

# Dynamic Efficiency Modelling for Technological Convergence \*

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## Abstract

This paper represents an important attempt to consider time delays in the adjustment process of efficiency. We propose a new approach to estimate stochastic frontier model with dynamic adjustments of efficiency. Our aim is to better disentangle causes and determinants of technological convergence. We follow recent developments of panel data studies and implement a factor model that allows for a certain degree of cross section dependence through unobserved heterogeneous time-specific effects. The estimation methodology proposed focuses on dynamic adjustments towards the technological frontier. Empirical results support the evidence of a slow technological catching-up process towards the frontier among 24 OECD countries over the observed period 1970-2005. Our findings demonstrate the importance of including short-term economic fluctuations in a stochastic frontier framework.

JEL: D24, O47, C13, C33.

Keywords: Stochastic Frontier in Heterogeneous Panels, Time-varying Efficiency, Common Correlated Effects, Technology Diffusion, Spectral Analysis, Panel VAR.

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# 1 Introduction

A large body of the growth literature highlight that capital accumulation and technological diffusion play an important role in promoting economic growth, e.g. Nelson and Phelps (1966), Jovanovic and Rob (1989), Romer (1990), Grossman and Helpman (1991), Segerstrom (1991) and Barro and Sala-i-Martin (1995). These growth models also aim to uncover the transmission channels in which technology catch-ups, defined as measuring individual countries' abilities to adopt and accumulate new technologies, will affect growth rates. The empirical evidence provided by Bernard and Jones (1996) clearly demonstrates that technological differences are a key factor in explaining income disparities across countries, suggesting that such technology catch-up will be a crucially dominant factor to reach the steady-state level of per capita output growth.

In general the relationship between economic growths and technology diffusions remains a conundrum. The issue of dynamic (partial) adjustments is at the centre of theoretical debates on efficiency. Most stochastic frontier models tend to focus on estimating the long-run equilibrium relationship between output and production factors without explicitly modelling dynamic adjustments towards an equilibrium. In practice the adjustment from the current input use to the desired future input use is far from perfect due to time delays, delivery lags and installation costs. This partial adjustment process cannot not be encapsulated by a frontier model based on the implicit assumption of complete adjustment. This neglect may result in an inappropriate conclusion that an intertemporally efficient producer can be classified as being inefficient. Inclusion of the short-run dynamics is likely to be relevant to a stochastic frontier approach, e.g. Park et al. (2003, 2006), though this approach is still not able to provide a good description of the dynamic interactions between efficiency and the catch-up process.

Alternatively, one may ask whether there exist a transmission mechanism in which technological diffusions play a significant role in spurring the productivity growth. This paper aims to address this issue by analysing the dynamic interactions between technological catch-ups and the transmission channels through which technology diffuses so that we can provide a better description of partial dynamic adjustments of efficiency and technological convergence among 24 OECD countries.

We employ stochastic frontier models with time-varying factors, examine productivity differentials across countries and analyse the causes of technological convergence. In a cross-country framework, inefficiencies in production can be identified as the distance of the individual production from the frontier as proxied by the maximum output of the benchmark country re-

garded as the empirical counterpart of an optimal boundary of the production set. Inefficiencies generally reflect a sluggish adoption of new technologies, and thus efficiency improvements will represent productivity catch-up from technology diffusion.<sup>1</sup> In particular, we consider the factor model where time-varying inefficiency can be represented as a linear combination of observed and/or unobserved factors,<sup>2</sup> and follow the common correlated estimation (hereafter, CCE) procedure proposed by Pesaran (2006).<sup>3</sup> By allowing cross-section error dependency via heterogeneous loadings on factors, inefficiency can be expressed as time-varying common effects. Our approach is thus more general than existing stochastic frontier models that usually neglect the cross-section dependence.<sup>4</sup> Furthermore, our approach does not require any distributional assumption on efficiency.

Next, in order to further deepen our understanding of the technological catching-up process, we compare common and country-specific stylised features of efficiency through a graphical representation. We also provide the spectral decomposition analysis to analyze co-movement and synchronisation of cycles of country-specific efficiency and of global efficiency. By decomposing the variance of each frequency band into explained and unexplained parts and following the dynamic correlation suggested by Croux et al. (2001), we are able to address the issue of synchronisation by distinguishing between in-phase and out-of-phase movements.

