alpha}_i + \hat{\boldsymbol{\gamma}}_i'\hat{\mathbf{f}}_t - \min_i\left(\hat{\alpha}_i + \hat{\boldsymbol{\gamma}}_i'\hat{\mathbf{f}}_t\right)\right]\right\}. \tag{17}$$

A score of zero indicates that a country on the frontier is zero per cent efficient, while non-frontier countries receive scores above zero. The empirical implementation of the above estimation strategy is commented in the following sections.

4 Data

Our investigation uses annual data on a balanced panel of 24 OECD countries[2] followed over a period of 28 years, between 1980 and 2008 (hence, in this application, $N = 24$, $T = 29$). Following Filippini and Hunt (2011), in our aggregate energy demand function we assume that

$$\mathbf{x}_{it} = (y_{it}, p_{it}, ind_{it}, serv_{it}, temp_{it}, sdtemp_{it})',$$

where y_{it} is real per-capita GDP, p_{it} is an index of real energy prices, ind_{it} and $serv_{it}$ are the shares of value added of the industrial sector and service sector, respectively, measured as percentage of GDP, $temp_{it}$ is average monthly temperature, and $sdtemp_{it}$ is the standard deviation of monthly temperature within the year.

Energy consumption (e_{it}) is measured as per-capita aggregate energy consumption, expressed in Tonnes of Oil Equivalent (TOE). Real per-capita GDP is expressed in thousand US dollars per person, while energy price is given by each country's index of real energy prices (2000=100). All regressors, except for climate variables, have been gathered from the IEA World Energy Statistics and Balances[3]. Average monthly temperature and its standard deviation have been computed using the CRUTEM4 global surface temperature data set from University of East Anglia's Climatic Research Unit (2013).[4] This data set has temperature data in degrees Celsius at a monthly frequency for around 4,820 meteorological stations across the world, over the period 1900 to 2011.

For our empirical analysis, all variables have been transformed in natural logarithms. Descriptive statistics on the variables under study (not expressed in logs) are reported in Table 1.

[2] The countries under investigation are: Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Turkey, UK and US.

[3] See http://www.oecd-ilibrary.org/energy/data/iea-world-energy-statistics-and-balances_enestats-data-en

[4] See http://www.cru.uea.ac.uk/cru/data/temperature/crutem4/station-data.htm.

Table 1: Descriptive statistics for the variables under study

Variable	Unit	Mean	Std. Dev.	Min	Max
e_{it}	TOE per person	2,919.2	1,467.8	577.6	8,566.3
y_{it}	1,000$ per person	21.096	8.831	5.097	65.396
p_{it}	(2000=100)	89.178	16.429	12.633	149.332
ind_{it}	%	31.002	5.354	15.400	46.200
$serv_{it}$	%	64.615	6.749	45.900	84.300
$temp_{it}$	$°C$	10.837	4.723	0.193	23.977
$sdtemp_{it}$	$°C$	6.675	1.924	2.398	12.111

5 Empirical results

5.1 Panel unit root tests results

Table 2 reports the Pesaran (2007) CIPS statistics for the variables under study for the lag orders $p = 0, 1, 2, 3$. The inclusion of lags allow us to control for possible serial correlation in the data. The bottom panel of the table reports results when the variables are expressed in their first-differences. Energy consumption is non-stationary when adding an intercept and a linear trend in the CADF regression, for any choice of p, while the unit root is not reject for e_{it} in the intercept only case, and when $p = 0, 1$. The non-stationarity properties of energy consumption have important implications for time series modelling of energy demand. Indeed, regressions involving I(1) variables will be spurious unless the variables are cointegrated. The non-stationarity properties of energy consumption have also important policy implications, given the impact of oil price shocks on macroeconomic variables linked to energy demand. Failure to reject the null hypothesis of non-stationarity implies that shocks to energy consumption will have permanent effects, for example due to path dependency or hysteresis in energy demand equations. Hence, structural changes in the oil market, due for example to the oil price shocks in the '70s, will have permanent effects on the energy consumed. Existing studies on the estimation of aggregate energy demand functions have yielded mixed results, depending on the size of the sample considered, and on the econometric methods adopted (for example, univariate vs panel unit root tests). Most studies employing univariate unit root tests have concluded that energy consumption is an I(1) process. When using panel data, a number of studies suggest the existence of unit root in per-capita energy consumption (see, among others, Huang (2011)), while other works support the hypothesis of stationary energy consumption (Narayan and Smyth (2007)).

