Is Globalization Driving Efficiency? A Threshold Stochastic Frontier Panel Data Modelling Approach*

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Abstract

Recently, Mastromarco, Serlenga and Shin (2010) propose a two-step approach to examine dynamic transmission mechanism under which globalization factors foster technology efficiency. In this paper, we extend the MSS model by combining panel threshold regression technique advanced by Hansen (1999). This threshold stochastic frontier panel data model enables us to analyze regime-specific stochastic frontiers and complex time-varying patterns of technical efficiencies in a robust manner. Using a dataset of 44 countries over 1970-2007, we find that income elasticities of labour and capital and time-varying common efficiencies are substantially different under superior and inferior frontiers. Capital and labour inputs are more productive under superior frontier. More importantly, common efficiencies have steadily increased under superior frontier, but technical efficiency has monotonically decreased for low income countries, supporting the so-called club convergence hypothesis. Furthermore, the VAR-based impulse response analyses suggest that openness factors through FDI and trade help the countries improve production technology and efficiency position relative to the frontier only after the country has reached a certain level of development.

JEL: D24, O47, C13, C33.

Keywords: Threshold Stochastic Frontier Models in Heterogeneous Panels, Globalization Factors and Unobserved Factors, Time-Varying Efficiencies, Impulse Response Analyses

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1 Introduction

Total factor productivity and technological progress together with human capital accumulation, can explain a large part of income differences and diverse growth patterns across countries (Parente and Prescott, 2004). Countries catch up by adopting foreign technologies and the best-practice technology (Temple, 1999). However, capacity to absorb new technology depends on institutional governance and level of development of individual country in a heterogeneous manner. In this regard, identifying the determinants of catching-up process from low productive countries to high productive ones has always been of great importance to economic theorists (Temple 1999; Durlauf and Quah 1999; Islam 2003). While exogenous growth theory highlights technological progress as the source of growth, endogenous growth theory emphasizes the role of capital (both physical and human) as the main determinant. Furthermore, the former stresses factor accumulation whereas the latter highlights time-varying technology differences across countries, as the main driver of (conditional) convergence.

In general, technological diffusion is likely to play a significant role in spurring productivity growth by lowering barriers to flows of imported goods and foreign direct investments. If knowledge transfer made available by FDI and trade creates efficiency externalities, openness is expected to raise total factor productivity through efficiency gains, e.g. Borensztein et al. (1998), Griffith et al. (2004), and Cameron et al. (2005). Hence, efficiency improvement will represent productivity catch-up via technology diffusion because inefficiencies generally reflect a sluggish adoption of new technologies. An exact dynamic mechanism as to how technology efficiency and globalization or openness factors relate to each other remains ambiguous and neglected in the existing literature on the stochastic frontier modelling. Recently, Mastromarco, Serlenga and Shin (2010, hereafter MSS) propose a pragmatic two-step approach to examine the dynamic transmission mechanism under which globalization factors foster technology efficiency. In the first step, MSS allow for cross section dependence through unobserved time-varying factors in the stochastic frontier panel by adopting the pooled common correlated effects estimation method advanced by Pesaran (2006) and Serlenga and Shin (2007), and derive estimates of both individual and common time-varying efficiencies in a robust manner. In the second step, MSS model dynamic interactions among common efficiency and globalization factors through the vector autoregressive (VAR) analysis.

In this paper we follow MSS and focus on two main channels of technological adoption from abroad: foreign direct investment (FDI) and trade, and aim to investigate the technological convergence process using a large pool of countries including both developed and developing countries. In this case, however, the maintained assumption that the stochastic production frontier is common to all countries, is too restrictive. In this regard, we propose to extend the MSS model by embedding a panel threshold regression technique advanced by Hansen (1999). This extended approach, called a threshold stochastic frontier panel model with both observed globalization factors and unobserved factors, enables us to overcome the limitations of several existing studies and to analyze regime-specific stochastic frontiers, simultaneously addressing time-varying individual heterogeneity and cross-section dependence. More specifically, the proposed approach also allows us to analyze (possibly) nonlinear and complex time-varying patterns of technical efficiency associated with the regime-switching heterogeneous production frontiers, individually or in aggregation, in a robust manner. Then, in the second stage, the regime-specific effects of openness on technological convergence or efficiency under heterogeneous stochastic frontiers can be easily analyzed by vector autoregressive modelling. The combined approach is then expected to shed further lights on an important policy issue of how technical efficiency can be improved through both FDI and trade channels and of whether or not the catch-up process is monotonic under regime-specific stochastic frontiers.

Using a dataset of 44 countries over the period, 1970-2007, we apply the proposed threshold stochastic frontier panel data model and find overwhelming evidence in favour of cross-section dependence and threshold effects. Using a practical grid search on the basis of the transition variable given by time-varying per capita income distance from the maximum (e.g. Girma, 2005), we can identify two different production frontiers, denoted the superior and inferior frontiers, respectively. Our main findings on stochastic frontiers are as follows: First, the income elasticity of labour is higher than that of capital under both superior and inferior frontiers. Second, both capital and labour inputs are more productive under superior frontier. Third, trade turns out to be a significant production factor only for superior frontier whilst FDI is significant only for inferior frontier.

We also find that time-varying patterns of common efficiency measures under superior frontier are substantially different from those under inferior frontier. Common efficiencies have increased by 20 percent per annum for high-medium income countries while technical efficiency has been monotonically decreasing for low income countries over the sample period. Furthermore, since mid 80's, growth disparities have increased for both groups, though the size of dispersion is much higher for low income countries, supporting pervasive evidence of increasing disparities among poor countries. These findings support the so-called club convergence (Howitt and Mayer-Foulkes, 2005); namely, the technology catch-up convergence for high-medium countries via an efficiency improvement and the divergence for low income countries through monotonic reduction in efficiency. Hence, low income countries have not escaped a poverty trap yet mainly due to their inefficient technology capabilities. This evidence is consistent with the predictions of endogenous growth theory, emphasizing technology differential as the main driver of (club) divergence across countries (Quah, 1997).

Finally, from the VAR model and the impulse response analyses, we find that both FDI and trade shocks improve common group efficiency for high-medium income countries, but the impacts of FDI shocks become more significant and persistent only under superior frontier, a finding qualitatively consistent with MSS. On the other hand, the positive impacts of FDI shocks on common efficiency are only short-lived while those of trade shocks are never significant for low income countries.

These findings highlight that globalization and openness factors will be a driving force in spreading technology efficiency, as suggested by Frankel and Romer (1999) and Barro and Sala-i-Martin (2004), but more importantly, the effectiveness of the openness channels depends crucially on the level of development and knowledge transfer, e.g. Durlauf and Johnson (1995) and Quah (1997). Hence, the policy implications are different; for developed countries governments need to facilitate the openness process for attracting multinational FDIs and promoting trades through incentive and benefit systems. On the other hand, for low income developing countries, governments should invest more in fundamental infrastructures and human capital, and stabilize governance quality of institutions so as to boost efficiency spillover through FDI and trade.

The paper is organized as follows: Section 2 develops the model and describes estimation strategies in details. Section 3 discusses the data and provides main empirical results. Section 4 concludes.

2 Methodology

An exact dynamic mechanism as to how technology efficiency and globalization or openness factors relate to each other remains ambiguous and neglected in the existing literature on the stochastic frontier modelling. Recently, Mastromarco, Serlenga and Shin (2010) have proposed a pragmatic two-step approach to examine the dynamic transmission mechanism under which globalization factors foster technology efficiency. In the first step, we allow for cross section dependence through common time-varying factors in the stochastic frontier panel, and thus obtain more robust estimates of both individual and common time-varying efficiency. In the second step, we model dynamic interactions among common efficiency and globalization factors through the vector autoregressive (VAR) analysis.