Finally, in order to examine the impacts of (channel) factors such as globalisation and technology innovation on efficiency we consider four different channels through which technology diffuses: trade, foreign direct investment, patents, and human capital.<sup>5</sup> In particular, we model dynamic interactions of (observed and unobserved) common factors and the efficiency terms consistently estimated by CCE by means of a panel VAR approach. This approach

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<sup>1</sup>What identified as technological catch-up can be triggered by the international cycle in factor utilisations. In empirical application to follow we will use the energy indicator and an index of human capital respectively to adjust the capital stock of utilisation and the labour force.

<sup>2</sup>See Forni and Lippi (1997), Forni and Reichlin (1998) and Kneip et al. (2005).

<sup>3</sup>Our choice of the PCCE estimation instead of the popular principal components approach is dictated by Monte Carlo evidence by Kapetanios et al. (2007).

<sup>4</sup>See also Ahn et al. (2007) for a similar approach that aims to deal with the panels with a fixed  $T$ .

<sup>5</sup>See Griffith et al. (2004) and Cameron et al. (2005) for the important role of R&D, trade and human capital in the process of convergence in technical efficiency; Borensztein et al. (1998), Findlay (1978), Pack (1988), Tybout (1992), Coe and Helpman (1995), Coe et al. (1997), Robbins (1996), Levin and Raut (1997), Pissarides (1997) and Lichtenberg and van Pottelsberghe de la Potterie (1998) for the relevance of FDI and trade; Krueger and Lindahl (2001), Bils and Klenow (2000), and Hanushek and Kimko (2000) for the significant role of human capital.

allows us to evaluate the dynamic responses of efficiency with respect to (unexpected) shocks of the respective factor equation (such as FDI, trade, education expenditure and patents) and vice versa. These important dynamic transmission mechanisms have so far been ignored in the literature.

Our empirical results show that the 24 OECD countries tend to converge towards the technological frontier over time and the technological convergence takes a cyclical pattern of 3 to 5 years with Canada being an exception with a longer cycle of 5 to 7 years. We also find that the structure of the cycles in the common efficiency is mostly similar across the European OECD countries. There is also clear evidence that efficiency is significantly affected over time by common factors that act as channels to diffuse common technology, suggesting the empirical usefulness of dynamic factor-based modelling for the analysis of efficiency. In particular, our findings provide evidence in favour of a significant role that the human capital investment in improving efficiency.

The paper is organized as follows: Section 2 overviews the literature on stochastic frontier modelling in panels. Section 3 describes our estimation strategies in details. Section 4 discusses the data and the main estimation results. Section 5 concludes with further discussions.

## 2 Overview on Stochastic Frontier Modelling in Panels

We begin with a brief overview on the large literature of stochastic frontier modelling. Assume that the countries follow the common production frontier:

$$y_{it} = f(x_{it}) \tau_{it} \omega_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T, \quad (1)$$

where  $\tau_{it}$  is the efficiency measure with  $0 < \tau_{it} < 1$ ,<sup>6</sup> and  $\omega_{it}$  captures the stochastic nature of the frontier. Further assuming that the production frontier,  $f(x_{it})$ , follows the Cobb-Douglas production function, then we obtain the following log-linear specification:

$$y_{it} = \alpha + \mathbf{x}'_{it} \boldsymbol{\beta} + \varepsilon_{it},$$

where  $y_{it}$  is output of country  $i$  at time  $t$ ,  $\mathbf{x}_{it}$  is a  $k \times 1$  vector of production factors, and  $\varepsilon_{it}$  is the stochastic error term. It is then assumed that  $\varepsilon_{it}$  consists of two components:

$$\varepsilon_{it} = v_{it} - u_{it},$$

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<sup>6</sup>When  $\tau_{it} = 1$ , the country  $i$  produces on the full efficiency frontier.

where  $v_{it} = \ln \omega_{it}$  is an idiosyncratic noise and  $u_{it} = -\ln \tau_{it} \geq 0$  (logged) technical inefficiency.<sup>7</sup> Then, technical efficiency of country  $i$  at time  $t$  can be easily obtained by

$$\tau_{it} = \exp(-u_{it}). \quad (2)$$

Battese and Coelli (1995) propose a model that allows us to directly analyse the impacts of explanatory variables on technical inefficiency:

$$u_{it} = \boldsymbol{\delta}' \mathbf{z}_{it} + \eta_{it},$$

where  $\mathbf{z}_{it}$  is a vector of explanatory variables,  $\boldsymbol{\delta}$  a vector of coefficients and  $\eta_{it}$  a truncated random disturbance usually assumed to follow a truncated normal distribution. Hence, both technical changes (captured by time dummies) and time-varying technical inefficiencies can be estimated. Similarly, Kumbhakar and Hjalmarrsson (1993) model the inefficiency term as

$$u_{it} = \alpha_i + \xi_{it}, \quad (3)$$

where  $\alpha_i$  is a (unobserved) producer-specific effect and  $\xi_{it}$  a time-varying component with a half-normal distribution.

