Global Dependence and Productivity Catching-up: A Conditional Nonparametric World Frontier Analysis

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Abstract: Increasing globalization and interconnection among countries generates spatial and temporal dependence which will affect the production process of each country. Many studies have analyzed the effect of cross-sectional dependence by using restrictive parametric models. We use a flexible nonparametric two-step approach on conditional efficiencies to eliminate the dependence of production inputs/outputs on these common factors. By using a dataset of 44 countries over 1970-2007, we estimate the global frontier and explore the channels under which Foreign Direct Investment (FDI) and time affect the production process and its components: impact on the attainable production set (input-output space), and the impact on the distribution of efficiencies. We extend existing methodological tools - flexible non parametric location-scale frontier model - to examine these interrelationships. We emphasize the usefulness of "pre-whitened" inputs/outputs to obtain more reliable measure of productivity and efficiency to better investigate the driven forces behind the catching-up productivity process. Furthermore, since the influence of external factors has been eliminated, our proposed approach mitigates the problem of endogeneity bias caused by reverse causality between the external factors as FDI and productivity.

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1 Introduction

Due to an increasing globalisation and interconnection among countries through history, geography and trade relations, technological interdependency generated by externalities is important in explaining conditional convergence process across countries. Total factor productivity has been recognized as the most important driver behind economic growth (Prescott 1998, Caselli 2005, Parente and Prescott 2005). The issue of cross section dependency or correlation has been widely discussed in the empirical panel data literature (Bai and Ng 2006, Pesaran 2006, Bai 2009, Kapetanios et al. 2011). The productivity analysis also recognises an importance of investigating the spillover effects of the global shocks and business cycles. Mastromarco et al. (2013) among others, demonstrate that it is crucially important to take into account globalisation factors for an analysis of productivity and output growth. Due to a certain degree of cross-section dependence (CSD) introduced by unobserved (heterogeneous) time-specific factors the conventional estimators would be seriously biased. The literature deals with cross section dependence, attributable to economy-wide shocks that affect all units in the cross section but with different intensities, by assuming a multifactor error process characterized by a finite number of unobserved common factors. According to this approach, the error term is a linear combination of a few common time-specific effects with heterogeneous factor loadings plus an idiosyncratic (individual-specific) error term.

Chudik et al. (2011) introduce the distinction between weak and strong cross section dependence. Specifically, a process is said to be cross sectionally weakly dependent at a given point in time, if its weighted average at that time converges to its expectation in quadratic mean, as the cross section dimension is increased without bounds. If this condition does not hold, then the process is said to be cross sectionally strongly dependent. The distinctive feature of strong correlation is that it is pervasive, in the sense that it remains common to all units however large the number of cross sectional units.[1]

Pesaran (2006) and Bai (2009) propose two alternative way to handle strong cross sectional dependence. Pesaran (2006) suggests a pooled common correlated estimator (PCCE) which approximates the linear combinations of the unobserved factors by cross section averages of the dependent and explanatory variables and then runs standard panel regressions augmented with the cross section averages. An advantage of this approach is that it yields consistent estimates even when the regressors are correlated with the factors, and the number of factors are unknown. Bai (2009) proposes a principal component (PC) interactive maximum likelihood estimator where the unobserved factors are identified by principal components. More recently Pesaran and Tosetti (2011) have presented a panel model in which the errors are

[1]Spatial dependence typically entertained in the literature turns out to be weakly dependent in this framework.

a combination of a multifactor structure and a spatial process, hence combining strong and weak CSD.

So far all of the studies analyzing effect of external common factors on productivity of countries have been in the stream of parametric modeling. However, the parametric approach suffers of misspecification problems when the data generating process is unknown, as usual in the applied studies, and the nonparametric methods often give the most reliable results. The purpose of this paper is to provide fully nonparametric location scale estimators of production frontiers and time variant technical efficiency in a dynamic framework which allows external and global (time specific) factors to affect technical efficiency.[2]

There is a fundamental measurement problem for total factor productivity (TFP). The usual approach to estimate TFP is through growth accounting to explain output growth as the accumulation of factor inputs and the growth of TFP. However this approach has an important drawback since it does not consider non-competitive markets, increasing returns to scale and factor utilisation over the business cycle. More importantly, growth accounting interprets the TFP (Solow residual) as "technical change". The interpretation of the TFP as technical change is reasonable only if all countries are producing on their frontier. Beyond factor inputs, we could have additional determinants of output growth affecting the efficiency with which real inputs are transformed into output and thus directly affecting productivity. TFP comprises two mutually exclusive parts, technological change and efficiency change, and frontier model allows us to distinguish between the two. Moreover our frontier model enables us to see whether the effect of environmental/global variables on productivity occurs via technology change or efficiency. We can then quantify the impact of environmental/global factors on efficiency levels and make inferences about the contributions of these variables in affecting efficiency.

We propose a full flexible non parametric two step approach to take into account the cross section dependence due to common factors attributable to global shocks. Following recent development in non parametric conditional frontier literature (Florens et al. 2014) we suggest a flexible nonparametric location-scale frontier model linking production inputs and output to the global and environmental factors. In the first step we clean the dependence of inputs and outputs on global and other environmental factors. In the second step we estimate the frontier and the efficiency using inputs and outputs whitened from the influence of global shocks and endogenous environmental factors. By eliminating influence of external factors our nonparametric estimator is also robust to the endogeneity bias caused by reverse causality between the external factors as FDI and productivity. Our approach deals with endogeneity

[2]The efficiency frontier literature defines environmental or external factors, those variables which might affect the production process but which are not under the direct control of the production unit.

by proposing an estimator of the boundary of the production set based on 'cleaned' output and inputs which are uncorrelated with global factors and FDI.

More fundamentally, we propose a robustness method which simultaneously addresses the problem of model specification uncertainty, potential endogeneity and spatial dependence in the analysis of productivity. It also accounts for heteroskedasticity.

The paper aims to examine the productivity catching up process using 44 countries over the period 1970-2009 and to investigate the role of global factor as FDI and time in spurring technological catching up (efficiency) among countries.

2 The Methodology

We apply Florens et al. (2014) methodology and consider a Data Generating Process (DGP) characterizing the production process in the presence of environmental factors and we extend their models to a dynamic framework to allow the introduction of the time dimension and cross section dependence (CSD). Consider a generic input vector $X \in \mathbb{R}^p_+$, a generic output vector $Y \in \mathbb{R}_+$ and we will denote by $Z \in \mathbb{R}^r$ the generic vector of environmental variables (FDI in our study). Since we are in a context of panel data, our sample will be denoted by (X_{it}, Y_{it}, Z_{it}), with $i = 1, \ldots, n$ being the firm index and $t = 1, \ldots, s$ the time index. For handling the time dimension, we will consider, with some abuse of notation, the time T as an additional conditioning variable. To better investigate the influence of globalization factors (e.g., technological shocks and financial crises) on the economic performance of countries under analysis, we develop a method to envelop the effect of CSD on the production process. Hence, we assume that the production process is function of unobserved time-varying factors. As proposed by Pesaran (2006), Bai (2009) we will consider $F_t = (t, X_{\cdot t}, Y_{\cdot t})$ as proxy for the unobserved nonlinear and complex trending patterns associated with globalisation and the business-cycle.

2.1 A short excursion in Frontier models

For unfamiliar readers, we can summarize the setup of frontier models as follows. The production process is a process generating pairs of inputs $X \in \mathbb{R}^p_+$ and outputs $Y \in \mathbb{R}_+$. We first define the unconditional (marginal) attainable set of feasible combinations of inputs and outputs as $\Psi = \{(x, y) \in \mathbb{R}^{p+1}_+ | x \text{ can produce } y\}$. It can be can be characterized by $\Psi = \{(x, y) | H_{X,Y}(x, y) > 0\}$, where $H_{X,Y}(x, y) = \text{Prob}(X \leq x, Y \geq y)$. So Ψ is the support of the joint random variable (X, Y). For the univariate output case, the frontier function can be defined for an input vector x as

$$\tau(x) = \sup\{y|H_{XY}(x,y) > 0\} = \sup\{y|S_{Y|X}(y|x) > 0\}, \tag{1}$$

where the conditional survivor function is $S_{Y|X}(y|x) = \text{Prob}(Y \geq y|X \leq x)$. Sometime, researchers reports also for a unit operating at the level (x, y), the Farrell-Debreu output efficiency score $\lambda(x, y) = \tau(x)/y = \sup\{\lambda|S_{Y|X}(\lambda y|x) > 0\} \geq 1$. An efficiency score equal to one, detects a unit on the efficient frontier.

When we want to condition the frontier analysis to some environmental factors (Z, F_t), as is our setup here, we have rather to define the attainable set $\Psi^{z,f_t} \subset \mathbb{R}_+^{p+1}$ as the support of the conditional probability (Cazals et al. 2002):

$$H_{X,Y|Z,F_t}(x, y|z, f_t) = \text{Prob}\left(X \leq x, Y \geq y \,|\, Z = z, F_t = f_t\right). \tag{2}$$

Accordingly, and following Daraio and Simar (2005), when the output is univariate, the conditional frontier function at input x, facing conditions z and f_t (in particular at time t), is defined as[3]

$$\tau(x, z, f_t) = \sup\{y|S_{Y|X,Z,F_t}(y|x, z, f_t) > 0\}, \tag{3}$$

where $S_{Y|X,Z,F_t}(y|x, z, f_t) = \text{Prob}(Y \geq y|X \leq x, Z = z, F_t = f_t)$ (note the difference in the conditioning for X, the inputs, and for Z and F_t, the environmental and global factors). Again we can report the Farrell-Debreu conditional efficiency scores as

$$\lambda\left(x, y|z, f_t\right) = \tau(x, z, f_t)/y = \sup\{\lambda|S_{Y|X,Z,F_t}(\lambda y|x, z, f_t) > 0\}. \tag{4}$$

The unconditional and conditional attainable sets can be estimated, for the unconditional set we can plug the empirical version of $S_{Y|X}$ in (1) providing the popular FDH (Free Disposal Hull) estimator of Ψ. A nonparametric estimator of the conditional survival function $S_{Y|X,Z,F_t}(y|x, z, f_t)$ could be obtained by using standard smoothing methods where a bandwidth h has to be determined for each component of (Z, F_t) (as e.g. in Badin et al., 2010). In summary, these nonparametric estimators are consistent with rate $n^{1/(p+1)}$ and Weibull limiting distribution for the unconditional FDH (see Park et al., 2000). For the conditional case, we have similar results where n is replaced by nh^d where d is the dimension of all the conditioning variables (in our setup, (Z, F_t), so $d = r + p + 2$) (see Jeong et al., 2010). So the rates of convergence of the conditional estimators are deteriorated by the dimension d.