2.1 Stochastic Frontier Panels with Time-varying Factors and Threshold Effects

Assuming that the production frontier follows the popular Cobb-Douglas form, we consider the following extended stochastic frontier panel data model recently advanced by Mastromarco, Serlenga and Shin (2010, henceforth MSS):

$$y_{it} = \beta' \mathbf{x}_{it} + \delta' \mathbf{s}_{it} + \varepsilon_{it},\ i = 1, ..., N,\ t = 1, ..., T \tag{1}$$

with the two-way error components structure given by[1]

$$\varepsilon_{it} = v_{it} + \eta_{it} = v_{it} + \delta_t - u_{it}, \tag{2}$$

$$\eta_{it} = \alpha_i + b_i t + \varphi_i \theta_t, \tag{3}$$

where y_{it} is a logarithm of output of country i at time t, $\mathbf{x}_{it}$ a $k \times 1$ vector of logged production inputs, $\mathbf{s}_{it}$ is an $s \times 1$ vector of observed factors such as FDI and trade, v_{it} is an idiosyncratic noise and u_{it} measures (logged) technical inefficiency with $\delta_t = \max_i \eta_{it}$ being the frontier intercept at time t. Following Schmidt and Sickles (1984), MSS suggest to measure individual technical inefficiencies by

$$u_{it} = \max_i \eta_{it} - \eta_{it} = \max_i (\alpha_i + b_i t + \varphi_i \theta_t) - (\alpha_i + b_i t + \varphi_i \theta_t) \tag{4}$$

for $i = 1, ..., N$ and $t = 1, ..., T$. The time-varying technical inefficiency (u_{it}) consists of three components: α_i is (unobserved) individual effects, the time trend, t, is supposed to capture an exogenous technological change (e.g. Ahn et al., 2000), and finally, the (unobserved) time-specific factors (θ_t) are expected to provide a good proxy for any remaining nonlinear and complex trending patterns associated with the globalization and the business-cycle events. Notice that most econometric specifications of the production frontier can be expressed as a variation of the model given by (1)-(3). Furthermore, this approach can accommodate a certain degree of cross section dependence through the heterogeneous factor loadings, φ_i for $i = 1, ..., N$. Hence, our approach is expected to capture time-varying technical inefficiency in a robust manner.

However, the maintained assumption in the literature that the stochastic production frontier is common to all countries, is too strong, when analyzing the frontier for a pool of countries including both developed and developing countries. In this regard, we propose to extend the above model by embedding a panel

[1] Notice that the specification, (3) can be regarded as a special case of the p-factor model considered by Ahn et al. (2007) with $p = 3$, but still more general than the model by Cornwell et al. (1990) with three factors of $(1, t, t^2)$ since we do not fully specify the time varying pattern of the changes in technical inefficiencies.

threshold regression technique advanced by Hansen (1999). This extended approach enables us to overcome the limitations of several cross-country studies that assume an equal quality of production factors and to analyze the regime-specific stochastic frontiers. Recently, the panel threshold regression model has been applied to an analysis of the translog cost frontiers in Taiwan's banking industry (Wang and Huang, 2009), and to stochastic frontier models of dairy production in Canada (Yélou eat al., 2010). Both studies clearly demonstrate the usefulness of threshold panel data modelling, though they do not examine in details how to measure individual technical inefficiency in a robust manner as will be discussed below.

We incorporate these important modelling issues and consider the following extended stochastic frontier panel data model:

$$\begin{aligned} &y_{it} = (\beta_1'\mathbf{x}_{it} + \delta_1'\mathbf{s}_{it})\, 1_{\{q_{it}\le c\}} + (\beta_2'\mathbf{x}_{it} + \delta_2'\mathbf{s}_{it})\, 1_{\{q_{it}>c\}} + \varepsilon_{it};\\ &i = 1, ..., N,\ t = 1, ..., T, \end{aligned} \tag{5}$$

where $1_{\{A\}}$ is an indicator function taking 1 if the event A is true and 0 otherwise, q_{it} is the stationary and exogenous transition variable with c being a threshold parameter, β_1, δ_1 and β_2, δ_2 are the heterogeneous slope parameters associated with two different regimes, and ε_{it} takes the same two-way error components structure given by (2) and (3). Model (5) also enables us to analyze the (possibly) nonlinear and complex time-varying patterns of technical inefficiency associated with the regime-switching heterogeneous production frontiers.

To simplify the notations, we rewrite (5) as

$$y_{it} = \phi_1'\mathbf{z}_{1it}(c) + \phi_2'\mathbf{z}_{2it}(c) + \varepsilon_{it} = \phi'\mathbf{z}_{it}(c) + \varepsilon_{it}, \tag{6}$$

where

$$\mathbf{z}_{1it}(c) = \begin{bmatrix} \mathbf{x}_{it} \\ \mathbf{s}_{it} \end{bmatrix} \times 1_{\{q_{it}\le c\}};\ \mathbf{z}_{2it}(c) = \begin{bmatrix} \mathbf{x}_{it} \\ \mathbf{s}_{it} \end{bmatrix} \times 1_{\{q_{it}>c\}};$$
$$\mathbf{z}_{it}(c) = \begin{bmatrix} \mathbf{z}_{1it}(c) \\ \mathbf{z}_{2,it}(c) \end{bmatrix};\ \phi_1 = \begin{bmatrix} \beta_1 \\ \delta_1 \end{bmatrix};\ \phi_2 = \begin{bmatrix} \beta_2 \\ \delta_2 \end{bmatrix};\ \phi = \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix}.$$

To deal with the potential bias of the fixed effects estimator of ϕ in (6) in the presence of heterogeneous time-specific effects, $\varphi_i\theta_t$ in (3), as confirmed by Kapetanios and Pesaran (2005) in the linear model, we follow the pooled common correlated effects (hereafter, PCCE) estimation method advanced by Pesaran (2006) and consider the following augmented specification of (6):

$$y_{it} = \phi'\mathbf{z}_{it}(c) + \pi_i'\mathbf{w}_t(c) + \alpha_i^* + v_{it}^*, \tag{7}$$

where $\mathbf{w}_t(c) = (\mathbf{w}_{1t}'(c), \mathbf{w}_{2t}'(c))'$, $\mathbf{w}_{1t}(c) = (\bar{y}_t, \bar{\mathbf{z}}_{1t}(c), t)'$, $\mathbf{w}_{2t}(c) = (\bar{y}_t, \bar{\mathbf{z}}_{2t}(c), t)'$, $\pi_i = (\pi_{1i}, \pi_{2i}', \pi_{3i}')' = \left(\frac{\varphi_i}{\bar{\varphi}}, \frac{-\varphi_i}{\bar{\varphi}}\phi', b_i - \frac{\varphi_i}{\bar{\varphi}}\bar{b}\right)'$, $\alpha_i^* = \alpha_i - \frac{\varphi_i}{\bar{\varphi}}\bar{\alpha}$, and $v_{it}^* = v_{it} - \frac{\varphi_i}{\bar{\varphi}}\bar{v}_t$ with the bar on the variable indicating the cross-section average, e.g. $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$. Setting the pooling weight equal to N^{-1}, and given c, the (concentrated) PCCE estimator of $\phi(c)$ is given by

$$\hat{\phi}(c) = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{z}_i(c)'\,\mathbf{M}(c)\,\mathbf{z}_i(c)\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{z}_i(c)'\,\mathbf{M}(c)\,\mathbf{y}_i\right) \tag{8}$$

where $\mathbf{z}_i(c) = (\mathbf{z}_{i1}(c), ..., \mathbf{z}_{iT}(c))'$, $\mathbf{M}(c) = \mathbf{I}_T - \mathbf{H}(c)\left(\mathbf{H}(c)'\,\mathbf{H}(c)\right)^{-1}\mathbf{H}'(c)$, $\mathbf{H}(c) = (\mathbf{1}_T, \mathbf{W}(c))$, $\mathbf{1}_T = (1, ..., 1)'$and $\mathbf{W}(c) = (\mathbf{w}_1(c), ..., \mathbf{w}_T(c))'$ and $\mathbf{y}_i = (y_{i1}, ..., y_{iT})'$.