Several studies have attempted to relax the assumption that inefficiency is time-invariant and suggest the following model:

$$y_{it} = \alpha_{it} + \boldsymbol{\beta} \mathbf{x}_{it} + v_{it}, \quad (4)$$

$$\alpha_{it} = \alpha - u_{it}, \quad u_{it} \geq 0.$$

Different specifications for  $\alpha_{it}$  have been proposed. For example, Cornwell et al. (1990) advance the following simple and intuitive specification:

$$\alpha_{it} = \boldsymbol{\delta}'_i \mathbf{w}_t = (\delta_{i1} \quad \delta_{i2} \quad \delta_{i3}) \begin{pmatrix} 1 \\ t \\ t^2 \end{pmatrix}. \quad (5)$$

This specification can be regarded as a model of productivity growth with rates that differ for each country so that country-specific productivity growth rates can be derived as the time derivatives of (5). See also Kumbhakar (1990), Battese and Coelli (1992) and Lee and Schmidt (1993) for alternative specifications. Once  $\alpha_{it}$ 's are estimated consistently based on certain restrictions,<sup>8</sup> inefficiency can also be estimated consistently as

$$\hat{u}_{it} = \hat{\alpha}_* - \hat{\alpha}_{it} \quad \text{where} \quad \hat{\alpha}_* = \max_i (\hat{\alpha}_{it}). \quad (6)$$

<sup>7</sup>Inefficiency is ranked as  $u_{Nt} \leq \dots \leq u_{1t}$  such that country  $N$  produces with maximum efficiency.

<sup>8</sup>It is important to find restrictions weak enough to allow for some degrees of flexibility.

To capture the dynamic adjustment in attaining a target level of production, most recently dynamic efficiency models have appeared in the literature.

In order to capture the dynamic adjustment towards a target level of production, dynamic efficiency models have also been developed.<sup>9</sup> In particular, Park et al. (2003) consider the following model with autocorrelated errors:

$$\begin{aligned} y_{it} &= \alpha_i + \boldsymbol{\beta}' \mathbf{x}_{it} + v_{it}, \\ v_{it} &= \rho v_{it-1} + \varepsilon_{it}, \end{aligned}$$

and Park et al. (2006) consider the dynamic model:

$$y_{it} = \gamma y_{it-1} + \mu_i + \boldsymbol{\delta}' \mathbf{x}_{it} + \varepsilon_{it},$$

where  $\alpha_i = \alpha - u_i$  and  $\varepsilon_{it} \sim iid(0, \sigma^2)$ .

Recently, there have been some attempts to deal with these issues so as to encompass the specifications proposed in the previous studies (Cornwell et al., 1990, Battese and Coelli, 1995, Lee and Schmidt, 1993). In particular, Ahn et al. (2006) propose the following generalised specification based on factors:

$$\begin{aligned} y_{it} &= \alpha_{it} + \mathbf{x}'_{it} \boldsymbol{\beta} + v_{it}, \\ \alpha_{it} &= \sum_{j=1}^p \theta_{jt} \alpha_{ij}, \end{aligned} \tag{7}$$

where  $\theta_{jt}$ ,  $j = 1, \dots, p$ , are unobservable factors. By estimating  $\theta_{jt}$  directly as parameters, this approach does not need to impose any particular factor structure. Ahn et al. (2006) suggest the GMM estimation when  $N$  is large and  $T$  is fixed, whereas (7) can be estimated by Bai and Ng (2002) methodology when both  $N$  and  $T$  are sufficiently large. See also Kneip et al. (2005) for a more flexible factor-based specification of the time-varying components where time-varying individual effects are represented by linear combinations of a small number of unknown basis functions with heterogeneous coefficients. These studies clearly demonstrate the important role of factors in the stochastic frontier approach.