In most of the empirical examples, a naive application of these nonparametric techniques

[3]We only focus the presentation on the output orientation version of the estimators, the same could be done for any other orientation (input, hyperbolic, directional distance).

may be problematic because real samples contain in general some anomalous data. In that case, the estimated frontier is fully determined by these outliers or extreme data points and the measurement of inefficiencies are totally unrealistic. Whereas most of the practitioners use a rule of thumb for outliers elimination, better approaches have been proposed in the frontier literature (Cazals et al., 2002; Daouia and Simar, 2007) to keep all the observations in the sample but to replace the frontier of the empirical distribution by (conditional) quantiles or by the expectation of the minimum (or maximum) of a subsample of the data. This latter method defines the order-m frontier that we will use here. To be short, the partial output-frontier of order-m is defined for any integer m and for an input x, as the expected value of the maximum of the output of m units drawn at random from the populations of firms using less inputs than x. Formally

$$\tau_m(x) = \mathbb{E}\left[\max(Y_1, \ldots, Y_m)\right], \tag{5}$$

where the Y_j are independently distributed as $S_{Y|X}(\cdot|X \leq x)$. The same applies for the conditional order-m frontier $\tau_m(x, z, f_t)$ where the Y_j are distributed as $S_{Y|X,Z,F_t}(\cdot|X \leq x, Z = z, F_t = f_t)$. Nonparametric estimators are obtained by plugging the nonparametric estimators of the survival functions in the formulae.

If m increases and converges to ∞, it has been shown (see Cazals et al., 2002) that the order-m frontier and its estimator converge to the full frontier, but for a finite m, the frontier will not envelop all the data points and so is much more robust than the FDH to outliers and extreme data points (see e.g. Daouia and Gijbels, 2011, for the analysis of these estimators from a theory of robustness perspective). Another advantage of these estimators is that they achieve the parametric rate $\sqrt{n}$ of convergence and have a normal limiting distribution.

2.2 The Location-Scale models

In this paper, for the conditional measures, we will rather follow the approach suggested in Florens et al. (2014) which avoids direct estimation of the conditional survival function $S_{Y|X,Z,F_t}(y|x, z, f_t)$. As pointed by Florens et al., the procedure is less impacted by the curse of dimensionality (of the conditioning variables Z, F_t) and requires smoothing in these variables in the center of the data cloud and so avoiding smoothing at the frontier where typically the data are rather sparse and estimators are more sensitive to outliers. Moreover the inclusion of time factor $F_t = (t, X_{\cdot t}, Y_{\cdot t})$ enables us to eliminate the common time factor effect, in a very flexible nonparametric location-scale model. The statistical properties of the resulting frontier estimators are established in Florens et al. (2014).

We thus assume that the data are generated by the following nonparametric location-scale regression model

$$\begin{cases} X_{it} & = \mu_x(Z_{it}, F_t) + \sigma_x(Z_{it}, F_t)\varepsilon_{x,it} \\ Y_{it} & = \mu_y(Z_{it}, F_t) + \sigma_y(Z_{it}, F_t)\varepsilon_{y,it} \end{cases}, \tag{6}$$

where μ_x, σ_x and ε_x have each p components and, for ease of notations, the product of vectors is componentwise. So the first equation in (6) represents p relations for each component of X. We assume that each element of ε_x and ε_y have mean zero and standard deviation equal to 1. The model also assume that $(\varepsilon_x, \varepsilon_y)$ is independent of (Z, F_t).

This model allows us to capture for any (z, f_t), for each input, $j = 1, \ldots, p$ and for the output, the locations $\mu_x^{(j)}(z, f_t) = \mathbb{E}\left[(X^{(j)}|Z = z, F_t = f_t)\right]$, $\mu_y(z, f_t) = \mathbb{E}\left[(Y|Z = z, F_t = f_t)\right]$ and the scale effects $\sigma_x^{(j),2}(z, f_t) = \mathbb{V}\left[(X^{(j)}|Z = z, F_t = f_t)\right]$, $\sigma_y^2(z, t) = \mathbb{V}\left[(Y|Z = z, F_t = f_t)\right]$ of the environmental and common factors on the production plans.[4]

As explained in Florens et al. (2014), ε_x and ε_y can be interpreted as "pure" inputs and output, because due to the independence between the vector $(\varepsilon_x, \varepsilon_y)$ and (Z, F_t), they can be viewed as "whitened" versions of X and Y respectively. Since no particular assumption is made on the distribution of $(\varepsilon_x, \varepsilon_y)$, the model remains basically nonparametric. Note also that in the case where (Z, F_t) would be independent of all the inputs X and of the output Y, the functions μ_ℓ and σ_ℓ would be constant for $\ell = x, y$ and $(\varepsilon_x, \varepsilon_y)$ would simply be a standardized version of the original inputs and output.

The pure efficiency measure - that we derive below - provides a better indicator to assess the economic performance of production units over time and allows the ranking of production units affecting by common shocks (captured by common factors f_t) and facing different environmental factors at different time periods (z_{it}).

To estimate the production frontier we follow the method proposed by Florens et al. (2014). First we estimate model (6) by using some usual nonparametric techniques (e.g. local constant or local linear) in two steps: (i) estimation of the location functions $\mu_\ell(z_{it}, f_t)$ and (ii) estimation of the variance functions $\sigma_\ell^2(z_{it}, f_t)$ by regressing the resulting square residuals of the first step on (z, f_t). For the first step we use local linear and for the second step local constant to avoid negative values of the estimated variances. From this first analysis we obtain the residuals

$$\widehat{\varepsilon}_{x,it} = \frac{X_{it} - \widehat{\mu}_x(Z_{it}, F_t)}{\widehat{\sigma}_x(Z_{it}, F_t)}, \tag{7}$$

$$\widehat{\varepsilon}_{y,it} = \frac{Y_{it} - \widehat{\mu}_y(Z_{it}, F_t)}{\widehat{\sigma}_y(Z_{it}, F_t)}, \tag{8}$$

where again, for ease of notation, a ratio of two vectors has to be understood component

[4]Hereafter, for a vector a, $a^{(j)}$ denotes its j^{th} component.

wise. These are the whitened inputs and output obtained by eliminating the influence of the external and other environmental variables as common factors. In practice we will need to test the independence between $(\widehat{\varepsilon}_{x,it}, \widehat{\varepsilon}_{y,it})$ and (Z_{it}, F_t), i.e. the independence of whitened inputs and output from the external and global effects to validate the location-scale model (see Florens et al. (2014)).

In the second stage, we can now estimate the production frontier for these whitened output and inputs and so we obtain for each observation (i,t) a measure of "pure" efficiency. This approach enables us to accommodate both time and cross-sectional dependence and obtain more reliable measure of efficiency. To some extent, the first step allows us also to control for endogeneity due to reverse causation between production process (labour, capital and output) and external variables (in our case FDI).

Moreover, as pointed by Florens et al. (2014), by cleaning external factors dependence in the first stage, we avoid the problem of curse of dimensionality due to the dimension of the external variables when estimating the production frontier. In practice this leads to estimate the attainable set of pure inputs and output $(\varepsilon_x, \varepsilon_y)$. The latter is defined as

$$\Psi_\varepsilon = \left\{(e_x, e_y) \in \mathbb{R}^{p+1} | H_{\varepsilon_x,\varepsilon_y}(e_x, e_y) = \text{Prob}(\varepsilon_x \leq e_x, \varepsilon_y \geq e_y) > 0\right\}.$$

The nonparametric estimator is obtained by plugging the empirical estimators $\widehat{H}_{\varepsilon_x,\varepsilon_y}(e_x, e_y)$ obtained with the observed residuals defined in (7) and (8). As shown in Florens et al. (2014), replacing the unobserved $(\varepsilon_x, \varepsilon_y)$ by their empirical counterparts $(\widehat{\varepsilon}_x, \widehat{\varepsilon}_y)$ does not change the usual statistical properties of frontier estimators. So we have the consistency for the full-frontier FDH estimator and $\sqrt{n}$-consistency and asymptotic normality for the robust order-m frontiers. It is conjectured in Florens et al. (2014), that if the functions μ_ℓ and σ_ℓ for $\ell = x, y$, are smooth enough, the conditional FDH estimator would keep its usual nonparametric rate of convergence i.e. $n^{1/(p+1)}$.

A "pure" measure of efficiency can also be obtained by measuring the distance of a particular point $(\varepsilon_{x,it}, \varepsilon_{y,it})$ to the efficient frontier. Since the pure inputs and output are centered on zero, they may have negative values and so radial distances are inappropriate. We should rather use directional distances defined for a particular unit (e_x, e_y) as

$$\delta(e_x, e_y; d_x, d_y) = \sup\{\gamma | H_{\varepsilon_x,\varepsilon_y}(e_x - \gamma d_x, e_y + \gamma d_y) > 0\}, \tag{9}$$

where $d_x \in \mathbb{R}^p_+$ and $d_y \in \mathbb{R}_+$ are the chosen direction. In our case here we choose an output orientation so that $d_x = 0$ and we can choose $d_y = 1$, for more general cases, see Simar and Vanhems (2012) (if only some elements of $d_x = 0$ see Daraio and Simar, 2014 for practical computations). So, for this particular output direction and in the case of univariate output we follow here, the optimal production frontier can be described at any value of the pure input $e_x \in \mathbb{R}^p$, by the function

$$\varphi(e_x) = \sup\{e_y | H_{\varepsilon_x,\varepsilon_y}(e_x, e_y) > 0\}, \tag{10}$$

so that the distance to the frontier of a point (e_x, e_y), in the output direction, is directly given by $\delta(e_x, e_y) = \varphi(e_x) - e_y$.

It is then shown in Florens et al. (2014) that for each units in the sample, the "pure" efficiency estimator is obtained through

$$\widehat{\delta}(\widehat{\varepsilon}_{x,it}, \widehat{\varepsilon}_{y,it}) = \widehat{\varphi}(\widehat{\varepsilon}_{x,it}) - \widehat{\varepsilon}_{y,it}, \tag{11}$$

where $\widehat{\varphi}(\cdot)$ is the FDH estimator of the pure efficient frontier in the output direction. It is simply obtained as

$$\begin{aligned} \widehat{\varphi}(e_x) &= \sup\{e_y | \widehat{H}_{\varepsilon_x,\varepsilon_y}(e_x, e_y) > 0\} \\ &= \max_{\{(i,t)|\widehat{\varepsilon}_{x,it} \le e_x\}} \widehat{\varepsilon}_{y,it}. \end{aligned} \tag{12}$$

Similar expressions are derived in Florens et al. (2014) for the robust version of this estimator, the order-m efficiency estimator. As explained above, the order-m frontier at an input value e_x, is the expected value of the maximum of the outputs of m units drawn at random in the population of units such that $\varepsilon_{x,it} \le e_x$. The nonparametric estimator is obtained by looking to its empirical version:

$$\widehat{\varphi}_m(e_x) = \widehat{E}\left[\max\left(\varepsilon_{y,1t}, \ldots, \varepsilon_{y,mt}\right)\right], \tag{13}$$

where the $\varepsilon_{y,it}$ are drawn from the empirical conditional survival function $\widehat{S}_{\varepsilon_y|\varepsilon_x}(e_y|\widehat{\varepsilon}_{x,it} \le e_x)$ (this can be computed by Monte-Carlo approximation or by solving a univariate numerical integral (for practical details see Simar and Vanhems 2012).