As for per capita GDP and energy price, the test statistics reject the unit root hypothesis both in the intercept only, and in the intercept and trend cases, for any choice of p. The null hypothesis is clearly rejected when these variables are transformed in first-differences. Given the trended nature of our variables, these results lead us to conclude that energy consumption, income and energy price are non-stationary. Our tests also point at the variables ind_{it} and $serv_{it}$ as I(1) processes. However, we observe that these variables are bounded by construction. Recent studies suggest that conventional unit root tests applied to bounded variables are potentially unreliable, since they tend to over-reject the null hypothesis of a unit root, even asymptotically (see, for example, Cavaliere and F.Xu (2013)). Our tests, however, indicate that these variables are stationary when transformed into first-differences. Finally, as expected, the null hypothesis of a unit root is clearly rejected for the variable $temp_{it}$ and $sdtemp_{it}$, both in the intercept only and in the intercept and trend cases, pointing at their stationarity.

Table 2: Unit roots tests for the variables under study

	CADF(0)	CADF(1)	CADF(2)	CADF(3)
	With an intercept only			
e_{it}	-2.309*	-2.129*	-2.050	-1.868
y_{it}	-1.496	-2.016	-1.518	-1.693
p_{it}	-2.358*	-2.077	-1.872	-1.573
ind_{it}	-0.345	0.019	0.409	-0.067
$serv_{it}$	-1.946*	-1.348	-0.216	-0.818
$temp_{it}$	-4.021*	-3.043*	-2.383*	-1.970*
$sdtemp$	-4.292*	-3.334*	-2.861*	-2.463*
	With an intercept and linear trend			
e_{it}	-2.582	-2.552	-2.609	-2.547
y_{it}	-1.529	-1.968	-1.456	-1.528
p_{it}	-2.610	-2.347	-2.159	-1.799
	With an intercept only			
Δe_{it}	-5.110*	-3.454*	-2.870*	-2.976*
Δy_{it}	-3.631*	-3.094*	-2.128*	-1.756
Δp_{it}	-18.688*	-10.925*	-6.487*	-4.018*
Δind_{it}	-14.035*	-8.204*	-3.462*	-1.518
$\Delta serv_{it}$	-16.224*	-9.035*	-4.474*	-1.068
$\Delta temp_{it}$	-2.964*	-4.003*	-4.984*	-6.116*
$\Delta std.temp$	-6.070*	-4.937*	-3.967*	-3.555*

Notes: The superscript "*" indicates that the test is significant at the 5% level. See Pesaran (2007) for critical values.

5.2 Estimation of the energy demand function

We now turn our attention to the estimation of the energy demand function. Table 3 reports results from the iterative PC estimator (9)-(10) (column I), the CCE Pooled estimator (column II), and the naive, fixed effects (FE) estimator (column III). We observe that the iterative PC estimator is performed on the variables expressed in their first-difference, as recommended by Bai and Carrion-i-Silvestre (2013). Overall, our results show that, as expected, growth in income boosts energy consumption, while rises in energy prices slow it down. Estimated income elasticities indicate that one percent increase in income is associated to an average increase of 0.54 and 0.65 per cent in energy consumption for the iterative

PC and CCE estimator, respectively. Under the factor approach, the climate variables significantly impact on energy consumption, while under the naive estimator, which ignores the factor structure, these variables are not significant.