Given the consistent estimator of the threshold parameter, denoted, $\hat{c}$, then, under fairly standard regularity conditions, it is easily seen by combining Hansen (1999) and Pesaran (2006) that as $(N, T) \to \infty$ jointly, the PCCE estimator, $\hat{\phi}(\hat{c})$, is consistent and follows the asymptotic normal distribution:

$$\hat{\phi}(\hat{c}) \overset{a}{\sim} N(\phi, \mathbf{\Omega}), \tag{9}$$

where the consistent estimate of $\mathbf{\Omega}$ can be obtained either by

$$\hat{\mathbf{\Omega}} = \hat{\sigma}^2\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{z}_i(\hat{c})'\,\mathbf{M}(\hat{c})\,\mathbf{z}_i(\hat{c})\right)^{-1}$$

if the errors are assumed to be iid, or by

$$\begin{aligned}\hat{\mathbf{\Omega}} = \; & \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{z}_i(\hat{c})'\,\mathbf{M}(\hat{c})\,\mathbf{z}_i(\hat{c})\right)^{-1} \\ & \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{z}_i(\hat{c})'\,\mathbf{M}(\hat{c})\,\mathbf{z}_i(\hat{c})\,\hat{\mathbf{v}}_i^*(\hat{c})'\,\hat{\mathbf{v}}_i^*(\hat{c})\right) \\ & \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{z}_i(\hat{c})'\,\mathbf{M}(\hat{c})\,\mathbf{z}_i(\hat{c})\right)^{-1}\end{aligned}$$

where $\hat{\mathbf{v}}_i^*(\hat{c}) = \mathbf{M}(\hat{c})\left(\mathbf{y}_i - \mathbf{z}_i(\hat{c})\,\hat{\phi}(\hat{c})\right)$, if the errors are conditional heteroskedastic.

Since the model, (6) is linear in ϕ_1 and ϕ_2 for each c, we can estimate the threshold parameter consistently using a grid search algorithm over the transition variable such that:

$$\hat{c} = \underset{c\in\mathcal{C}}{\arg\min} S(c) = \hat{\varepsilon}_{it}(c)'\hat{\varepsilon}_{it}(c), \tag{10}$$

where $S(c)$ is the sum of squared residuals of the OLS regression associated with a particular value of $c \in \mathcal{C}$, with $\mathcal{C}$ being the grid set consisting of the partial support of the transition variable, q_{it}, after 'trimming' extreme observations (the established practice is to trim at the 15th and 85th percentiles).

Chan (1993) theoretically shows that under the assumption of exogenous transition variable, the threshold estimate, $\hat{c}$, is super-consistent, though its asymptotic distribution is complex and depends on nuisance parameters, which is not useful for inference in practice. Hansen (2000) suggests constructing a confidence interval for c by forming a non-rejection region using the LR statistic, $LR(c_0) = \frac{S(c_0)-S(\hat{c})}{\hat{\sigma}^2}$, testing $H_0 : c = c_0$ where $\hat{\sigma}^2$ is the residual variance. The LR test rejects the null at level α if $LR(c_0)$ is greater than the critical value, $cv(\alpha) = -2\log\left(1-\sqrt{1-\alpha}\right)$. The $(1-\alpha)$-level confidence set is therefore defined by the no-rejection region of the LR test as $CS(c;\alpha) = \{c_0 : LR(c_0) \leq cv(\alpha)\}$.

Notice that under the maintained assumption that the transition variable, q_{it} is exogenous, the PCCE estimators, $\hat{\phi}_1(\hat{c})$ and $\hat{\phi}_2(\hat{c})$, are asymptotically independent of the threshold estimate such that inference on ϕ_1 and ϕ_2 can proceed as if $\hat{c}$ were the true value, see Hansen (2000) and Caner and Hansen (2004). However, the testing for the null hypothesis of no threshold effects, namely $H_0: \ \phi_1 = \phi_2$ in (6) is non standard since the threshold parameter, c is unidentified under the null. We follow Hansen (1996, 1999) and obtain a valid asymptotic p-value of the Wald statistic for threshold effects through employing bootstrap techniques, and using the distribution result in Hansen (1999).

Next, we follow MSS and employ the following approximation for measuring technical inefficiency, u_{it} in (11) at each time period:

$$u_{it} \simeq \max_i \left(\alpha_i^* + \pi_i^{'}\mathbf{w}_t(c)\right) - \left(\alpha_i^* + \pi_i^{'}\mathbf{w}_t(c)\right),\ t = 1,...,T \tag{11}$$

To obtain the consistent estimate of u_{it}, we first need to derive consistent estimates of heterogeneous parameters of α_i^* and π_i for $i = 1,...,N$ in (7). Replacing ϕ by $\hat{\phi}(\hat{c})$ in (7) and rearranging the result, we obtain:

$$\tilde{y}_{it} = \alpha_i^* + \pi_i'\mathbf{w}_t(c) + \tilde{v}_{it},\ i = 1,...,N,\ t = 1,...,T, \tag{12}$$

where $\tilde{y}_{it}$ and $\tilde{v}_{it}$ are defined as follows: $\tilde{y}_{it} = y_{it} - \hat{\phi}(\hat{c})'\mathbf{z}_{it}(c)$, $\tilde{v}_{it} = v_{it}^* - \left(\hat{\phi}(\hat{c}) - \phi\right)'\mathbf{z}_{it}(c) = v_{it}^* + o_p(1) = v_{it} + o_p(1)$. For sufficiently large T, α_i^* and π_i can be consistently estimated by OLS estimators, denoted $\hat{\alpha}_i^*$ and $\hat{\pi}_i$, by running the regression of (12) separately for each country.

Hence, (overall) time-varying individual technical inefficiencies can be consistently estimated by

$$\hat{u}_{it} = \max_i \left(\hat{\alpha}_i^* + \hat{\pi}_i'\mathbf{w}_t(c)\right) - \left(\hat{\alpha}_i^* + \hat{\pi}_i'\mathbf{w}_t(c)\right),\ t = 1,...,T. \tag{13}$$

Notice that the transition variable, q_{it}, varies across cross-section units and over time periods such that a subset of cross-section units may switch from one regime to the other over time periods. But, it is straightforward to evaluate the regime-specific individual technical inefficiencies, denoted u_{1it} for $q_{it} \leq c$ and u_{2it} for $q_{it} > c$, as follows:

$$\hat{u}_{1it} = \max_i \left(\hat{\alpha}_i^* + \hat{\pi}_{1i}' \mathbf{w}_{1t}(c)\right) - \left(\hat{\alpha}_i^* + \hat{\pi}_{1i}' \mathbf{w}_{1t}(c)\right), \tag{14}$$

$$\hat{u}_{2it} = \max_i \left(\hat{\alpha}_i^* + \hat{\pi}_{2i}' \mathbf{w}_{2t}(c)\right) - \left(\hat{\alpha}_i^* + \hat{\pi}_{2i}' \mathbf{w}_{2t}(c)\right). \tag{15}$$

Accordingly, the overall and the regime-specific time-varying individual technical efficiencies can be obtained by[2]

$$\hat{\tau}_{it} = \exp\left(-\hat{u}_{it}\right), \;\; \hat{\tau}_{1it} = \exp\left(-\hat{u}_{1it}\right), \;\; \hat{\tau}_{2it} = \exp\left(-\hat{u}_{2it}\right) \tag{16}$$

and finally for $t = 1, ..., T$, the overall and the regime-specific common technical efficiencies by

$$\begin{aligned} \overline{\hat{\tau}}_t &= \exp\left(-\sum_{i=1}^{N} w_{it}\hat{u}_{it}\right), \;\; \overline{\hat{\tau}}_{1t} = \exp\left(-\sum_{i=1}^{N_{1t}} w_{1it}\hat{u}_{1it}\right), \\ \overline{\hat{\tau}}_{2t} &= \exp\left(-\sum_{i=1}^{N_{2t}} w_{2it}\hat{u}_{2it}\right) \end{aligned} \tag{17}$$

where the weights, w_{it}, w_{1it} and w_{2it}, are given by the share of GDP such that $\sum_{i=1}^{N} w_{it} = 1$, $\sum_{i=1}^{N_{1t}} w_{1it} = 1$ and $\sum_{i=1}^{N_{2t}} w_{2it} = 1$ with N_{1t} and N_{2t} being the number of cross-section units belonging to the first and the second regime for each t.[3]

We note in passing from (7) and (11) that observed factors, $\mathbf{s}_{it}$, affect the stochastic frontier through $\delta' \mathbf{s}_{it}(c)$, and technical inefficiency (movement towards or away from the frontier) through $\pi_i' \mathbf{w}_t(c)$, simultaneously,[4] while allowing for the regime-dependent time-varying frontiers and technical inefficiencies.