It is also possible to recover the conditional output-oriented frontier in the original units of the inputs and output. It is directly obtained at any value of (x, z, f_t) as

$$\tau(x, z, f_t) = \mu_y(z, f_t) + \varphi(e_x)\sigma_y(z, f_t), \tag{14}$$

where e_x is the p-vector with components $(x - \mu_x(z, f_t))/\sigma_x(z, f_t)$. In terms of estimates, this gives for a particular point (x_{it}, z_{it}, f_t) the estimated frontier point in the original units

$$\widehat{\tau}(x_{it}, z_{it}, f_t) = \widehat{\mu}_y(z_{it}, f_t) + \widehat{\varphi}(\widehat{\varepsilon}_{x,it})\widehat{\sigma}_y(z_{it}, f_t). \tag{15}$$

By using (6) and (11) above we see that this can be equivalently written as

$$\widehat{\tau}(x_{it}, z_{it}, f_t) = y_{it} + \widehat{\delta}(\widehat{\varepsilon}_{x,it}, \widehat{\varepsilon}_{y,it})\widehat{\sigma}_y(z_{it}, f_t), \tag{16}$$

which has a nice interpretation: we see that the directional distance from the observed input-output point (x_{it}, y_{it}) facing external conditions (z_{it}, f_t) to the efficient frontier is given by the "pure" efficiency measure evaluated at the pure input-outputs $(\widehat{\varepsilon}_{x,it}, \widehat{\varepsilon}_{y,it})$ rescaled by the local standard deviation $\widehat{\sigma}_y(z_{it}, f_t)$.

Finally is Farrell-type efficiency estimates are wanted, as in (4), an estimate is given by

$$\widehat{\lambda}_t\left(x_{it}, y_{it}|z_{it}, f_t\right) = \frac{\widehat{\tau}(x_{it}, z_{it}, f_t)}{y_{it}} \geq 1, \tag{17}$$

with equality to 1 for points on the estimated conditional frontier (having pure efficiency $\widehat{\delta}$ equal to zero).

Note that when back to original coordinates, we are back to the curse of dimensionality, typically the n appearing in the rates for the frontier estimates in the "pure" units is replaced by nh^d where d is the dimension of all the conditioning variables (Z, F_t) (see Florens et al. (2014) for details).

After estimating the conditional and unconditional 'pure' efficiency measure, we can analyze the effects of the global factors (FDI and time specific factors F_t) on the production process and disentangle the potential effects of these environmental variables on the boundary (shift of the frontier) and on the distribution of the inefficiencies (as explained in Bădin et al. 2012). The first effect can be investigated by considering the ratios of conditional to unconditional efficiency measures, which are measures relative to the full frontier of respectively, the conditional and the unconditional attainable sets. In our setup, we are mainly interested on the effects of FDI on these ratios[5]

$$R_O(x, y|z, f_t) = \frac{\lambda(x, y|z, f_t)}{\lambda(x, y|f_t)}. \tag{18}$$

By construction, for the output orientation, $R_O(x, y|z, f_t) \leq 1$ (the conditional efficient boundary is below the unconditional one) and $R_O(x, y|z, f_t) = 1$ if and only if, at time t, there is no shift of the efficient boundary of the two attainable sets due to z. Looking to these ratios as a function of z allows to investigate the effect of the environmental factor ($Z = FDI$ in our case) on this potential shift. A global tendency of the ratios to increase with the conditioning variables indicates a favorable effect (the conditional efficient frontier moves up to the

[5]Because we are not interested on the potential effects of X, the analysis of these ratios has to be done for fixed level of inputs x.

unconditional one when the variables increase, i.e. the variables act as freely available inputs) and unfavorable in the opposite case (the conditional efficient boundary moves away form the marginal one when the variables increase, the variables act as undesirable outputs).

As suggested in Bădin et al. (2012), the full frontier ratios in (18) indicate only the influence of Z on the shape of the frontier, whereas the the partial frontiers allow to investigate the effect of Z on the conditional distribution of inefficiencies. The ratios to be analyzed are now

$$R_{O,m}(x, y|z, f_t) = \frac{\lambda_m(x, y|z, f_t)}{\lambda_m(x, y|f_t)}. \tag{19}$$

Some potential shifting effect already observed with (18) could be enhanced (or reduced) if the effect is different with the ratios (19). Here typically we use smaller value of m since we want to explore the distribution of the output inside the corresponding attainable sets (in the limit, if $m = 1$, we analyze to the mean). As explained in Bădin et al. (2012), the ratios are not bounded by 1, because the order-m efficiency scores are not bounded by 1. The latter equal to 1 if and only if (x, y) is on the m-frontier, bigger than 1, if they are below the m-frontier and smaller than 1 if they are above the m-frontier. But, as for the full ratios above, a tendency of $R_{O,m}(x, y|z, f_t)$ to increase with the conditioning variables indicates a favorable effect of these variables on the distribution of the efficiencies (the conditional distribution is more concentrated to its upper boundary when the conditioning variables increase) and the opposite in the case of a unfavorable effect. If this effect is similar to the one shown with the ratios with full frontier, we can conclude that we have a shift of the frontier while keeping the same distribution of the efficiencies when the conditioning variable Z change; if the effect with the partial frontiers is more important than for the full frontier, this indicates that in addition to a shift of the frontier, we have also an effect on the distribution of the efficiencies.

2.3 Parametric fit of the nonparametric frontiers

It has been argued that parametric models provide much richer interpretations of the production process in terms of elasticities, etc. This is true if the chosen parametric model is a reasonable approximation of the true frontier. On the other hand, and as discussed in details in Florens and Simar (2005), most of the methods of estimation of these parametric frontier models suffer from some drawbacks, in case of heterogeneity of the efficiency distribution over the input values and /or in case of outlying data points.

If indeed a researcher want to fit a particular parametric model to the frontier, Florens and Simar (2005) suggest an approach that address most of the drawbacks of the usual methods and provide robust fits of the frontier. Suppose we want to see if a parametric model (e.g. Cobb-Douglas) is appropriate, Florens and Simar (2005) propose to project all the input-output data points on the FDH frontier or even better on the robust order-m frontier and then adjust the chosen parametric model to this cloud of "efficient" points, e.g. by simple OLS (ordinary least squares). Florens and Simar (2005) analyze the statistical properties of the resulting estimators and show that we have consistent estimators of the parameters of the fitted model to pseudo-true values of the parameters. If we use the order-m robust version we have even $\sqrt{n}$-consistency and limiting unbiased normal distribution with a given variance, that can be estimated by bootstrap techniques. The pseudo-true values are the ones given by best approximation of the true unknown frontier (in some sense, like integrated squared errors); if the selected parametric model (like Cobb-Douglas) is true, these pseudo-true values are the true values of the parameters. The analysis of traditional goodness of fit measures would help the researcher to assess if the chosen parametric model is a reasonable approximation.

In our case here, we will do so for the frontier in the "pure" inputs-output space (for all the resins explained in the preceding section). The advantage of the Florens-Simar semiparametric approach with respect to a standard parametric one, is that first its relies on a fully nonparametric model and only search for the best parametric approximation; second, the method does not require any parametric assumption regarding technology or the distribution of the inefficiencies. In particular, the assumption of complete homogeneity of considered economic units is not needed. Therefore the economic units under investigation can potentially consist of different groups of populations governed by different distributional laws of the generation of input-output mix and on efficiency. This means that, if the sample is formed by developed and developing countries, as in our case, these groups of countries can have different distributions of efficiency scores. This enables us to analyze the world production technology and have a direct economic interpretation in terms of elasticity and technology progress. In addition when using the order-m approach we are robust to outliers and extreme data points.

We can for example estimate the following Cobb-Douglas parametric frontier model (in a linear form because we assume units of measurement are already in log)

$$\widehat{\varepsilon}^{\delta}_{y,it} = \alpha + \beta' \widehat{\varepsilon}_{x,it} + \eta_{it} \tag{20}$$

where $\widehat{\varepsilon}_{x,it}$ and $\widehat{\varepsilon}^{\delta}_{y,it} = \widehat{\varphi}(\widehat{\varepsilon}_{x,it})$ were defined above and η_{it} is the fitting noise. We obtain the estimated fitted Cobb-Douglas production frontier $\widehat{\widehat{\varepsilon}}^{\delta}_{y,it} = \widehat{\alpha} + \widehat{\beta}' \widehat{\varepsilon}_{x,it}$. If we come back to the original units, the estimated Cobb-Douglas frontier parametric model is thus given by (we use the shortcut notation $w_{it} = (f_t, z_{i,t})$):

$$\widehat{y}^{\delta}_{it}(x_{it} \mid w_{it}) = \mu_y(w_{it}) + \sigma_y(w_{it}) \widehat{\widehat{\varepsilon}}^{\delta}_{y,it} \tag{21}$$

It can be shown that this can be written as

$$\widehat{y}_{it}^{\delta}(x_{it} \mid w_{it}) = \widetilde{\alpha}(w_{it}) + \widetilde{\beta}'(w_{it})x_{it}, \tag{22}$$

where (using again for ease of notations, the component wise division of vectors)

$$\widetilde{\alpha}(w_{it}) = \mu_y(w_{it}) + \sigma_y(w_{it}) \left[\widehat{\alpha} - \widehat{\beta}' \frac{\mu_x(w_{it})}{\sigma_x(w_{it})}\right] \tag{23}$$

$$\widetilde{\beta}(w_{it}) = \sigma_y(w_{it}) \frac{\widehat{\beta}}{\sigma_x(w_{it})} \tag{24}$$

To assess the characteristics in terms of technology, capital and labour elasticities of the production frontier, we can look at the exponential of the latter coefficients as a function of time (see below in the application). Technological changes is captured by $\widetilde{\alpha}(w_{it})$ which indicates if the world frontier itself has moved outward (progress) or inward (regress) over time. The evaluation over time of the components of $\widetilde{\beta}(w_{it})$ enables us to assess if technology over time has been more capital or labour deepening and, hence, to appraise policy implications in favor of capital or labour accumulation in less developed countries to promote convergence towards richest ones.

3 Empirical Application

Our non parametric approach in constructing the worldwide production frontier does not require the specification of the production functional form, and also limit the problem of 'curse of dimensionality' at the second stage of our methodology. We consider the simplest production model with only three macroeconomic variables: aggregate output and two aggregate inputs (labour and capital).

The dataset is collected over the period, 1970-2007 (38 years) for a total of 44 countries using data from the Penn; 26 are developed OECD countries (Australia, Austria, Belgium, Canada, Chile, Hong Kong, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Turkey, the United Kingdom and the United States) and 18 are developing countries (Argentina, Bolivia, Côte d'Ivoire, Dominican Republic, Ecuador, Honduras, Jamaica, Kenya, Madagascar, Malawi, Morocco, Nigeria, Panama, Philippines, Thailand, Venezuela, Zambia, Zimbabwe).[6]

Using data from the Penn World Tables (version 6.3) we calculate as measure of output

[6]The choice of countries depends on data availability. Developed and developing countries are classified following the World Bank (2007) classification. See Appendix for data description.

the real gross domestic product and it is obtained as $RGDPCH * POP$, where $RGDPCH$ is per capita real GDP computed via the chain method, POP is the population. The resulting output is GDP measured in million US dollars at 2005 constant prices. For labor input, we use the number of workers as $RGDPCH * POP/RGDPWOK$, where $RGDPWOK$ is real GDP per worker. For the capital input, we proceed as follow. Real aggregate investment in million US dollars at 2005 constant prices is computed as $I = RGDPL * POP * KI$, where $RDGPL$ is the real GDP, and KI is the investment share of real GDP. Capital K which is our chosen input is then measured in million US dollars at 2005 constant prices and constructed applying the perpetual inventory method (PIM) by using the real investment series.[7] All three variables are logged and normalized with respect to the median - to ensure homogeneity assumption in inputs and outputs - before estimation. For globalization factor we identify one of the most important channels: FDI inflows, measured as net inflows of foreign direct investment, which are then transformed as a ratio to GDP.[8]

Our external variable, FDI, might suffer from endogeneity bias. The endogeneity caused by reverse causality is still an open issue in the empirical studies investigating the relationship between TFP and FDI. In this paper we explicitly address this issue by eliminating in the first stage the dependence of the FDI on the production process. Furthermore, the global economy becomes increasingly integrated, all the individual countries are likely to be exposed more to global shocks. To this end, we employ a robust estimation procedure dealing with unobserved factors in nonparametric frontier panel data framework, which enables us, in the first stage, to better capture the impacts of global shocks (such as FDI, trade policy and cycle fluctuations) and, hence, CSD on the production frontier and technical efficiency.