Following most recent trends in the literature, this paper aims to explicitly investigate the dynamics of time-varying efficiencies. To this end we now turn to the alternative approaches advanced by Coakley et al. (2002) (hereafter, CFS) and Pesaran (2006). CFS define factors as global variables that underlie common shocks, drive the comovement of the variables but are not explicitly

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<sup>9</sup>See for example Desli et al. (2002), Mouelhi and Goaid (2003) and Tsionas (2006).

specified in the baseline regression (i.e. ignored in stochastic frontier models), and consider the following model:

$$y_{it} = \beta'_i \mathbf{x}_{it} + \boldsymbol{\gamma}'_i \mathbf{g}_t + v_{it}, \quad (8)$$

where  $\mathbf{g}_t$  is a  $q \times 1$  vector of factors. CFS show that omitting factors leads to serial and cross units correlated residuals, and develop the consistent estimation procedure based on the principal components analysis. However, Pesaran (2006) demonstrates that the CFS estimator will become inconsistent in the general case where factors and regressors are correlated. Pesaran (2006) distinguishes between observed and unobserved factors by considering the data generating processes for dependent and explanatory variables jointly:

$$y_{it} = \alpha'_i \mathbf{d}_t + \boldsymbol{\beta}' \mathbf{x}_{it} + \varepsilon_{it} \quad (9)$$

$$\varepsilon_{it} = \boldsymbol{\gamma}'_i \mathbf{g}_t + v_{it} \quad (10)$$

$$\mathbf{x}_{it} = \alpha'_i \mathbf{d}_t + \Gamma'_i \mathbf{g}_t + \boldsymbol{\nu}_{it}$$

where  $\mathbf{d}_t$  is a  $(c \times 1)$  vector of observed common effects,  $\mathbf{g}_t$  is a  $(q \times 1)$  vector of unobserved common effects and  $\varepsilon_{it}$ ,  $\boldsymbol{\nu}_{it}$  are respective disturbance terms assumed to be independently distributed of  $\mathbf{d}_t$  and  $\mathbf{x}_{it}$ . Pesaran (2006) proposes the Pooled Common Correlated Effects (hereafter, CCEP) estimator for consistently estimating  $\boldsymbol{\beta}$ .<sup>10</sup>

This framework is particularly useful in modelling the diffusion of common technology as the cross-correlation across countries is a more natural issue to address. Therefore, we consider the following generalized panel data model:

$$y_{it} = \boldsymbol{\beta}' \mathbf{x}_{it} + \boldsymbol{\pi}'_i \mathbf{s}_t + \varepsilon_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T, \quad (11)$$

with the two-way error components structure,

$$\varepsilon_{it} = v_{it} - u_{it} = v_{it} - (\alpha_i + \varphi_i \theta_t), \quad (12)$$

where  $\theta_t$  is the time-specific effects common to all cross section units, and  $\alpha_i$  is an individual specific effect. Moreover,  $\mathbf{s}_t = (s_{1,t}, \dots, s_{s,t})'$  is an  $(s \times 1)$  vector of observed time-specific factors with conformable parameter vector,  $\boldsymbol{\pi}_i = (\pi_{1,i}, \dots, \pi_{s,i})'$ , and  $\varphi_i$ 's capture heterogeneous individual responses with respect to common time-specific effects,  $\theta_t$ .<sup>11</sup>

<sup>10</sup>Pesaran (2006), Kapetanios et al. (2006) also show that this estimator is consistent even when the variables are non-stationary.

<sup>11</sup>We assume: (i)  $v_{it} \sim iid(0, \sigma_v^2)$ . (ii)  $\alpha_i \sim iid(\alpha, \sigma_\alpha^2)$ . (iii)  $E(\alpha_i v_{jt}) = 0$  and  $E(\theta_t v_{it}) = 0$  for all  $i, j, t$ . (iv)  $E(\mathbf{x}_{it} v_{js}) = \mathbf{0}$ ,  $E(\mathbf{s}_t v_{is}) = \mathbf{0}$  for all  $i, j, s, t$ , so all the regressors are exogenous with respect to the idiosyncratic errors,  $v_{it}$ . (vi) Both  $N$  and  $T$  are sufficiently large. See Serlenga and Shin (2007) for more details.

The distinguishing feature of the model given by (11) and (12) is that it allows us to accommodate certain degrees of cross section dependence of  $\varepsilon_{it}$  in (12) via heterogeneous factor loading coefficient,  $\varphi_i$ . It is easily seen that various econometric specifications proposed in the literature can be expressed as a variation of (11) and (12), (Cornwell et al., 1990, Battese and Coelli, 1995, Lee and Schmidt, 1993). In model (11),  $\mathbf{s}_t$  and  $\theta_t$  are considered as proxies for common global shocks (such as changes in oil prices), that could arise as a result of global unobserved factors (such as the diffusion of technological progress). In particular, in the context of stochastic frontier, this specification allows us to consider four fundamental aspects: (i) to relax the problematic assumption that efficiency is independent of the regressors (Schmidt and Sickles, 1984); (ii) to study the effect of factors on efficiency; (iii) to accommodate possibly nonstationary variables; (iv) to follow technological catch up effect over time through factors.