Table 3 also shows the estimated number of common factors in the residuals, using the Bai and Ng (2002) IC_{p2} model selection criterion, and setting $m_{max} = 5$. The criterion suggests the presence of one unobservable common factor (i.e., $\hat{m} = 1$), when adopting either the interactive PC or the pooled CCE estimator.[5] Finally, the table reports the Bai and Carrion-i-Silvestre (2013) cointegration MSB statistics (12)-(13), suitable when $\widehat{m} = 1$, on the estimated, re-cumulated common factor and idiosyncratic error. Both MSB_f and MSB_v reject the null hypothesis of non-stationarity of the common factor and idiosyncratic component, respectively, when using either the iterative PC or the pooled CCE estimator. Hence, these statistics point at the existence of a long-run relationship between energy consumption and included regressors. In addition, stationarity of the unobservable common factor indicate that in our sample low efficiency countries tend to catch up in the long-run with more efficient countries.

Table 3: CCE, PC and FE estimation results

	(I): Iterative PC estimation		(II): Pooled CCE estimation		(III): FE estimation	
	Parameter	Std.err.	Parameter	Std.err.	Parameter	Std.err.
y_{it}	0.656*	0.097	0.543*	0.084	0.452*	0.119
p_{it}	-0.056*	0.017	-0.097*	0.040	-0.079*	0.028
ind_{it}	0.026	0.064	0.237	0.166	0.095	0.160
$serv_{it}$	-0.003	0.122	0.302	0.248	0.002	0.323
$temp_{it}$	-0.015*	0.004	-0.018*	0.005	-0.023	0.014
$std.temp.$	0.021*	0.008	0.014	0.016	0.025	0.022
$\widehat{m}$	1		1		-	
MSB_f	-7.299*	[0.00]	-8.201*	[0.00]	-	
MSB_v	-14.99*	[0.00]	-15.66*	[0.00]	-	

Notes: The superscript "*" indicates that the test on the estimated coefficient is significant at the 5% level. Standard errors are robust to serial correlation, in all regressions. p-values in square brackets.

5.3 Estimation of efficiency scores

We now turn to the estimation of efficiency scores using formula (17), which involves estimation of the country-specific effects, α_i, using (14). One problem related to the computation of the level of inefficiency using the group effects, is that time-invariant unobserved variables are considered as inefficiency. In this study, in order to deal with this problem we follow

[5] We tried varying the maximum number of factors between 1 to 5, and obtained the same result.

Farsi, Filippini, and Kuenzle (2005) and Filippini and Hunt (2012) and apply the Mundlak (1978)'s adjustment. Such adjustment improve the precision of the inefficiency estimates by separating inefficiency from time-invariant unobserved heterogeneity. Specifically, we have regressed the estimated $\hat{u}_{it}$ on the time averages of the regressors, $\bar{\mathbf{x}}_i = T^{-1}\sum_{t=1}^{T}\mathbf{x}_{it}$, and then plugged the residuals from such regression into (17).

Table 4 reports the time averages of efficiency scores, $\bar{\hat{\tau}}_i$, where unobservable common factors are proxied by principal components (column I), and by the cross-section averages as in Mastromarco, Serlenga, and Shin (2009) and Mastromarco, Serlenga, and Shin (2013) (column II). As a comparison, the table also reports efficiency scores obtained by assuming the conventional half normal distribution of u_{it} in a fixed effects model with time dummies (Column III) (see Filippini and Hunt (2011), Table 5). In Column I, common factors have been obtained by following Step 1-2 above. We have also tried using the CCE approach in step 1 and obtained very similar results which are available upon requests. We observe that when using cross-section averages as proxies for the unobservable common factors, the average efficiency scores are much lower then when using principal component analysis. Such result can be explained by the fact that the CCE approach, while estimating consistently the slope coefficients, is not designed to estimate consistently the unobserved common factors and attached loadings. Results in column I points at countries from Europe, with an average efficiency score of 0.791, as being the most efficient in consuming energy, while non-European countries such as US, New Zeland and Korea have the lowest positions in the ranking with an average score of 0.673.