2.2 Dynamic Analysis of Common Efficiency and Globalization Factors

We now investigate dynamic interactions between time-varying common efficiencies and global factors respectively for each regime determined by the threshold

[2]Notice that $\hat{\tau}_{it} = \exp\left(-\hat{u}_{it}\right)$ is measured against the best frontier at each time period, t, since $\hat{u}_{it} = \max_i \left(\hat{\pi}_{1i}^{*\prime} \mathbf{w}_{1t}^*(c)\right) - \hat{\pi}_i^{*\prime} \mathbf{w}_t^*(c)$.

[3]For the detailed construction of weights see footnote 5 below.

[4]The omission of these factors - which are likely to be correlated with the productivity and the production factors - may lead to serially and cross-sectionally correlated residuals.

parameter. In particular, we analyze the impacts of globalization factors on diffusion of the technology efficiencies under different regimes. Then, we employ the VAR(p) model for the m-dimensional variates, $\mathbf{z}_t$:

$$\mathbf{z}_t = \alpha + \sum_{j=1}^{p} \mathbf{\Phi}_j \mathbf{z}_{t-j} + \mathbf{e}_t,\ \mathbf{e}_t \sim iid\left(\mathbf{0}, \mathbf{\Sigma}\right), \tag{18}$$

where α is an $m \times 1$ vector of intercepts, $\mathbf{\Phi}_i$'s an $m \times m$ matrix of unknown coefficients, p is the lag order, and it is assumed that $E\left(\varepsilon_{it}\right) = \mathbf{0}$ and $E\left(\varepsilon_{it}\varepsilon_{is}'\right) = \mathbf{\Sigma}$ for $t = s$ with $\mathbf{\Sigma}$ being an $m \times m$ positive definite matrix. Notice here that $\mathbf{z}_t = \left(\bar{\mathbf{g}}_{jt}', \widehat{\bar{\tau}}_{jt}\right)'$ where $\widehat{\bar{\tau}}_{jt}$ for $j = 1, 2$, is the regime-specific common inefficiency given by (17), and $\bar{\mathbf{g}}_{jt}$ for $j = 1, 2$, is an $(m-1)\times 1$ vector of common globalization factors obtained under different regimes. We then follow MSS and employ the impulse response analysis as a main tool for uncovering important transmission channels through which technology diffuses.

3 Empirical Results

Within the SF framework there has been relative silence on the issue of dynamic adjustments of efficiency in conjunction with factors, which is mainly due to their possible endogeneity.[5] This issue can be explicitly addressed within the second-stage VAR framework where efficiency and globalization factors are modelled simultaneously. By analyzing the flexible dynamic interactions between efficiency and globalization factors, we aim to contribute to agnostic empirical evidence on the issue whether globalization and efficiency gains can be mutually determined.

3.1 The Data

The dataset are collected over the period, 1970-2007 (38 years) for a total of 44 countries; 26 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, Philip-

[5]A small number of studies address similar dynamic issues, e.g. Tsionas (2006) and Mastromarco and Woitek (2009) However, these studies assume that factors are strictly exogenous with respect to inefficiency. Our approach relaxes this assumption by explicitly allowing global factors to be correlated with inefficiency and production factors.

pines, Thailand, Venezuela, Zambia, Zimbabwe).[6]

GDP is measured in million US dollars at the 2005 price and labour measured as total employment in thousands. Capital is measured in millions US dollars at 2005 and constructed using the perpetual inventory method (PIM).[7] All three variables are logged before estimation. For globalization factors we identify two most important channels: trade (imports+exports/GDP) and FDI inflows, measured as net inflows of foreign direct investment, which are then transformed as a ratio to GDP.[8]

In order to develop the threshold frontier panel data model we should select the relevant transition variable (q_{it}) such that we can overcome the limitations of several cross-country studies that assume equal quality of production factors such as level of education, skills and depreciation rates. To this end we follow Girma (2005) and consider the per capita output gap defined as $\max_{jt} GDPPC_{jt} - GDPPC_{it}$ as stationary and exogenous transition variable. This selection is natural in the sense that if the country i's per capita outcome is far below from the best, this country is less developed such that it is likely to adopt a less productive technology. Hence, such distance can be regarded as measuring the level of inefficiency.

3.2 Stochastic Frontier and Efficiency

Table 1 provides the estimation and test results for the threshold PCCE estimators. First of all, we find the presence of cross-section dependence and threshold effects as confirmed by the results of cross-section dependency (CD) test, advanced by Pesaran (2004), and the LR test for the existence of threshold effects, proposed by Hansen (1999).

Using a grid search, we find that the threshold parameter is estimated at 5.24.[9]

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

[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, $K_{1970} = K_{1970}/(g+\theta)$, where g is the 10-year output growth rate from 1970 to 1980. Estimated capital stock includes both residential and non-residential capital.

[8] Capital is sourced from PWT 6.2, labour from OECD Labour Force Statistics; GDP, trade and FDI from the World Bank World Development Indicators and Unctad. The observation period is selected by the data availability.

[9] The transition variable used, the distance of the individual country's per capita output from the maximum, has a mean, 4.49 with minimum, 0 and maximum, 8.44. After trimming at the 15th and 85th percentiles, the grid set consists of the partial support, $[2.68, 6.22]$. The grid search is conducted with 400 steps. The probability of being above and under the threshold estimate,

This implies that the countries, whose per capita income distance from the maximum is lower than 5.2 units at each point of time period, entertain the more efficient production frontier. On the other hand, those countries, whose distance is higher than 5.2 units at each point of time period, adopt less efficient productivity technology. We call them the superior and inferior frontiers, respectively. Using the threshold estimate, over the whole sample period, we can split the whole 44 countries into a group of countries with superior frontier (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, Argentina, Ecuador, Morocco, Nigeria, Philippines, Thailand, Venezuela) and a group of countries with inferior frontier (Bolivia, Côte d'Ivoire, Dominican Republic, Honduras, Jamaica, Kenya, Madagascar, Malawi, Panama, Zambia, Zimbabwe). Table 2 (fourth and eighth columns) reports the average proportion of individual countries belonging to inferior frontier.[10] Henceforth, without loss of generality, we denote two different groups of countries with superior and inferior frontiers by high-medium income countries and low income countries, respectively.[11]

The two-regime PCCE estimation results, reported in Table 1, show that labour and capital elasticities are all statistically significant. The labor and capital elasticities are estimated at 0.455 and 0.459 under the inferior frontier while they are 0.541 and 0.587 under the superior frontier.[12] As expected, capital and labour are more productive in high -medium income countries than in low income countries. Regarding the impacts of two globalization factors, we find that the contribution of trade to production only is positive and significant for high-medium countries whereas only FDI becomes a positive and significant production factor in low income countries. This finding reflects that the degree of openness is significantly lower in the group of low income countries with inferior production frontier. Although many developing and export-oriented countries, mainly in Asia and Latin America, have opened their own economies to achieve development successfully through trade, most countries in Africa failed to do so. On the other hand, trade barriers in industrial countries are concentrated mainly in the agricultural and labor-intensive sectors in which developing countries have a comparative advan-

5.24, is 0.76 and 0.24, respectively.