### 3 Estimation Strategy in Details

In this section we describe our estimation steps in details. First, in order to obtain the proxies of unobservable efficiency terms, we employ the generalised stochastic frontier specification described in Section 2, and obtain consistent estimates of efficiency measures. Second, we will provide time-varying statistical properties of countries' efficiency terms using the panel-based convergence test and the spectral analysis. Finally, we apply the VAR to investigate the dynamic interactions between efficiency measures and observed factors proxing technology and globalisation impacts for the individual country case and the globally aggregated case, respectively. In particular, we examine the common shocks and the transmission mechanisms of technology diffusion by an impulse response analysis.

#### 3.1 Estimation of Efficiency

For simplicity we consider the model, (11) with only unobserved factors:

$$y_{it} = \boldsymbol{\beta}' \mathbf{x}_{it} + \varepsilon_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T, \quad (13)$$

$$\varepsilon_{it} = \alpha_i + u_{it}, \quad u_{it} = \varphi_i \theta_t + v_{it}. \quad (14)$$

The conventional panel data estimation such as the fixed or the random effects estimator of  $\boldsymbol{\beta}$  obtained from (11) or (13) would be seriously biased without properly accommodating the error component structure given by (12), as confirmed by Monte Carlo studies by Pesaran (2006) and Kapetanios

and Pesaran (2005). Hence, in order to obtain consistent estimates of  $\beta$ ,  $\alpha_i$  and  $f_{it} = \varphi_i \theta_t$ , we consider the approximated transformation, which is obtained by augmenting (13) with cross-sectional averages of  $y_{it}$  and  $\mathbf{x}_{it}$ :

$$y_{it} = \beta' \mathbf{x}_{it} + \pi_i' \mathbf{f}_t + \alpha_i^* + v_{it}, \quad (15)$$

where  $\mathbf{f}_t = (\bar{y}_t, \bar{\mathbf{x}}_t)'$ . As  $N, T \rightarrow \infty$ ,  $\beta$ ,  $\pi_i$  and  $\alpha_i^*$  can be consistently estimated by the PCCE estimator denoted  $\hat{\beta}_{PCCE}$ , which is simply the pooled OLS estimator obtained from (15). See Pesaran (2006) for further details on estimation and inference theory.

It is easily seen from (13) and (14) that inefficiency is measured with respect to  $\max_i (\alpha_i + \varphi_i \theta_t)$  at each point of time such as

$$e_{it} = u_{it} - \max_i u_{it} = (\alpha_i + \varphi_i \theta_t) - \max_i (\alpha_i + \varphi_i \theta_t), \quad (16)$$

which shows that we need to obtain consistent estimates of heterogeneous parameters of  $\alpha_i$  and  $\pi_i$  for  $i = 1, \dots, N$ . Replacing  $\beta$  by  $\hat{\beta}_{PCCE}$  in (15) and rearranging the result, we have:

$$\tilde{y}_{it} = \alpha_i^* + \pi_i' \mathbf{f}_t + \tilde{u}_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T, \quad (17)$$

where  $\tilde{y}_{it} = y_{it} - \hat{\beta}_{PCCE}' \mathbf{x}_{it}$ . Assuming that  $T$  is sufficiently large,  $\alpha_i^*$  and  $\pi_i$  can be consistently estimated by the OLS estimators, denoted respectively by  $\hat{\alpha}_i^*$  and  $\hat{\pi}_i$ , for each country regression. It then follows that  $\alpha_i + \varphi_i \theta_t$  can be consistently estimated by  $\hat{u}_{it} = \hat{\pi}_i' \mathbf{f}_t + \hat{\alpha}_i^*$ . Therefore, inefficiency measures of each country can be consistently estimated as follow:

$$\hat{e}_{it} = \hat{u}_{it} - \max_i \hat{u}_{it} = (\hat{\pi}_i' \mathbf{f}_t + \hat{\alpha}_i^*) - \max_i (\hat{\pi}_i' \mathbf{f}_t + \hat{\alpha}_i^*). \quad (18)$$

### 3.2 Spectral Analysis of Efficiency

In this subsection we employ the spectral analysis [e.g. Priestly (1981) and Harvey (1993)] and describe how the relative importance of efficiency cycle of each country can be analysed.