Thus, first it is interesting to evaluate whether the effects of our Z variables and global factors F_t on the production process have been eliminated to verify whether the hypothesis of the "separability" condition might be not rejected in our 'pure' data generation process. This would validate our approach of conditional efficacy scores in evaluating the performance of different countries when facing different environmental and global conditions with respect to the standard two-stage procedure (Simar and Wilson 2007). Figure 1 shows the p-value of the hypothesis of independence following the test suggested by Florens et al. (2014) confirming that the influence of FDI and the cross section dependence has been removed in our data.

[7]PIM is necessitated by the lack of capital stock data across all the countries. For an individual country, the capital stock is constructed as $K_t = K_{t-1}(1-\theta) + I_t$, where I_t is investment and θ the rate of depreciation assumed to be 6% (*e.g.*, Hall and Jones, 1999; Iyer *et al.*, 2008). Repair and maintenance are assumed to keep the physical production capabilities of an asset constant during its lifetime. Initial capital stocks are constructed, assuming that capital and output grow at the same rate. Specifically, for country with investment data beginning in 1970, we set the initial stock, $K_{1970} = I_{1970}/(g+\theta)$, where g is the 10-year output growth rate from 1970 to 1980. Estimated capital stock includes both residential and non-residential capital.

[8]FDI is sourced from the World Bank World Development Indicators and Unctad, all the other data from PWT 6.3. The observation period is selected by the data availability.

Figure 2 displays the values of the estimated pure inputs $\hat{\epsilon}_{X1}$ and $\hat{\epsilon}_{X2}$ and pure output $\hat{\epsilon}_Y$ showing an increasing relationship between production output and labour and capital inputs. Figure 3 exhibits the values of $\hat{\epsilon}_{X1}$ and $\hat{\epsilon}_{X2}$ with the full frontier $\hat{\phi}$ and order-m frontier $\hat{\phi}_m$. We observe that for the full frontier there are some influential units, whereas the order-m frontier is not attracted by these extreme data points. We decide to leave out 8.5% of data points (m=800), and the units are benchmarked against partial frontiers which are less extreme than the boundary of the support and enables us to estimate frontier and efficiency that are less sensitive to the extreme or outlying data points (Cazals et al. 2002, Daraio and Simar 2005, Daouia and Simar 2007). As sensitive analysis, Figure (4) shows percent of points outside the order m-frontier at each value of m.

The distribution of estimated inefficiency (Fig. 5) reveals most of the OECD countries under analysis efficient and some rare very inefficiency countries. Table 1 summarises descriptive statistics for 'pure efficiency' for the 44 countries. We find that the most efficient countries over the sample period are USA, Japan, Germany and Ivory Coast (CVI), while the least efficient are Chile, Zambia, Philippines and Nicaragua. Positive performance observed in Ivory Coast is also documented in other studies (see Koop et al. 2000).

Ivory Coast has, for West Africa region, a relatively high income per capita (USD 1014.4 in 2013) and plays a key role in transit trade for neighboring, landlocked countries. The country is the world's largest exporter of Cocoa beans, and the fourth largest exporter of goods, in general, in sub-Saharan Africa (following South Africa, Nigeria and Angola). As the second largest economy in West Africa and a top world exporter of cocoa and cashews, Ivory Coast boasts enormous economic potential. Macroeconomic performance continued to be impressive in 2013, with economic activity expanding by an estimated 8.7%. Inflation remained subdued at 2.5%. The macroeconomic prospects for 2014 remain positive, especially given the expectations of a vigorous growth rate and low inflation. Continued strong macroeconomic performance and further progress on the governments structural reform program is necessary in order to support GDP growth, improve living standards for the most vulnerable populations, and allow Ivory Coast to transform itself into an emerging economy.[9]

To give a visual impression of the change in 'pure' efficiency over time, average 'pure' efficiency for each year is displayed in Figure 6 for the USA, Japan, Germany (the best countries in our analysis) Nicaragua, Philippines, Zambia (the worst performing countries), Belgium and Italy.

By applying spectral analysis (Mastromarco and Woitek 2007) we examine the business cycles of our pure measure of efficiency which gives insights on prevailed cycles of the technological catch-up process of the countries under analysis. Table (2) describes the relative

[9]"Country Report 2014, The World Bank Group, web site http://www.worldbank.org/afr/.

importance of efficiency cycles. The column on share of total variance' reports the estimated variance shares in the frequency bands, i.e. the cycles with a length of 3-5 years (the Kitchin cycle), 5-7 years and 7-10 years (the Jugular cycle).[10] The dominant frequencies contain important information of the structure of efficiency. The efficiency is dominated by the shorter cycle of 3-5 years and 5-7 years cycle for all countries, except Austria, Ivory Coast, Dominican Republic, Greece, Jamaica, Morocco, New Zeeland, Panama, Spain, Zambia.

To assess the influence of FDI on the production process, we investigates the ratios of conditional and unconditional efficiency measures for full and partial frontier. Figure 7 exhibits the pictures of all the ratios from a marginal point of view (as a function of two inputs and as a marginal function of FDI). The full frontier ratios (three top panels at 25, 50, 75 percent of two production inputs - labour and capital -) show an inverted 'U' effect of Z=FDI at low and big values of production inputs (first and third top panels). We might have some shift of the frontier when FDI increases, but with a decreasing effect at large values of Z. In order to check the robustness of our result and to inspect if some extreme observations would hide some effect, we calculate the ratios for partial frontiers - $order - m$ - and we obtain very similar results, see Figure 7 (bottom panel), i.e., a slight positive effect of Z for small and big countries (small and large values of labour and capital inputs). This confirms a favourable effect of FDI which is very similar to the effect detected for the shift of the frontier (full frontier). So, FDI act on the shift of the boundary. Hence, from this evidence, FDI appear to play an important role in accelerating the technological change (shifts in the frontier). This result seems to confirm the theoretical hypothesis that FDI leads to increase in productivity by spurring competition: foreign firms have to invest even more in innovation in order to keep up with their technological advantage (Glass and Saggi 1998). To a lesser extent, FDI can also increase efficiency. This occurs with the adoption of foreign technology through technology licensing or technology purchase, imports of high technology capital goods, and the skills acquired by the local labour force as they are trained by the foreign firms (Borensztein et al. 1998, De Mello 1999, Xu 2000). The evidence of decreasing returns of FDI can be easily explained by the adjustment costs involved in FDI, e.g. Tybout (1992) and Coe and Helpman (1995).

Another interesting issue is to investigate the channels through which FDI affects the production process whether through technological change - shifts of the frontier - or through factor accumulation. This can be assessed by analysing the evolution over time of the production frontier. We estimate Cobb-Douglas production frontier by projecting all data point on the FDH frontier using OLS (see Florens and Simar 2005).

Table 3 reports the estimates of constant (α_1) and output elasticities of capital (β_1) and

[10] The traditional business cycle ranges are 3-5 years (Kitchin cycle), 5-7 years and 7-10 years (Juglar cycle).

labour (β_2) of world frontier using Florens and Simar (2005) estimator on the nonparametric frontier points of $order - m$ - first row - and full FDH frontiers - second row - and parametric COLS estimator - third row -. The estimates of output elasticities are similar using full or partial FDH frontier points for Florens and Simar (2005) approach. We relies on the estimates of $order-m$ frontiers whose asymptotic properties have been established (see Florens and Simar 2005). Technology at the world frontier production reveals that output is elastic especially with respect to labour (about 0.70) , while the output elasticity with respect to capital is lower (around 0.30).[11] The sum of the output elasticities is approximately equal to one indicating constant returns the scale. Given this evidence, we base the following analysis on the assumption of constant returns to scale technology (CRS), which enables us to interpret world production technology in the $y = Y/L$ and $k = K/L$ space.

Figure 8 contains the empirically constructed full and partial production world frontiers - FDH and Cobb-Douglas - in 1970 and 2007, along with scatterplots of labour productivity and the capital-labour ratios of our observations and, at the bottom panel, the global frontier for the whole observation period. This figure provides evidence that technology change over this period has been nonneutral. In particular, Hicks-neutral technological change would shift the frontier in in the $y = Y/L$ and $k = K/L$ space vertically by the same proportional amount at all capital-labour ratios. The change in the technologies between 1970 and 2007 is also inconsistent with Harrod-neutral (labour-augmenting) technological change, which would shift the frontier radially (i.e., by equal proportional factors along rays from the origin). In 1970 at very low capital-labour ratios, it appears to be technological frontier countries as US and Canada and, surprisingly, also very poor country as Jamaica. The last year 2007, displays an outward shift in frontier for higher but still quite low capital-labour ratios as Germany and the UK, very little change in the frontier for the middle of the distribution of capital-labour ratios and a sizeable expansion of potential output at very high capital-labour ratios as the Netherlands (not the large technological-change for the New Zeeland). The frontier countries - the US, Germany and Canada - indicate that production technology on the frontier is capital saving (labour using). Global frontier, at the bottom, confirms the evidence that the frontier production is at low level of capitalization.

Figure 9 displays Cobb-Douglas and non-parametric fit of the full and $order - m$ frontiers in the original and pure units. As expected, the $order - m$ frontiers are resistant to outlying data points, which is not the case for the full frontiers estimates. Moreover, the results in the original units are different because the units are compared to non feasible frontiers: each country is facing different exogenous conditions determined by external variables (FDI and

[11] Labours contributions are higher as expected, implying that it is easier to maintain output and profitability by reducing employment or increasing labour productivity rather than by dismissing capital stocks.

global shocks in our case). So, the approach using conditional efficiency scores seems to be much more appropriate. We observe a very good quality of the Cobb-Douglas fit of our estimator, better than the FDH ones.

Our FDH estimates of non-parametric frontier and Cobb-Douglas fit of full frontier at data points are visible in figure 10 that validates our previous conclusion of very good fit of Cobb-Douglas frontier production technology.

The time variation in the technology and output elasticity of capital and labour is displayed in Figure 11. More interesting is the time-variant technology and factors output elasticity dependent on FDI as illustrated in figure 12. The bottom panel of this figure reveals a positive effect of FDI on constant, this indicates indicates a favourable effect of FDI on the production process via technological change. This result seems to confirm the theoretical hypothesis that FDI leads to increase in productivity by spurring competition: foreign firms have to invest even more in innovation in order to keep up with their technological advantage (Glass and Saggi 1998).