[10]For those countries whose technology belongs to the inferior frontier for a majority of time periods, it is worthwhile to investigate the distinguishing roles of catching up towards their own frontier and switching to the superior frontier.

[11]Given the considerable number of countries facing the superior frontier, we also test the hypothesis of the existence of an additional threshold among them and reject at a 18% significant level ($LR = 69.115$, $p - value = 0.18$).

[12]We have also estimated a number of specifications using different combinations of factors including the full set as described in Subsection 2.1, and find that overall estimation results are qualitatively similar.

tage, see World Bank (2001).

[Table 1 about here]

Next, using equation (17), we obtain consistent estimates of individual efficiency and two regime-specific common efficiency measures, denoted $\hat{\tau}_{it}$, $\overline{\hat{\tau}}_{1t}$ and $\overline{\hat{\tau}}_{2t}$, respectively. Notice that our proposed approach can control for the effects of globalization factors on production structure and efficiency separately. In particular, this decomposition enables us to identify the efficiency changes (movement towards/away from the frontier) related to globalization factors.

Table 2 shows the country ranking on the basis of the time average (median) of individual efficiency. For the group of high-medium income countries we find that the US is most efficient, followed by Japan and Germany while Belgium and Hong Kong are least efficient. Turning to the group of low income countries, the most efficient country is Kenya, followed by Zimbabwe whereas Zambia and Panama are least efficient. These findings are generally consistent with the empirical evidence that more efficient export-sectors play a significant role in the group of medium-high income countries, especially, Germany and Japan whilst the agriculture sector reforms and infrastructure investments effectively took place during the 90s only in Zimbabwe and Kenya, e.g., World Bank (1994).

[Table 2 about here]

Figure 1 displays common efficiency measures for superior and inferior frontiers, $\overline{\hat{\tau}}_{1t}$ and $\overline{\hat{\tau}}_{2t}$, respectively. We find substantial differences between time-varying patterns of $\overline{\hat{\tau}}_{1t}$ and $\overline{\hat{\tau}}_{2t}$. For high-medium income countries common efficiency tends to increase by about 20 percent per annum over the whole period, implying that there has been steady technological catch-up toward the best frontier (mostly, the US). Due to flexible labour market conditions, product market regulation and the uptake of technology, historically, the US has maintained a higher productivity growth than Europe (EU KLEMS Productivity Report, Van Ark et al., 2007). Since the beginning of the new millennium, however, several European countries have surpassed the US in terms of average labour productivity.

By contrast, efficiency has been monotonically decreasing for low income countries, implying that they are on average diverging from the optimal frontier even though the average distance from the frontier was significantly lower at the beginning of the sample period. There are still substantial regional differences across low income countries. Middle East and North African (MENA) countries have experienced a rather disappointing macroeconomic performance over the past decades, especially when compared with Asian countries. According to the classification of the World Bank, the average growth rate of MENA countries reached 3.8% in the

90s and 4.1% from 2000 to 2006 while East Asia and Pacific countries registered 8.5% and 8.4% respectively over the same period (World Bank, 2008).[13] Furthermore, World Bank official statistics show that most developing economies starting with a significantly lower GDP per capita have not systematically caught up with developed counterparts, mainly due to their relatively low economic growth during the 90s and 2000s. Indeed, their investments in human and physical capital are much lower. Since the 90s, the average yield on these expenditures is about 2% of annual per capita GDP in low-income countries, as compared with more than 3% in high-middle income countries (World Bank, 2008).

In sum, our regime-dependent frontiers in Figure 1 supports the so-called club convergence argument; namely (i) the technology catch-up convergence for high-medium countries through efficiency improvement and (ii) the divergence for low income countries through monotonic reduction in efficiency. This evidence confirms the predictions of endogenous growth theory, emphasizing the possibility that there may be more than one steady state, and advancing technology differential as the main driver of divergence across countries. Slow convergence in terms of output per worker is mainly caused by slow technological catch-up (Mankiw et al., 1992; Barro and Sala-i-Martin, 2004; Quah, 1997). Quality of institutions, human capital accumulation and openness are regarded as important factors for reaching higher equilibrium of per capital output. In the current study, output gap is selected as transition variable that can naturally capture the level of development (e.g. infrastructure, financial system and good governance), the elements of which make the individual country absorb new technology and thus escape the poverty trap. However, it is clear from Figure 1 that low income countries have not escaped a poverty trap yet due to their inefficient technology capabilities.

[Figure 1 about here]

Next, we follow Sala-i-Martin (1996) and consider σ-convergence in order to better investigate the cross-sectional efficiency disparities between two group of countries. To this end we construct the regime-specific coefficients of variation, $\widehat{\sigma}_{1t}/\overline{\hat{\tau}}_{1t}$ and $\widehat{\sigma}_{2t}/\overline{\hat{\tau}}_{2t}$ for $t = 1, ..., T$, where $\widehat{\sigma}_{1t}$ and $\widehat{\sigma}_{2t}$ are standard deviations of $\hat{\tau}_{1it}$ and $\hat{\tau}_{2it}$, respectively. The coefficients of variations for two groups, displayed in Figure 2, demonstrate that income or growth disparities kept decreasing until 1985, but then have monotonically increased for high-medium countries by 21%. On the other hand, there is a surge in dispersion by 223%, especially after mid-80's for low income countries. Such a big differential clearly support previous evidence of increasing disparities among poor countries. As documented in Tsagkanos et al. (2006), this alternation presumably came from the big recession during the period

[13]This is clearly reflected in our finding that all Asian countries in our sample belong to the high-medium countries with the superior frontier.

1980-1982, resulting from continuous oil price hikes. This crisis influenced the financially weaker countries more severely, leading to a more critical divergence.

[Figure 2 about here]

For a comparison, in Figure 3, we also plot the time-varying paths of common technical efficiencies, $\bar{\hat{\tau}}_t$, and the associated coefficient of variation, $\widehat{\sigma}_t/\bar{\hat{\tau}}_t$ with $\widehat{\sigma}_t$ being the standard deviation of $\hat{\tau}_{it}$, obtained as if there were a common frontier. They are substantially different from those in Figures 1 and 2, hiding clear heterogeneous patterns between high-medium and low income countries. This clearly highlights the peril of ignoring regime-specific frontiers under the restrictive assumption that the quality of production factors is homogeneous for both developed and developing countries.

[Figure 3 about here]

3.3 Dynamic Analysis of Regime-specific Common Efficiency and Factors

We now examine dynamic interactions between the common time-varying efficiencies and two global factors, trade and FDI for each of two groups of countries with inferior and superior frontiers. After complying with the usual procedure for determining the lag order and checking for stability conditions, we fit the trivariate VAR(2) model for $\mathbf{z}_t = \left(\overline{FDI}_{jt}, \overline{td}_{jt}, \bar{\hat{\tau}}_{jt}\right)'$ where $j = 1, 2$ is the regime indicator, and $\overline{FDI}_{jt}$ and $\overline{td}_{jt}$ are the regime-specific cross-section weighted averages of the ratios of FDI and trade to GDP.[14] Based on the VAR(2) estimation results, we extrapolate evidence on the time delayed effects on efficiency (technological catch-up) of shocks to both openness factors.