Consider a stationary time series  $x_t$  that can be decomposed into superimposed waves with frequencies  $\omega \in [-\pi, \pi]$ . Define the spectrum by the Fourier transform of the autocovariance function,  $\gamma_x$ :

$$f_x(\omega) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{\infty} \gamma_x(\tau) e^{-i\omega\tau}, \quad \omega \in [-\pi, \pi],$$

that measures the (marginal) contribution of each wave to the overall variance. The contribution or the relative importance of cyclical components in a frequency band  $[\omega_1, \omega_2]$  to the overall variance can then be evaluated by

$$2 \times \int_{\omega_1}^{\omega_2} \frac{f_x(\omega)}{\gamma_x(0)},$$

where  $\gamma_x(0) = \int_{-\pi}^{\pi} f_x(\omega) d\omega$  is the long-run variance of  $x_t$ .

Extension to the multi-dimensional case is also straightforward. The bivariate spectrum of two stationary time series  $x_t$  and  $y_t$  is defined as the Fourier transform of the covariance function,  $\mathbf{\Gamma}_{xy}(\tau)$ :

$$\mathbf{F}_{xy}(\omega) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{\infty} \mathbf{\Gamma}_{xy}(\tau) e^{-i\omega\tau}, \quad \omega \in [-\pi, \pi], \quad (19)$$

where the off-diagonal cross-spectrum at frequency  $\omega$  is given by

$$f_{xy}(\omega) = c_{xy}(\omega) - iq_{xy}(\omega), \quad \omega \in [-\pi, \pi],$$

where  $c_{xy}(\omega)$  is the co-spectrum measuring the covariance between the "in-phase" components of  $x_t$  and  $y_t$ , and  $q_{xy}(\omega)$  is the quadrature spectrum, measuring the covariance between the "out-phase" components of  $x_t$  and  $y_t$ . Then, the squared coherency is obtained by

$$sc(\omega) = \frac{|f_{xy}(\omega)|^2}{f_x(\omega) f_y(\omega)}, \quad 0 \leq sc(\omega) \leq 1,$$

which assesses the degree of a linear relationship between  $x_t$  and  $y_t$  at each frequency.<sup>12</sup>

Using  $sc(\omega)$ , we can now decompose the variance of cyclical components of  $y_t$  in a frequency band  $[\omega_1, \omega_2]$  into explained (by the variance of cyclical components of  $x_t$ ) and unexplained parts as follow:

$$\int_{\omega_1}^{\omega_2} f_y(\omega) d\omega = \int_{\omega_1}^{\omega_2} sc(\omega) f_x(\omega) d\omega + \int_{\omega_1}^{\omega_2} f_u(\omega) d\omega. \quad (20)$$

This decomposition enables us to compare the degree of a linear relationship between cycles of different series for frequency intervals of interest, e.g. given by the classical business cycle structure: the Kitchin cycle with a length of 3-5 years and/or Jugular cycle with a length of 7-10 years.

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<sup>12</sup>This has a similar interpretation to  $R^2$  obtained from linear regressions in time domain.

The squared coherency may not be suitable for analysing the co-movement of time series, because it does not contain information about a possible dynamic phase shift between cycles in  $x_t$  and  $y_t$ . Croux et al. (2001) propose an alternative measure called the dynamic correlation,  $\rho(\omega)$ , which measures the correlation between the “in-phase” components of the two series at frequency  $\omega$ :

$$\rho(\omega) = \frac{c_{xy}(\omega)}{\sqrt{f_x(\omega) f_y(\omega)}}, \quad -1 \leq \rho(\omega) \leq 1.$$

Furthermore, we follow Mastromarco and Woitek (2007) and decompose the explained variance into the in-phase component and the out-of-phase component respectively by

$$\int_{\omega_1}^{\omega_2} sc(\omega) f_x(\omega) d\omega = \int_{\omega_1}^{\omega_2} \frac{[c_{xy}(\omega)]^2}{f_x(\omega) f_y(\omega)} f_x(\omega) d\omega + \int_{\omega_1}^{\omega_2} \frac{[q_{xy}(\omega)]^2}{f_x(\omega) f_y(\omega)} f_x(\omega) d\omega, \quad (21)$$

where we use  $|f_{xy}(\omega)|^2 = [c_{xy}(\omega)]^2 + [q_{xy}(\omega)]^2$ . (21) clearly shows that the importance of the phase shift in a frequency interval is now explicitly incorporated to (20). Notice that information about co-movement or synchronisation in the frequency bands of interest are provided by the in-phase component of explained variance.