On the contrary the top left panel demonstrates that FDI does not impact the output elasticity of labour whereas it is visible a scale effect on capital elasticity - left top panel of figure 12 - which is higher for high level of FDI. This evidence suggests that high level of foreign direct investments are complement with high level of domestic capital investments. This confirms that the separability condition is not reasonable, and so, two stage approaches are meaningless.

This finding reveals that FDI influences positively the production process through different channels as technological changes and scale effects. This proves that knowledge embodied in FDI is transferred for technology externalities (shifts of the frontier). Hence, from this evidence, FDI appears to play an important role in accelerating technological change (shifts in the frontier). This result corroborates the theoretical hypothesis that FDI increases productivity by stimulating competition and inducing the foreign firms to invest more in innovation in order to keep their technological advantage (Glass and Saggi 1998). To a lesser extent, FDI can also increase factor accumulation by influencing output elasticity. This occurs with the adoption of foreign technology through technology licensing or technology purchase, imports of high technology capital goods, and the skills acquired by the local labour force as they are trained by the foreign firms (Borensztein et al. 1998, De Mello 1999, Xu 2000).

4 Conclusion

We propose the unified non parametric framework for accommodating simultaneously the problem of model specification uncertainty, potential endogeneity and cross-section dependence in modelling technical efficiency in frontier models. In particular, we adopt the two-step procedure advanced by Florens et al. (2014), which enables us to deal with both endogeneity and cross section dependence jointly by combining location scale model and conditional efficiency estimation to eliminate the dependence of production inputs/outputs on the common factors. Our non parametric approach to estimate conditional efficiency does not require any parametric assumption regarding technology or efficiency term. Moreover, the assumption of complete homogeneity of considered units is not needed. Therefore the economic units under investigation, can potentially consist of different groups of population governed by different distributional laws of the generation of input-output mix and on efficiency. This is an advantage in our sample formed by developed and developing countries which most likely have different distributions of efficiency scores.

According to the literature (Borensztein et al. 1998, De Mello 1999, Xu 2000, Mastromarco and Ghosh 2009, Iyer et al. 2008), one of the main channels through which the foreign technology diffusion occurs is through foreign direct investment. Our paper extends previous studies on similar topics by investigating this channel in full nonparametric framework which avoids some restrictive and often unverifiable prior assumptions on functional relationships and distributions.

We focus on the effect of FDI on economic performance of 44 countries over the period 1970-2007. In a cross-country framework, production inefficiencies can be identified as the distance of the individual country's production from the frontier as proxied by the maximum output of the reference country (regarded as an empirical counterpart of an optimal production boundary). Hence, efficiency improvement will represent productivity catch-up via technology diffusion because inefficiencies generally reflect a sluggish adoption of new technologies (Ahn and Sickles 2000).

In this paper we aim to assess the diffusion dynamics of a technology (frontier) in the countries under analysis with respect to FDI. We then intend to redress an important policy issue of whether the protection-oriented policy will hamper the production efficiency through limiting FDI by explicitly analysing dynamic interactions between efficiency and openness factor FDI.

Our empirical evidence reveals that FDI influence production process through different channels and by enhancing technological changes. We find that FDI has a scale effects on capital by enhancing capital output elasticity but does not influence the output elasticity of labour. Our results confirm that knowledge embodied in FDI is transferred for technology externalities (shift of the frontier) (Cohen and Levinthal 1989). Hence, our findings support the studies highlighting that lowering barriers to entry of foreign goods and investments have exerted a significantly positive effects on productivity through efficiency and technology gains, e.g. Borensztein et al. (1998), Cameron et al. (2005).

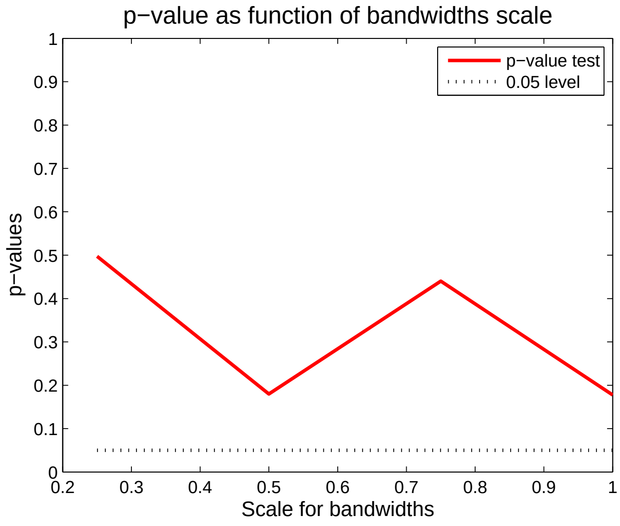


Figure 1: *Test of* $\widehat{\varepsilon}^{(j)}_{1,it}$ *and* $\widehat{\varepsilon}_{2,it} \perp (z_{it}, f_t)$, *i.e. the independence of whitened inputs and output from the external* $(Z = FDI)$ *and global effects* $f_t = (t, x_{.t}, y_{.t})$ *(Florens et al. 2014).*

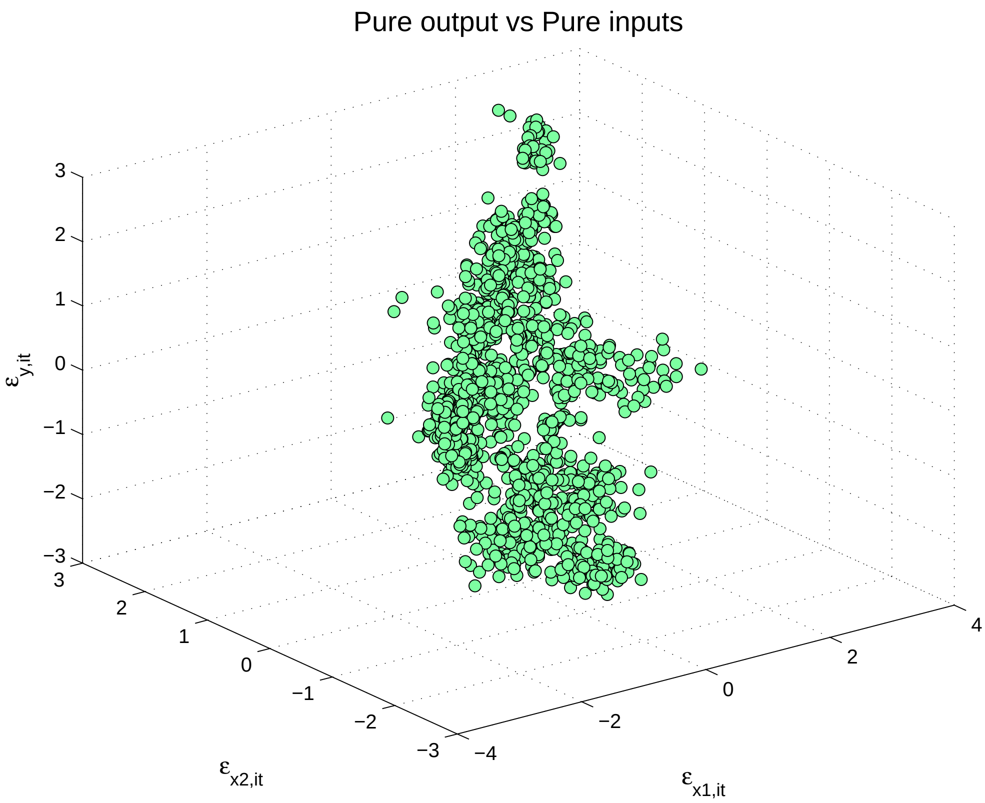


Figure 2: *Estimated "pure" output* $\widehat{\varepsilon}_{y,it}(Z)$ *and inputs* $\widehat{\varepsilon}_{x1,it} = labour$ *and* $\widehat{\varepsilon}_{x2,it} = capital$.

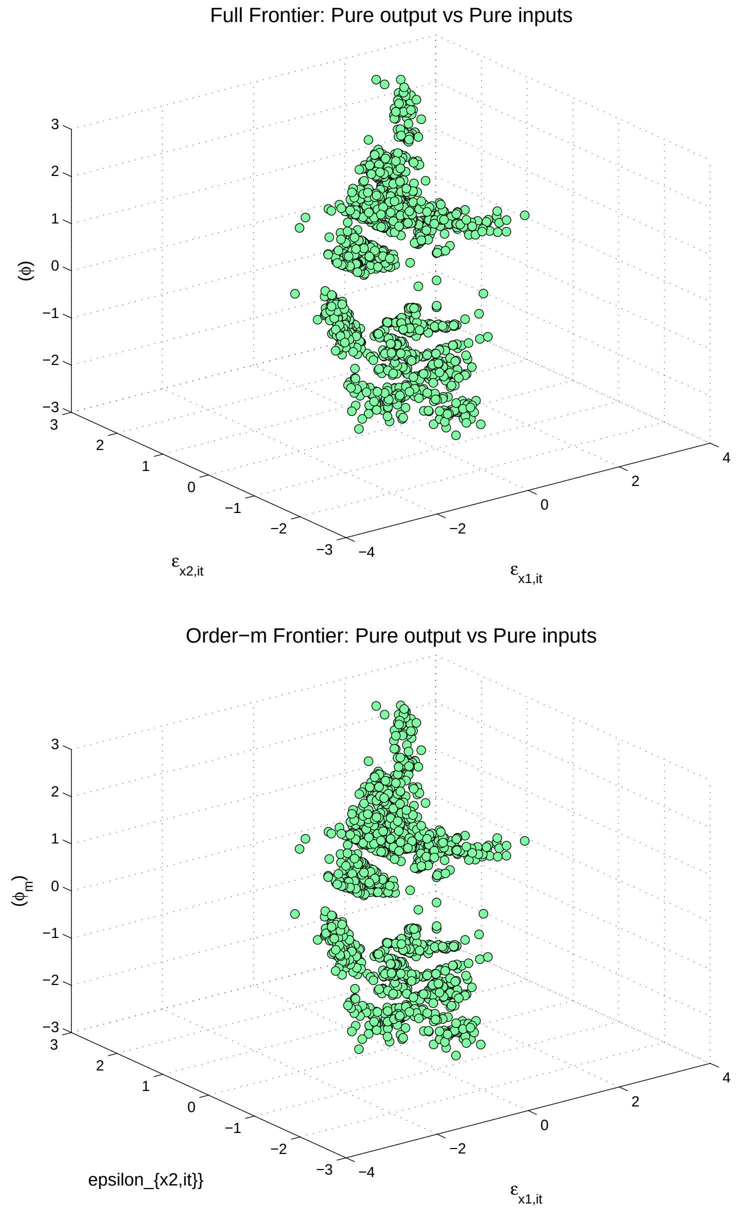


Figure 3: *Estimated "pure" efficiency output and efficiency inputs* $\widehat{\varepsilon}_{x1,it} = labour$ *and* $\widehat{\varepsilon}_{x2,it} = capital$ *relative to the full frontier* ϕ *and to the order-m frontier* ϕ_m *(top panels) and estimated "pure" output* $\widehat{\varepsilon}_{y,it}$ *and inputs* $\widehat{\varepsilon}_{x1,it} = labour$ *and* $\widehat{\varepsilon}_{x2,it} = capital$ *(bottom panel).*