Dynamic transmission channels between common factors and efficiency Figures 4 and 5 display the orthogonalized impulse response functions (OIRF) of regime-specific common efficiencies, $\bar{\hat{\tau}}_{1t}$ and $\bar{\hat{\tau}}_{2t}$ with respect to one standard deviation shocks to FDI and trade factors, along with associated confidence intervals computed using bootstrap.[15] We find that the impacts of FDI

[14]Regime-specific trade and FDI factors are computed as $\overline{td}_{jt} = \sum_{i=1}^{N_{ji}} w_{jit} td_{jit}$ and $\overline{FDI}_{jt} = \sum_{i=1}^{N_{ji}} w_{jit} FDI_{jit}$ for $j = 1, 2$, where $td_{1it} = td_{it} \times 1_{\{q_{it} \leq c\}}$, $td_{2it} = td_{it} \times 1_{\{q_{it} > c\}}$, $FDI_{1it} = FDI_{it} \times 1_{\{q_{it} \leq c\}}$, and $FDI_{2it} = FDI_{it} \times 1_{\{q_{it} > c\}}$. The weights, w_{1it} and w_{2it}, are the same as used in constructing $\bar{\hat{\tau}}_{1t}$ and $\bar{\hat{\tau}}_{2t}$. To save space we do not report the VAR(2) estimation results, which do not suffer from any serious misspecification.

[15]In order to facilitate the interpretation, we consider it prudent to normalise IRF such that the effect of a shock to the j-th equation on the j-th variable is unity on impact.

shocks on common efficiencies are initially negative for both high-medium and low income countries. But, the FDI impacts become significantly positive over the 2-3 years for high-medium income countries - the OIRFs reaching a peak after 2 years at which 1% increase in FDI raises efficiency by 0.3%. On the other hand, the positive FDI impact is only short-lived for low income countries with a peak impact of about 0.04% only after 1 year and quickly dying out to zero. This suggests that overall lagged effects of FDI on common technical efficiency are more significant and persistent only under superior frontier.[16] Turning to the influences of trade shocks on common efficiency, we find that they are positive and significant only for high-medium income countries but also display lagged impacts; the OIRFs reach a peak after 1 year at which a 1% increase in trade raises efficiency by 0.65%. By contrast, the trade impacts on efficiency under inferior frontier are rather oscillating but statistically insignificant.

In sum, the above findings clearly suggest that for openness channels through trade and FDI to be effective in diffusing efficiency externalities, individual countries should achieve a certain threshold level of development and knowledge transfer. Only after reaching such a threshold of institutional development, openness will become a vital factor in fostering the technology catch-up. This is consistent with theoretical predications made by Durlauf and Johnson (1995) and Quah (1997), who emphasize the role of structural economic differences in technology catch-up process. Hence, the policy implications are different for developed countries and developing countries. For high-medium income countries, governments need to facilitate the openness process for attracting multinational FDIs and promoting trade through incentive and benefit systems. On the other hand, for low income countries, governments should invest more in fundamental infrastructures and stabilize governance of institutions so as to drive more persistent productivity effects and thus boost efficiency spillover through FDI and trade.[17]

[Figures 5 and 4 about here]

[16] These findings are qualitatively in line with MSS who find that the positive impacts of FDI on technical efficiency are more persistent in accelerating technology catching-up in the EU over the medium- to the long-term.

[17] In general, there are two views on the benefits of openness in relation to productivity in low-development countries. On the one hand, the infant-industry argument argues that protectionist policy can help domestic (import-substitution) industries to develop (Rodriguez and Rodrik, 2000). On the other hand, it is suggested that trade liberalization increases the production of import-competition industries through using the production technology and the capital goods imported from developed countries (Tybout, 1992 and Pissarides, 1997).

4 Conclusion

This paper assesses diffusion dynamics of a regime-specific common technology with respect to two openness factors: FDI and trade by explicitly taking into account the structural differences in production technology between developed and developing countries. To this end we combine the robust two-step stochastic frontier approach advanced by Mastromarco, Serlenga and Shin (2010) with the threshold panel data model developed by Hansen (1999). In the first step we estimate the threshold stochastic frontier panel data model with both observed and unobserved factors and can obtain consistent estimates of individual and common efficiency measures separately for low and high-medium income countries. In the second step, we investigate dynamic interactions among regime-specific common efficiencies and two globalization factors proxied by FDI and trade by employing a trivariate VAR model. In this regard, our proposed methodology enables us to investigate the influences of globalization factors on common efficiencies under both superior and inferior frontiers in a fully dynamic setting.

We find that income elasticities of labour and capital and the associated time-varying common efficiency measures are substantially different under superior and inferior frontiers, which are identified by time-varying per capita income distance from the maximum used as the transition variable. Both capital and labour inputs are more productive under superior frontier. More importantly, common efficiencies have steadily increased under superior frontier, but technical efficiency has been monotonically decreasing for low income countries, supporting the so-called club convergence hypothesis. Furthermore, the impulse response analyses suggest that openness factors through FDI and trade clearly help the countries to improve both production technology and efficiency position relative to the frontier only after the country has reached a certain level of development. This suggests that openness will be a vital factor in fostering the technology catch-up, providing support for the beneficiary implication of the global trade expansion for developing countries as documented by Edwards (1998), Frankel and Romer (1999) and Alcalà and Ciccone (2004).

Table 1: Threshold Stochastic Frontier Panel Data Estimation Results

	Inferior Frontier				Superior Frontier			
	$\beta_{capital}$	β_{labour}	δ_{open}	δ_{FDI}	$\beta_{capital}$	β_{labour}	δ_{open}	δ_{FDI}
PCCE	0.455*	0.459*	0.036	0.449**	0.541*	0.587*	0.078**	0.095
	(0.066)	(0.085)	(0.033)	(0.166)	(0.065)	(0.044)	(0.038)	(0.097)
$\hat{c}$	5.235				$\hat{c}_L$	5.099	$\hat{c}_U$	5.484
CD	13.010				p-value 0.00			
LR	105.12				p-value 0.04			

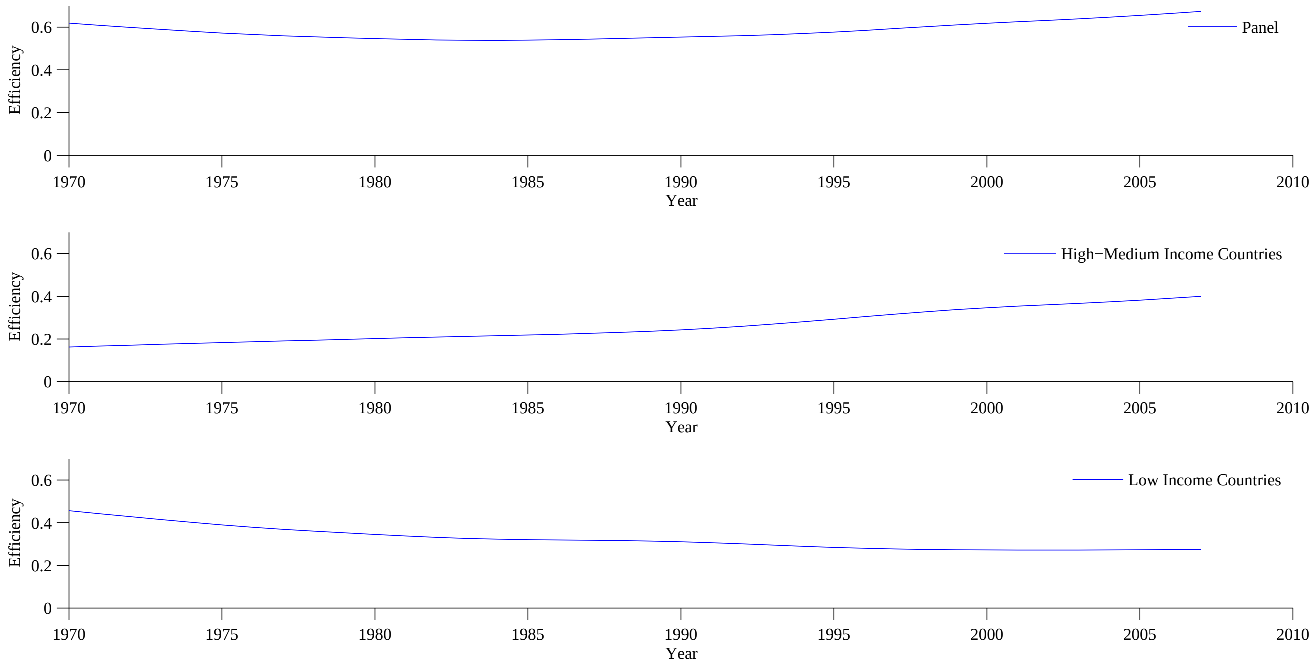
Notes: All the coefficients are elasticity. Labour is measured by total employment and Capital is measured as stock of capital, PCCE estimates have been performed using the following augmentations of unobserved factors $(\bar{k}_t)$. We have estimated a number of specifications augmented with several combinations of factors including the full set as described in Subsection 2.1, and find that overall results are more or less qualitatively similar. The final specification selected in this Table have been selected on the basis of overall statistical significance and empirical coherence. To save space we do not report all other coefficients, but available upon request. CD denotes the general diagnostic test statistic for cross-section dependency in Pesaran (2004), and LR indicates the likelihood ratio test statistic in Hansen (1999) for presence of one threshold effect which is obtained using 2,000 bootstrapping replications with bootstrap critical value, 83.79. * and ** denote significance at 1 and 5 per cent level, respectively. Standard errors robust to heteroskedasticity are in parenthesis. $\hat{c}$ is the point estimate of the threshold parameter with $\hat{c}_L$ and $\hat{c}_U$ denoting the lower and upper bounds of 95% confidence interval.