Finally, we describe how to estimate the spectra. To this end we fit autoregressive models in the time domain, and obtain the spectra from the estimated models.<sup>13</sup> Consider a univariate AR( $p$ ) model for  $x_t$ ,

$$x_t = \sum_{j=1}^p \phi_j x_{t-j} + \varepsilon_{xt}, \quad \varepsilon_t \sim iid(0, \sigma^2).$$

The spectrum of  $x_t$  is then computed by

$$f_x(\omega) = \frac{1}{2\pi} \frac{\sigma^2}{\left| 1 - \sum_{j=1}^p \phi_j e^{-i\omega\tau} \right|}, \quad \omega \in [-\pi, \pi].$$

In the case where we consider for VAR( $p$ ) model for the  $m \times 1$  vector,  $\mathbf{x}_t$ ,

$$\mathbf{x}_t = \sum_{j=1}^p \mathbf{\Phi}_j \mathbf{x}_{t-j} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim iid(\mathbf{0}, \boldsymbol{\Sigma}),$$

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<sup>13</sup>This method is based on the seminal work by Burg (1967), who shows that the resulting spectrum is identical to a spectrum derived on the Maximum Entropy Principle. This is a more reasonable approach than the normally-used periodogram estimator that imposes too restrictive assumption that all the covariances outside the sample period in the infinite sums are zero (e.g Priestley, 1981, pp.604-607). See also Woitek (1996) and A’Hearn and Woitek (2001) for applications.

the  $m \times m$  spectral density matrix is given by

$$\mathbf{F}_{\mathbf{x}}(\omega) = \frac{1}{2\pi} \mathbf{\Phi}(\omega)^{-1} \mathbf{\Sigma} \mathbf{\Phi}(\omega)^{-1*}, \quad \omega \in [-\pi, \pi],$$

where  $\mathbf{\Phi}(\omega)$  is the Fourier transform of the matrix lag polynomial  $\mathbf{\Phi}(L) = \mathbf{I}_m - \sum_{j=1}^p \mathbf{\Phi}_j L^j$  and  $^*$  denotes the complex conjugate transpose.

Synchronization describes the relationship between cycles of country-specific efficiency and of global efficiency. In empirical applications below we fit the bivariate VAR model and estimate the spectral density matrix given by (19). We then use the cross-spectra and derive the in-phase explained variance. This enables us to judge the extent to which the country-specific efficiency cycle and the global efficiency cycle move together.

### 3.3 VAR Analysis of Efficiency and Factors

We now employ the VAR analysis and examine the dynamic evolution of efficiency with respect to two main factors or determinants that proxy for globalization and technology effects. Using the flexible impulse response analysis, we will be able to uncover the important transmission channels through which technology diffuses.

We first consider the country-specific tri-variate VAR model for each country  $i = 1, \dots, N$ :

$$\mathbf{z}_{it} = \mathbf{\Phi}_1 \mathbf{z}_{it-1} + \dots + \mathbf{\Phi}_p \mathbf{z}_{i,t-p} + \boldsymbol{\varepsilon}_{it}, \quad t = 1, \dots, T, \quad (22)$$

where  $\mathbf{z}_{it} = (g_{it}, t_{it}, e_{it})'$ ,  $\mathbf{\Phi}_i$ 's a  $3 \times 3$  matrix of unknown coefficients,  $p$  is the lag order selected on the basis of the information selection criteria, and it is assumed that  $E(\boldsymbol{\varepsilon}_{it}) = \mathbf{0}$  and  $E(\boldsymbol{\varepsilon}_{it} \boldsymbol{\varepsilon}_{is}') = \mathbf{\Sigma}$  for  $t = s$  with  $\mathbf{\Sigma}$  being a  $3 \times 3$  symmetric positive definite matrix and 0 otherwise. Here  $g_{it}$  is a globalization factor,  $t_{it}$  technology factor and  $e_{it}$  inefficiency terms.<sup>14</sup> Following now the standard derivations (e.g. Pesaran and Shin (1998)) we obtain the  $3 \times 1$  vector of the orthogonalized impulse response function of a unit shock to the  $j$ th equation's orthogonalised innovation on  $\mathbf{z}_{i,t+h}$  can be obtained by

$$\mathbf{o}_{ij}(h) = (\mathbf{\Theta}_{ih} \mathbf{P}_i) \mathbf{e}_j, \quad h = 0, 1, 2, \dots, \quad i = 1, \dots, N, \quad (23)$$

where  $\mathbf{\Theta}_{ih}$  is a  $3 \times 3$  VMA coefficient matrix obtained from (22),  $\mathbf{P}_i$  a  $3 \times 3$  lower triangular matrix obtained from the Cholesky decomposition of  $\mathbf{\Sigma}_i =$

<sup>14</sup>From the literature we have identified four of those most important channels: trade, FDI, investments in innovation and in human capital. In empirical applications below we thus consider  $\mathbf{g}_{it} = FDI_{it}$  or  $trade_{it}$  and  $t_{it} = EducExp_{it}$  or  $Patents_{it}$ .