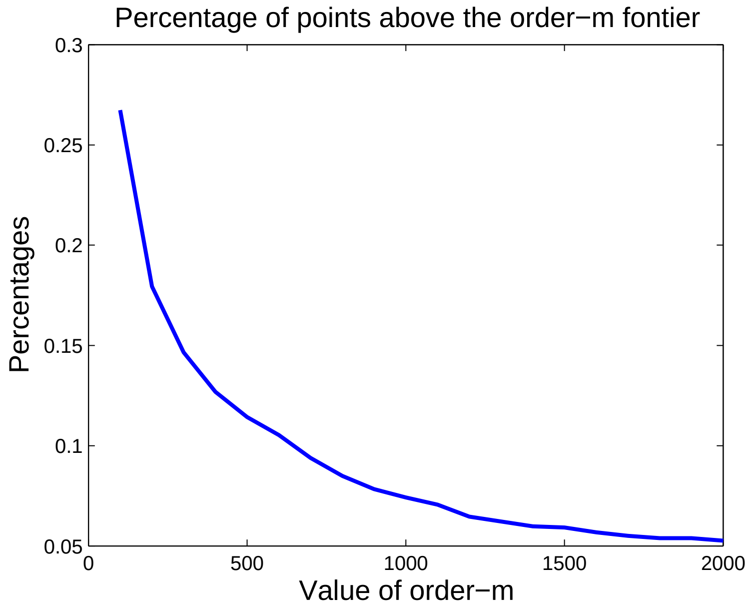


Figure 4: *Percent of points outside the m-frontier at each value of m.*

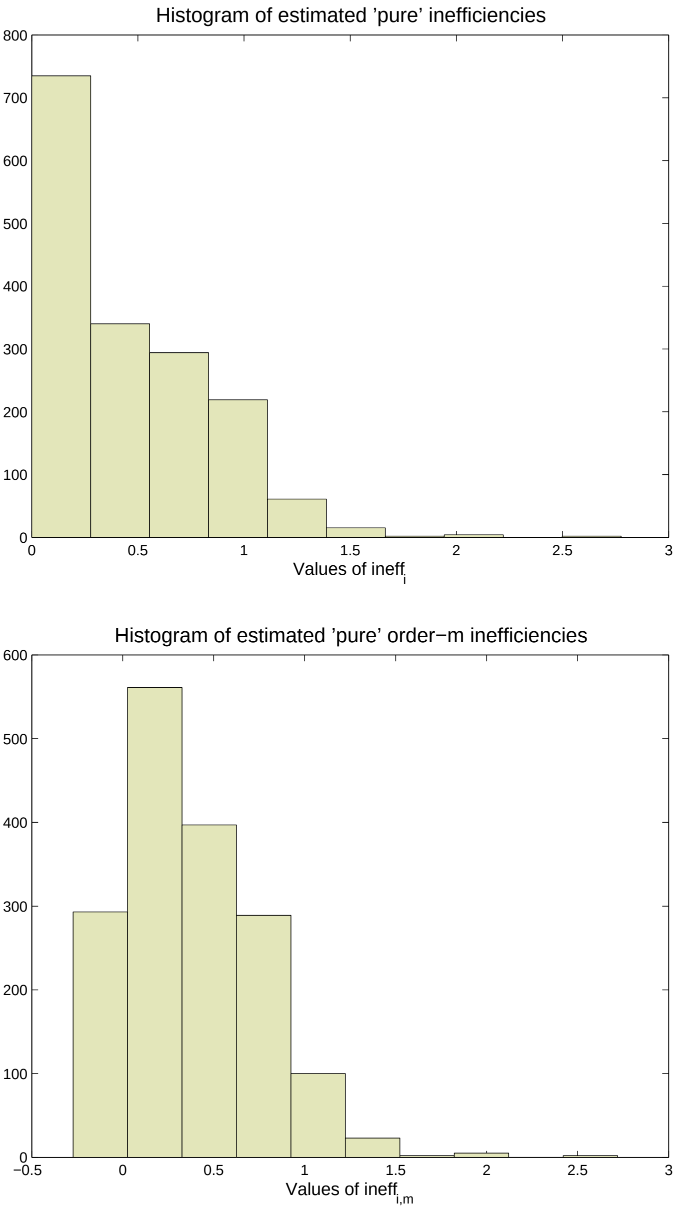
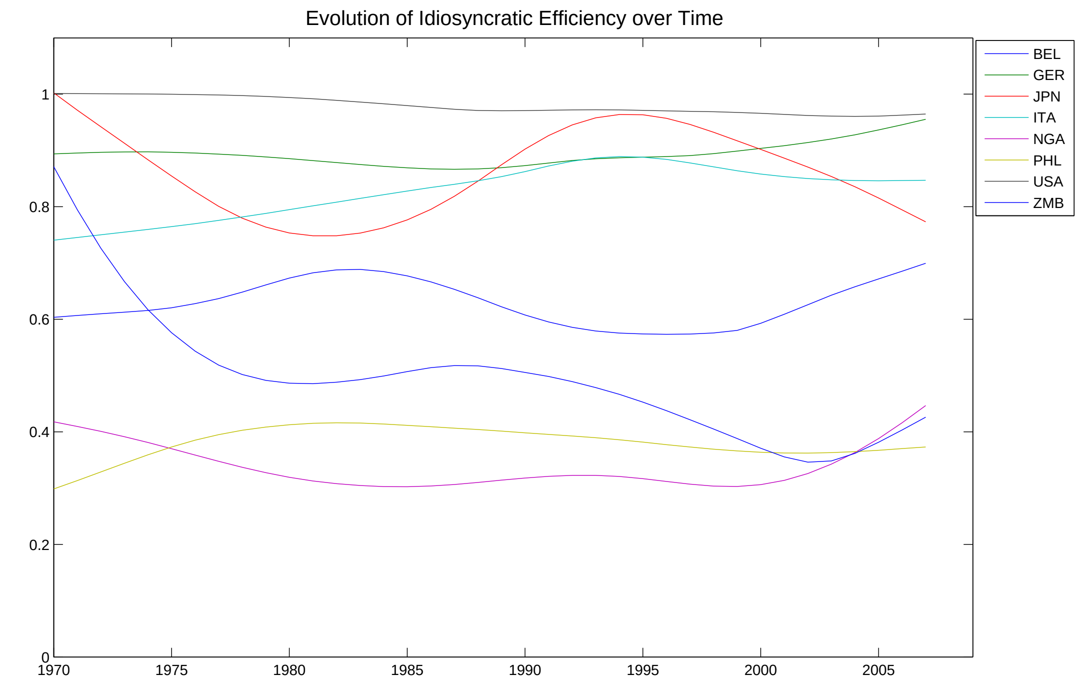


Figure 5: *Distribution of the estimated inefficiencies, relative to the full frontier* ϕ *and to the order-m frontier* ϕ_m *.*

Table 1: ‘Pure efficiency’ of 44 countries over 1970 2007 (average over time)

	Mean	Standard Deviation	Change (%) 1970 to 2007
USA	0.761	0.078	-0.077
JPN	0.685	0.055	-0.183
GER	0.680	0.071	0.125
CIV	0.659	0.064	0.259
ISR	0.651	0.097	0.445
FRA	0.650	0.047	0.010
CAN	0.642	0.051	-0.022
ITA	0.637	0.043	-0.049
DOM	0.622	0.068	-0.175
GBR	0.608	0.103	0.428
ESP	0.596	0.041	-0.015
MEX	0.581	0.058	-0.151
HND	0.579	0.117	0.637
NLD	0.572	0.087	0.337
PAN	0.569	0.160	0.091
BOL	0.560	0.120	0.000
IRL	0.544	0.174	-0.506
JAM	0.538	0.143	-0.016
NZL	0.535	0.186	0.919
AUS	0.528	0.073	0.069
MDG	0.525	0.162	0.153
ZWE	0.504	0.093	-0.019
HKG	0.503	0.149	-0.018
BEL	0.498	0.112	0.150
SWE	0.481	0.041	-0.086
ECU	0.480	0.147	-0.043
NOR	0.478	0.166	0.020
ARG	0.471	0.040	-0.046
MWI	0.469	0.139	0.084
AUT	0.466	0.063	-0.274
GRC	0.461	0.099	-0.140
KOR	0.455	0.095	-0.062
KEN	0.452	0.148	0.534
VEN	0.409	0.099	-0.003
DNK	0.402	0.137	-0.032
PRT	0.400	0.045	-0.349
MAR	0.398	0.215	-0.073
FIN	0.387	0.146	-0.022
TUR	0.368	0.043	-0.025
THA	0.363	0.079	0.021
CHL	0.355	0.074	0.043
ZMB	0.344	0.144	-0.357
PHL	0.336	0.033	-0.055
NGA	0.298	0.056	-0.128

Notes: Mean, standard deviation and percentage change of Pure efficiency see Eq. (11) .



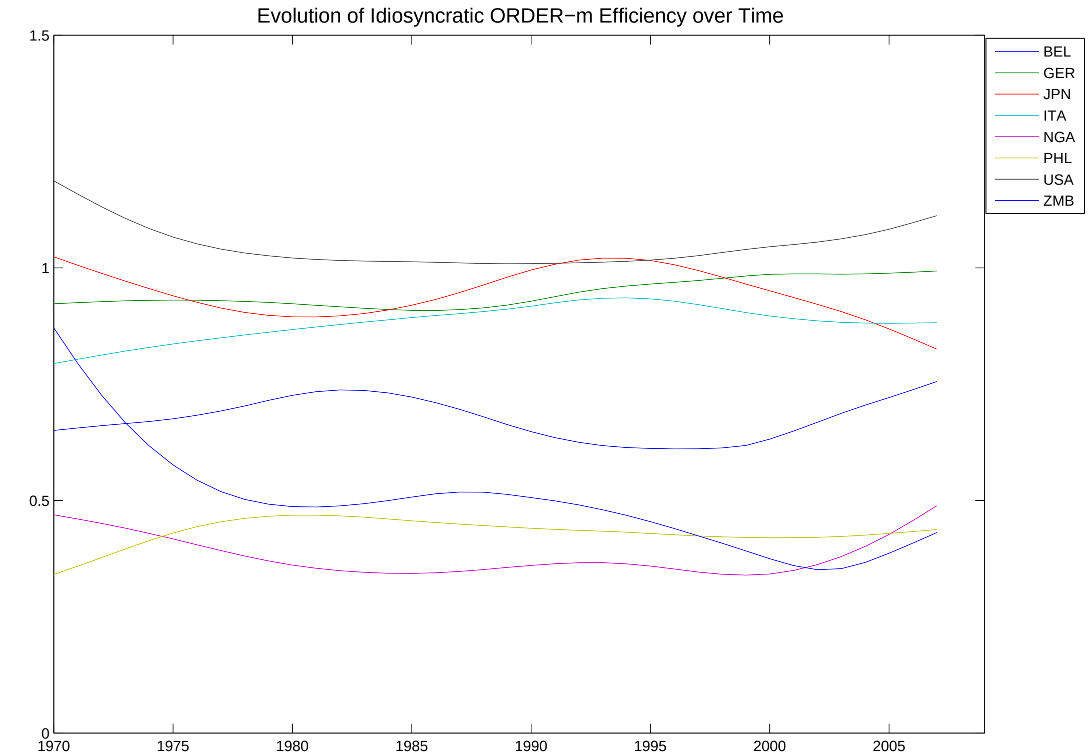


Figure 6: *Time-varying idiosyncratic efficiency for Belgium (BEL), Germany (GER), Italy (ITA), Japan (JPN), Nicaragua (NGA), Philippines (PHL), United States (USA) and Zambia (ZMB).*

Note also that we use the Hodrick and Prescott (1996) filter to smooth the time paths with a smoothing weight equal to 100.