Table 2: Descriptive Statistics for Efficiency and Regime Probability for Individual Countries

Superior Fr.	$\bar{\bar{\tau}}_{1t}$	IRQ	$Pr(q_{it} > \hat{c})$	Inferior Fr.	$\bar{\bar{\tau}}_{2t}$	IQR	$Pr(q_{it} > \hat{c})$
USA	1.000	0.000	0.000	KEN	1.000	0.156	0.500
JPN	0.566	0.187	0.000	ZWE	0.965	0.638	0.632
GER	0.252	0.125	0.000	CIV	0.389	0.270	0.947
ITA	0.159	0.052	0.000	DOM	0.372	0.222	0.658
FRA	0.151	0.096	0.000	HND	0.205	0.273	1.000
GBR	0.078	0.067	0.000	MDG	0.195	0.235	1.000
KOR	0.069	0.042	0.000	JAM	0.119	0.195	1.000
MEX	0.064	0.031	0.000	BOL	0.110	0.209	1.000
ESP	0.055	0.036	0.000	MWI	0.107	0.048	1.000
CAN	0.047	0.034	0.000	ZMB	0.062	0.163	1.000
ARG	0.041	0.027	0.000	PAN	0.042	0.159	1.000
TUR	0.037	0.023	0.000				
AUS	0.030	0.004	0.000				
GRC	0.020	0.005	0.000				
VEN	0.020	0.013	0.000				
AUT	0.018	0.013	0.000				
PHL	0.017	0.003	0.000				
NLD	0.015	0.023	0.000				
SWE	0.014	0.020	0.000				
THA	0.012	0.007	0.000				
DNK	0.012	0.009	0.000				
FIN	0.011	0.011	0.000				
PRT	0.011	0.005	0.000				
NOR	0.011	0.003	0.000				
MAR	0.010	0.006	0.000				
NGA	0.007	0.005	0.000				
ISR	0.006	0.005	0.079				
CHL	0.005	0.007	0.000				
BEL	0.004	0.033	0.000				
NZL	0.003	0.001	0.053				
ECU	0.003	0.003	0.289				
IRL	0.002	0.004	0.211				
HKG	0.001	0.002	0.158				

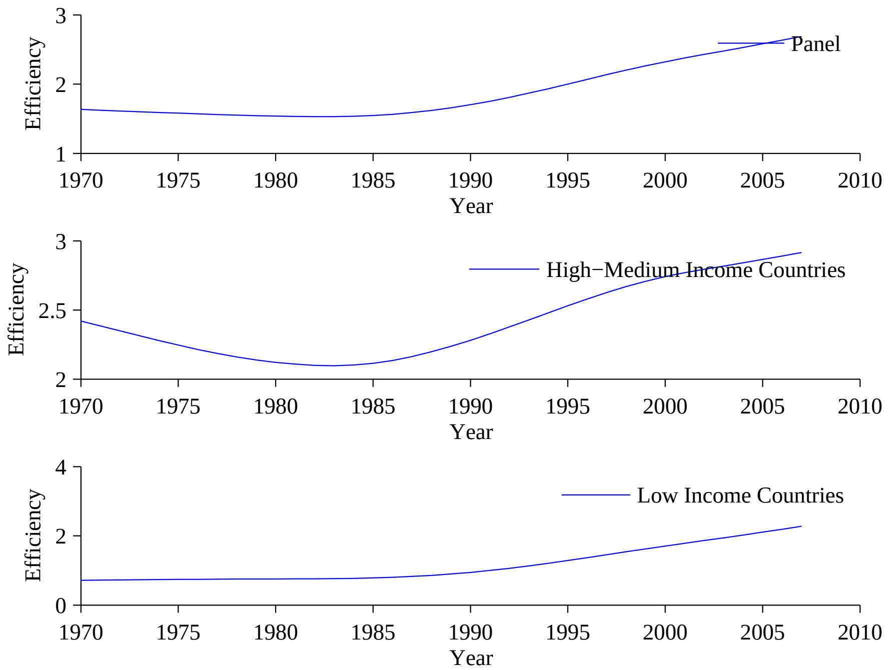
Notes: Second and third columns show the median and interquartile range (IQR) of individual technical efficiency for the high-medium income countries, obtained as $\hat{\tau}_{1it} = \exp(-\hat{u}_{1it})$ under superior frontier over the whole period. Similarly, sixth and seventh columns present the median and interquartile range of individual technical efficiency for the low income countries, obtained as $\hat{\tau}_{2it} = \exp(-\hat{u}_{2it})$ under inferior frontier. Fifth and eighth columns show the probability of each country that belong to inferior frontier, where we use the output gap as the transition variable, q_{it}, and the threshold is estimated as $\hat{c} = 5.24$.