The middle panel of Table 4 provides a set of descriptive statistics for the overall underlying energy efficiency estimates of the countries, showing that the average efficiency is around 74 per cent when taking common factors into account, with a fair degree of variability around it. Finally, the bottom panel reports the correlation among the efficiency scores. It is interesting to note that the scores under the PC approach are highly correlated with those under the CCE and under the Pooled model, while there is weaker correlation between the scores under the CCE approach and those with the Pooled model.

Table 4: Estimation of inefficiency scores

	Factor approach				Pooled model(+)	
	PC		CCE			
Country	Av. eff	Rank	Av. eff	Rank	Av. eff	Rank
Australia	0.710	16	0.359	19	0.904	8
Austria	0.756	10	0.632	8	0.93	1
Belgium	0.690	19	0.837	2	0.864	17
Canada	0.701	17	0.512	12	0.852	18
Denmark	1.000	1	0.972	1	0.916	4
Finland	0.644	21	0.368	18	0.872	15
France	0.756	11	0.406	16	0.896	10
Germany	0.783	9	0.626	9	0.873	14
Greece	0.829	7	0.698	6	0.923	2
Ireland	0.727	13	0.232	23	0.888	11
Italy	0.980	2	0.434	15	0.923	2
Japan	0.698	18	0.505	1	0.916	4
Korea	0.562	22	0.326	21	0.878	13
Luxembourg	0.651	20	0.215	24	0.845	20
Mexico	0.717	15	0.605	10	0.922	3
Netherlands	0.754	12	0.502	14	0.865	16
New Zealand	0.559	23	0.368	17	0.91	6
Norway	0.867	4	0.722	3	0.922	3
Portugal	0.726	14	0.662	7	0.912	5
Spain	0.829	8	0.515	11	0.922	3
Sweden	0.831	6	0.699	5	0.909	7
Turkey	0.900	3	0.700	4	0.887	12
UK	0.834	5	0.358	20	0.9	9
USA	0.543	24	0.236	22	0.846	19
Min	0.543		0.062		0.647	
Average	0.754		0.534		0.897	
Median	0.745		0.516		0.919	
Max	1.000		1.000		0.992	
Std.dev.	0.117		0.220		0.075	
	Correlation coefficients					
PC	-	-	0.590	[0.00]	0.517	[0.00]
CCE	-	-	-	-	0.397	[0.00]

(+): Efficiency scores and relative ranking for the pooled model have been extracted from Filippini and Hunt (2011), Table 5. Time dummies are included in this model. p-values in square brackets.

6 Concluding remarks

From a methodological point of view, this paper has outlined an estimation strategy of a stochastic frontier model when N and T are both large. A panel data model with group effects and unobservable common factors has been proposed and estimated using data on OECD countries over the years 1980 to 2008. This approach has not, as far is known, been attempted before. From a policy makers perspective, the indicators of energy efficiency obtained using this approach can be used in addition to the simple measure of energy intensity.

It is important to stress some limitations of the proposed approach. First, technological advances may not be fully captured by the country-specific trends, and part of it may be incorporated in the common factors structure. Another limitation is that time-invariant heterogeneity across countries may not be fully captured by Mundlak adjustment, and hence, the estimated efficiency component may be inflated.

References

Ahn, S., Y. H. Lee, and P. Schmidt (2007). Stochastic frontier models with multiple time-varying individual effects. *Journal of Productivity Analysis 27*, 1–12.

Ahn, S. C. and R. C. Sickles (2000). Estimation of long-run inefficiency levels: a dynamic frontier approach. *Econometric Reviews 19*, 461–492.

Aigner, D. J., C. A. K. Lovell, and P. Schmidt (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics 6*, 21–37.

Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica 77*, 1229–1279.

Bai, J. and J. L. Carrion-i-Silvestre (2013). Testing panel cointegration with unobservable dynamic common factors. *The Econometrics Jounal 16*, 222–249.