Table 2: Spectral analysis of pure efficiency

Country	$7-10$ years	$5-7$ years	$3-5$ years
A R G	0.0191	0.0611	0.0011
A U S	0.0264	0.0007	0.0394
A U T	0.1842	0.0003	0.0395
B E L	0.0042	0.0869	0.0019
B O L	0.0042	0.0007	0.0088
C A N	0.0045	0.0350	0.0034
C H L	0.0001	0.1763	0.0020
H K G	0.0001	0.0001	0.0016
C I V	0.1132	0.0006	0.0000
D N K	0.0156	0.0818	0.0003
D O M	0.0144	0.0008	0.0004
E C U	0.0167	0.0007	0.0326
F I N	0.0030	0.1622	0.0017
F R A	0.0049	0.0008	0.0361
G E R	0.0108	0.0007	0.0033
G R C	0.0347	0.0007	0.0011
H N D	0.0295	0.0004	0.1649
I R L	0.0566	0.0030	0.0074
I S R	0.0080	0.0190	0.0014
I T A	0.0235	0.0001	0.0274
J A M	0.0568	0.0047	0.0077
J P N	0.0132	0.0231	0.0157
K E N	0.0060	0.0002	0.3042
K O R	0.0011	0.0055	0.0243
M D G	0.0063	0.0811	0.0155
M W I	0.0015	0.0003	0.0154
M E X	0.0040	0.0010	0.0424
M A R	0.1004	0.0005	0.0455
N L D	0.0692	0.0094	0.1219
N Z L	0.0780	0.0057	0.0301
N G A	0.0009	0.0023	0.0849
N O R	0.0108	0.0021	0.0922
P A N	0.2324	0.0020	0.0402
P H L	0.0110	0.0007	0.1333
P R T	0.0041	0.0011	0.2447
E S P	0.1493	0.0025	0.0048
S W E	0.0087	0.0287	0.0031
T H A	0.0076	0.0035	0.0012
T U R	0.0162	0.0022	0.0196
G B R	0.0001	0.0065	0.0960
U S A	0.0007	0.0078	0.2496
V E N	0.0032	0.0108	0.0015
Z M B	0.0235	0.0103	0.0044
Z W E	0.0148	0.0018	0.0324

Notes: The column on share of total variance reports the estimated efficiency variance shares over each frequency range.

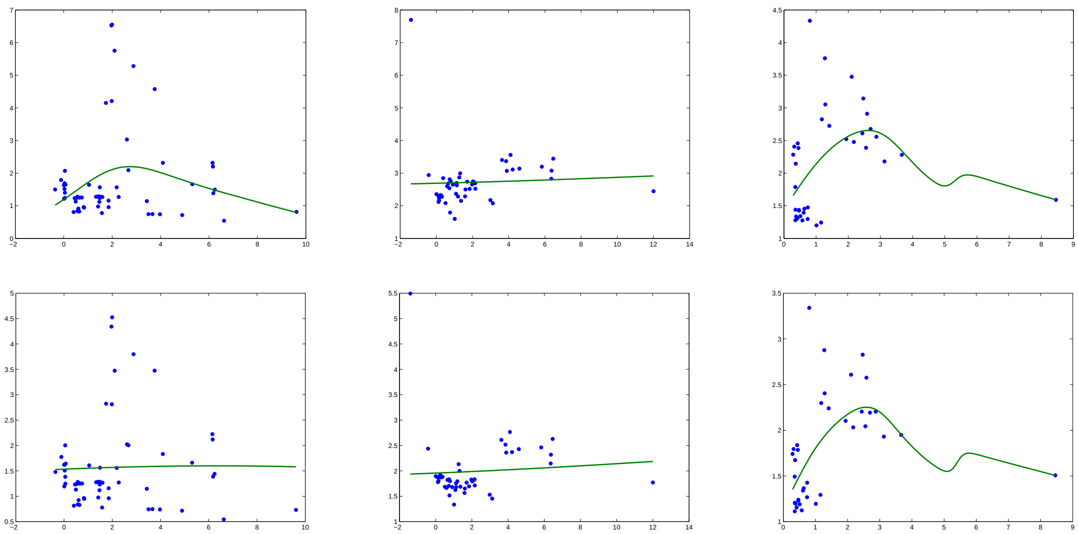


Figure 7: *The first three top panels represent the full ratios $\widehat{R}_O(x, y|z, f_t)$ as a marginal function of FDI at the 25 and 50 and 70 quartiles of the two inputs (labour and capital); the bottom panels are the conditional ratios - order-m - $\widehat{R}_{O,m}(x, y|z, f_t)$ for the three quartiles of production inputs.*

Estimator	α	β_1	β_2	R^2
m	0.3766	0.3145	0.7199	0.89
FDH	0.4335	0.3359	0.7335	0.89
Shifted OLS (COLS)	-0.0084	0.2337	0.8133	0.95

Table 3: *Estimates of constant (α_1) and output elasticities of capital (β_1) and labour (β_2) of world frontier using Florens and Simar (2005) estimator on the nonparametric frontier points of order $-m$ - first row - and full FDH frontiers - second row - and parametric COLS estimator - third row -.*

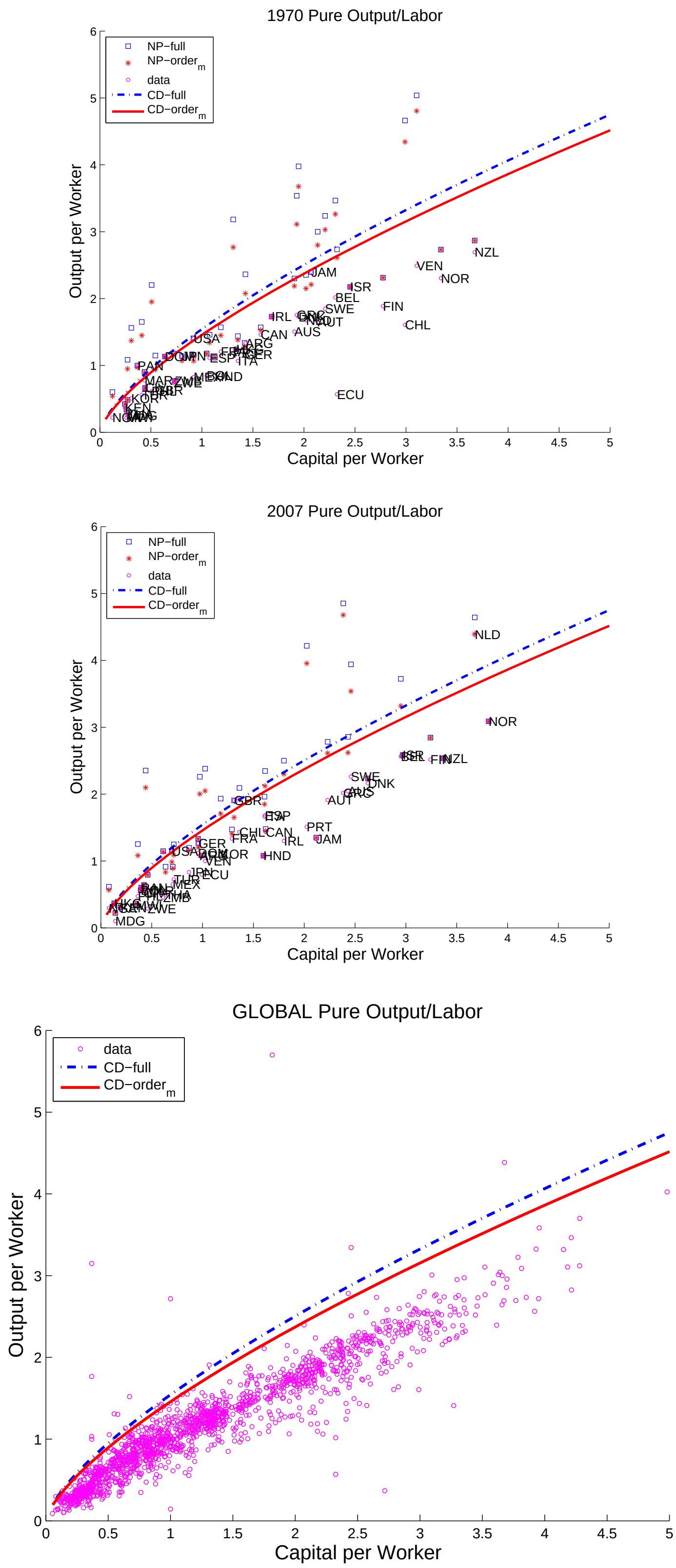


Figure 8: *1970 and 2007 Non-parametric and Cobb-Douglas full and order* $-$ *m frontiers in pure output per labour and capital per labour units, (top panels); global frontier in pure output per labour and capital per labour units (bottom panel).*