Figure 1: Time Varying Patterns of Regime-Specific Common Technical Efficiencies



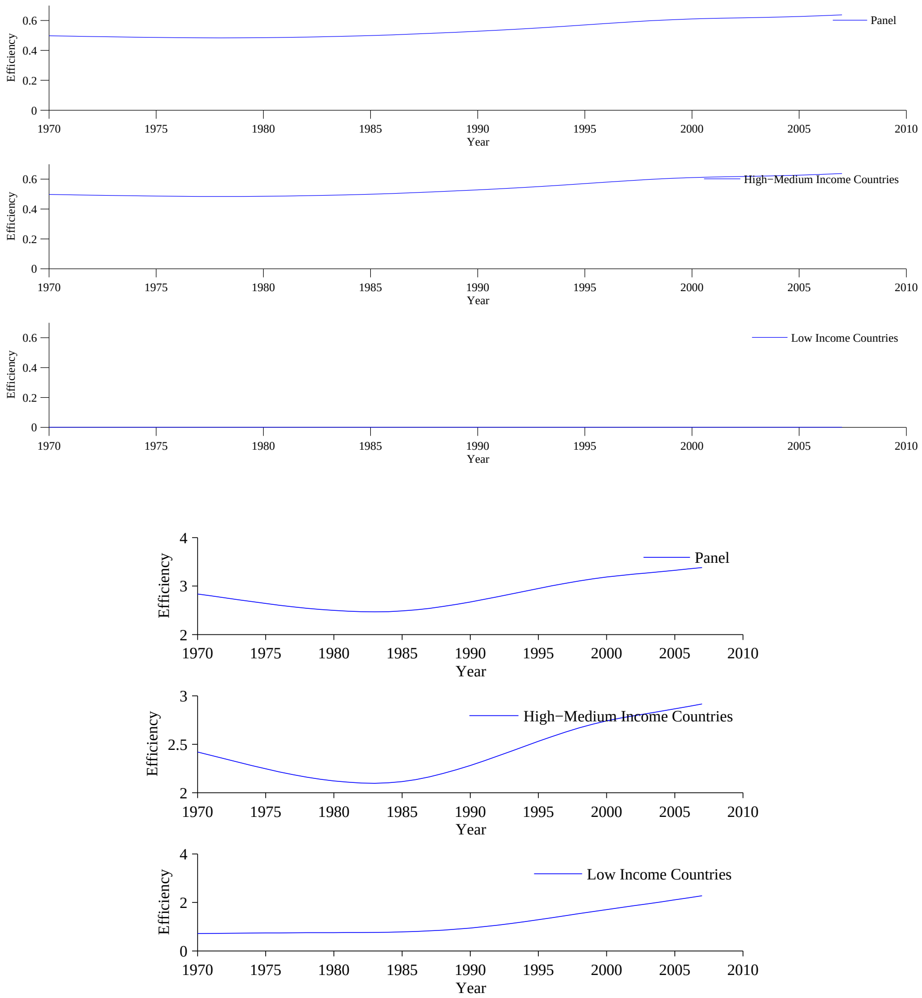
Notes: Both panels plot common technical efficiencies, $\overline{\hat{\tau}}_{1t}$ and $\overline{\hat{\tau}}_{2t}$, associated with superior and inferior stochastic frontiers. We use the Hodrick and Prescott (1997) filter to smooth the time paths.

Figure 2: Time Varying Patterns of Regime-Specific Coefficients of Variation



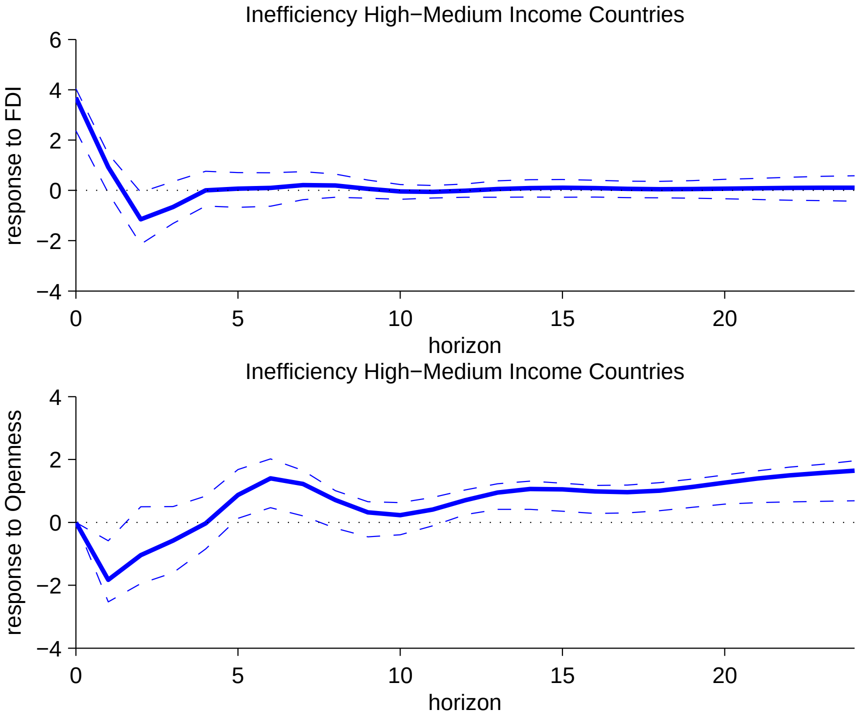
Notes: Both panels plot the coefficients of variation of common technical efficiencies, $\hat{\sigma}_{1t}/\overline{\hat{\tau}}_{1t}$ and $\hat{\sigma}_{2t}/\overline{\hat{\tau}}_{2t}$, associated with superior and inferior stochastic frontiers. We use the Hodrick and Prescott (1997) filter to smooth the time paths.

Figure 3: Time Varying Patterns of Common Technical Efficiency and Common Coefficients of Variation



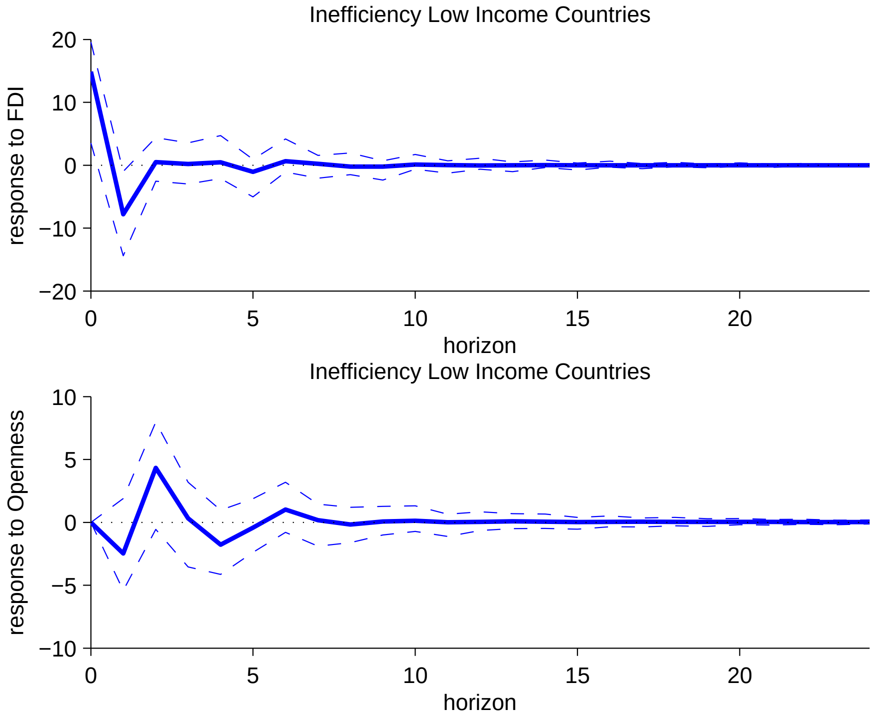
Notes: Those panels plot common technical efficiencies, $\overline{\hat{\tau}}_t$ and coefficients of variation of common technical efficiencies, $\hat{\sigma}_t/\overline{\hat{\tau}}_t$. We use the Hodrick and Prescott (1997) filter to smooth the time paths.

Figure 4: Impulse Response Functions of Common Efficiency under Superior Frontier



Notes: Both figures display orthogonalized impulse response of common technical efficiency with respect to one standard deviation shock to FDI and trade (OPEN) for those countries with superior frontier. All the figures are estimated from the VAR(2) model for $z_t = \left(\overline{FDI}_{1t}, \overline{td}_{1t}, \overline{\hat{\tau}}_{1t}\right)'$The dashed lines represent the 95% confidence interval obtained using the bootstrap with 2,000 bootstrap replications.

Figure 5: Impulse Response Functions of Common Efficiency under Inferior Frontier



Notes: Both figures display orthogonalized impulse response of common technical efficiency with respect to one standard deviation shock to FDI and trade (OPEN) for those countries with superior frontier. All the figures are estimated from the VAR(2) model for $z_t = \left(\overline{FDI}_{2t}, \overline{td}_{2t}, \overline{\hat{\tau}}_{2t}\right)'$. The dashed lines represent the 95% confidence interval obtained using the bootstrap with 2,000 bootstrap replications.

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