Bai, J. and S. Ng (2002). Determining the Number of Factors in Approximate Factor Models. *Econometrica 70*, 191–221.

Bai, J. and S. Ng (2004). A panic attack on unit roots and cointegration. *Econometrica 72*, 1127–1177.

Battese, G. E. and T. J. Coelli (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in india. *Journal of Productivity Analysis 3*, 153–169.

Cavaliere, G. and F.Xu (2013). Testing for unit roots in bounded time series. *Journal of Econometrics*, Forthcoming.

Cornwell, C., P. Schmidt, and R. Sickles (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics 46*, 185–200.

Cornwell, C. M. and J. Wachter (1999). Productivity convergence and economic growth: A frontier production function approach. ZEI working paper N. B 06-1999.

Engle, R. F. and C. W. J. Granger (1987). Co-integration and Error Correction: Representation, Estimation and Testing. *Econometrica 55*, 251–276.

Farsi, M., M. Filippini, and M. Kuenzle (2005). Unobserved heterogeneity in stochastic frontier models: an application to swiss nursing homes. *Applied Economics 37*, 2127–2141.

Filippini, M. and L. C. Hunt (2011). Energy demand and energy efficiency in the OECD countries: a stochastic demand frontier approach. *Energy Journal 32*, 59–80.

Filippini, M. and L. C. Hunt (2012). US residential energy demand and energy efficiency: A stochastic demand frontier approach. *Energy Economics 34*, 1484–1491.

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis 23*, 7–32.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics 126*, 269–303.

Greene, W. H. (2008). The econometric appappro to efficeffic analysis. In H. O. Fried, C. A. K. Lovell, and S. S. Schmidt (Eds.), *The Measurement of Productive Efficiency and Productivity Growth*, Chapter 2, pp. 92–250. Oxford.

Hsu, C. C., C. C. Lin, and S. Y. Yin (2012). Estimation of a panel stochastic frontier model with unobserved common shocks. MPRA Paper No. 37313.

Huang, Y. (2011). The drivers of rising global energy demand: New evidence. Environmental Economy and Policy Research Discussion Paper n. 52.

Kapetanios, G. and M. H. Pesaran (2007). Alternative approaches to estimation and inference in large multifactor panels: Small sample results with an application to modelling of asset returns. In G. Phillips and E. Tzavalis (Eds.), *The Refinement of Econometric Estimation and Test Procedures: Finite Sample and Asymptotic Analysis*. Cambridge: Cambridge University Press.

Kapetanios, G., M. H. Pesaran, and T. Yagamata (2011). Panels with nonstationary multifactor error structures. *Journal of Econometrics 160*, 326–348.

Kneip, A., R. Sickles, and W. Song (2003). On estimating a mixed effects model with applications to the US banking industry. Mimeo, Rice University.

Mastromarco, C., L. Serlenga, and Y. Shin (2009). Dynamic efficiency modelling for technological convergence. Mimeo, Leeds University Business School.

Mastromarco, C., L. Serlenga, and Y. Shin (2013). Globaliglobal and echnological convergence in the eu. *Journal of Productivity Analysis 40*, 15–29.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica 46*, 69–85.

Murillo-Zamorano, L. R. (2004). Economic efficiency and frontier techniques. *Journal of Economic Surveys 18*, 33–77.

Narayan, P. K. and R. Smyth (2007). Are shocks to energy consumption permanent or temporary? Evidence from 182 countries. *Energy Policy 35*, 333–341.

Park, B. U., R. C. Sickles, and L. Simar (2003). Semiparametric efficient estimation of AR(1) panel data models. *Journal of Econometrics 117*, 279–309.

Pesaran, M. H. (2006). Estimation and inference in large heterogenous panels with multi-factor error structure. *Econometrica 74*, 967–1012.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross section dependence. *Journal of Applied Econometrics 22*, 265–312.

Porcelli, F. (2009). Measurement of technical efficiency: A brief survery on parametric and non-parametric techniques. Mimeo, Universiy of Warwick.

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