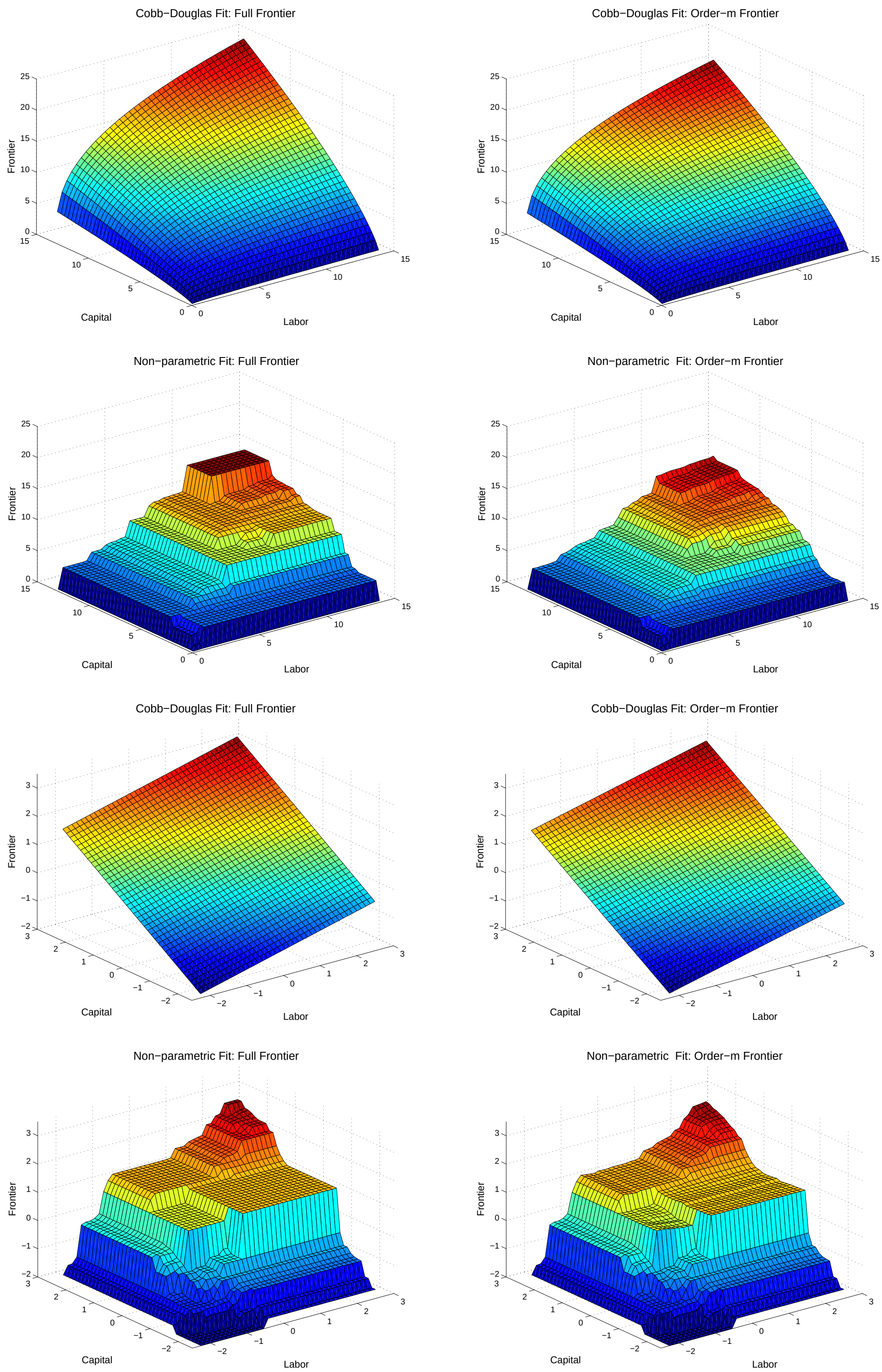


Figure 9: *The first four top panels represent the Cobb-Douglas and non-parametric fit of full and order − m frontiers in the original units; the bottom 4 panels are the Cobb-Douglas and non-parametric fit of full and order − m frontiers in the pure units.*

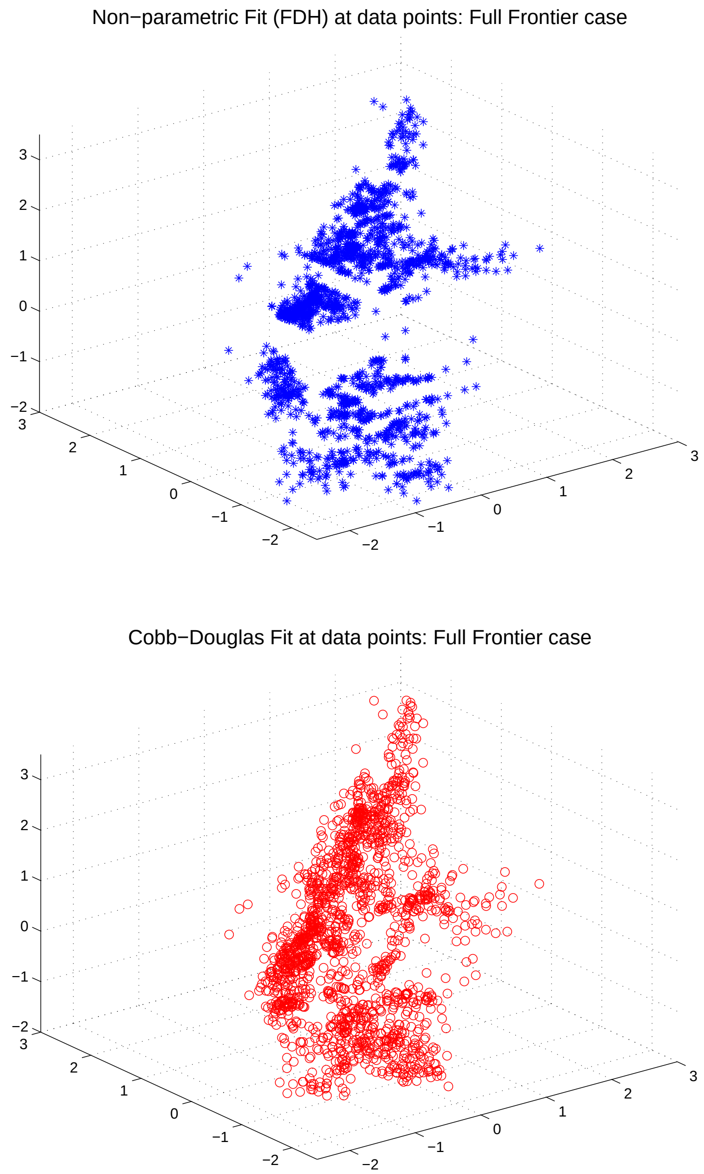


Figure 10: *FDH estimates of non-parametric frontier (top panel) and Cobb-Douglas fit (bottom panel) of full frontier at data points in pure units.*

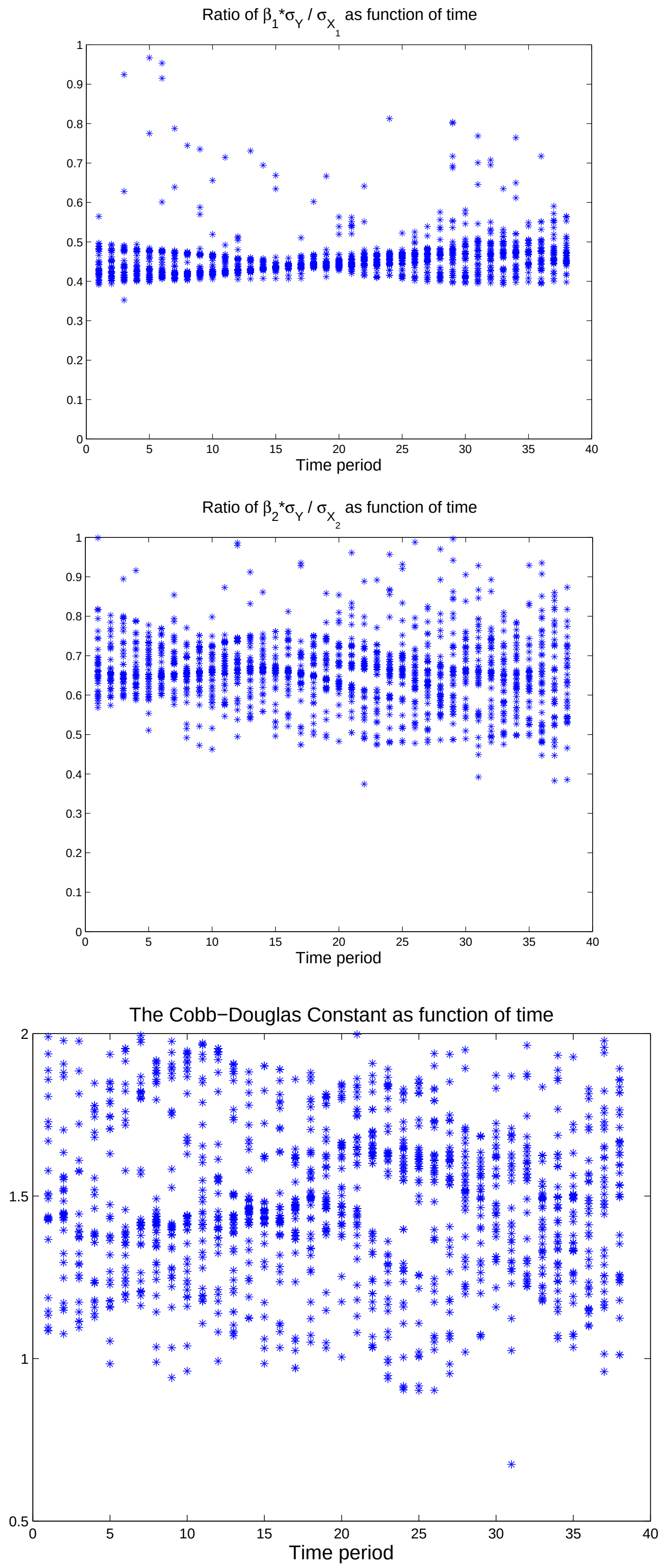


Figure 11: *Parameters estimates of Cobb- Douglas World Production frontier: output elasticities of capital and labour (top panels) and technological shift captured by the constant parameter (bottom panel).*

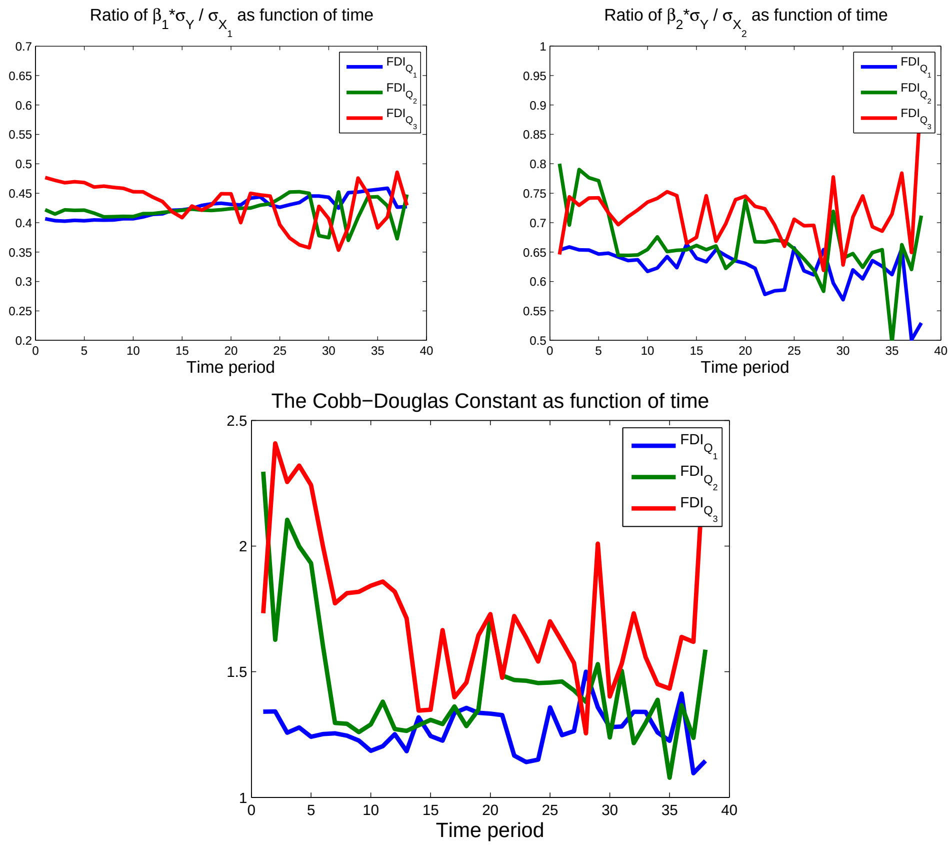


Figure 12: *Parameters estimates of Cobb- Douglas World Production frontier when fixing the level of $Z = FDI$ and f_t. Here f_t is fixed at its median value, and FDI is fixed at its 3 quartiles. Output elasticities of capital and labour (top panels) and technological shift captured by the constant parameter (bottom panel).*

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