$\mathbf{P}_i \mathbf{P}_i'$ , and  $\mathbf{e}_j$  a  $3 \times 1$  selection vector with unity as its  $j$ th element and zeros elsewhere. Similarly, we obtain the generalized impulse response function by

$$\mathbf{g}_{i,j}(h) = \sigma_{i,jj}^{-\frac{1}{2}} \boldsymbol{\Theta}_{ih} \boldsymbol{\Sigma}_i \mathbf{e}_j, \quad h = 0, 1, 2, \dots, \quad i = 1, \dots, N. \quad (24)$$

which measures the effect of one standard error shock to the  $j$ th equation's (reduced form) disturbance,  $\varepsilon_{j,it}$  at time  $t$  on expected values of  $\mathbf{z}_{it}$  at time  $t + h$ , where  $\sigma_{i,jj}$  is a  $j$ -th diagonal term of  $\boldsymbol{\Sigma}_i$ .

Next, to further investigate the aggregate or common global patterns of the transmission mechanisms of technology diffusion, we consider two different aggregation methods. We first consider the following aggregate tri-variate VAR model:

$$\bar{\mathbf{z}}_t = \boldsymbol{\Phi}_1 \bar{\mathbf{z}}_{t-1} + \dots + \boldsymbol{\Phi}_p \bar{\mathbf{z}}_{t-p} + \bar{\boldsymbol{\varepsilon}}_t, \quad t = 1, \dots, T, \quad (25)$$

where  $\bar{\mathbf{z}}_t = (\bar{g}_t, \bar{t}_t, \bar{e}_{it})'$  and  $\bar{g}_t, \bar{t}_t, \bar{e}_{it}$  are cross-sectional averages (i.e.  $\bar{g}_t = N^{-1} \sum_{i=1}^N g_{it}$ ). Then the associated impulse response functions can be easily obtained by a simple modification of (23) or (24); namely

$$\mathbf{o}_j(h) = (\boldsymbol{\Theta}_h \mathbf{P}) \mathbf{e}_j, \quad h = 0, 1, 2, \dots, \quad (26)$$

$$\mathbf{g}_j(h) = \sigma_{jj}^{-\frac{1}{2}} \boldsymbol{\Theta}_h \boldsymbol{\Sigma} \mathbf{e}_j, \quad h = 0, 1, 2, \dots \quad (27)$$

Alternatively, we consider (22) as the heterogeneous panel VAR,<sup>15</sup> and apply the panel-based techniques. In this case the most obvious candidate is the mean group estimates of the impulse response functions, which are obtained by the average of the individual impulse response functions: namely,

$$\bar{\mathbf{o}}_j(h) = N^{-1} \sum_{i=1}^N (\boldsymbol{\Theta}_{ih} \mathbf{P}_i) \mathbf{e}_j, \quad h = 0, 1, 2, \dots, \quad (28)$$

$$\bar{\mathbf{g}}_j(h) = N^{-1} \sum_{i=1}^N \left( \sigma_{i,jj}^{-\frac{1}{2}} \boldsymbol{\Theta}_{ih} \boldsymbol{\Sigma}_i \mathbf{e}_j \right), \quad h = 0, 1, 2, \dots \quad (29)$$

Notice that the size of the shock is standardised to unity for the orthogonalized impulse response function whilst it is one standard deviation for the generalized impulse response functions. Since the individual error variances are allowed to be heterogeneous, the size of the individual shock in GIR is not necessarily the same. To fix this, we may set  $\delta_j = 1$  and obtain the following modified mean group estimates of GIR:

$$\bar{\mathbf{g}}_j^*(h) = N^{-1} \sum_{i=1}^N \left( \sigma_{i,jj}^{-1} \boldsymbol{\Theta}_{ih} \boldsymbol{\Sigma}_i \mathbf{e}_j \right), \quad h = 0, 1, 2, \dots \quad (30)$$

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<sup>15</sup>It is also possible to allow for different lag orders for different countries.

In empirical section below we will report the estimation results of the impulse responses and thus analyse the dynamic interactions between efficiency and factors using both country-specific and aggregated or Panel VAR for 24 OECD countries.<sup>16</sup>

## 4 Empirical Results

The data used cover 24 countries of the OECD members (Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US) over a period of 36 years (1970-2005). GDP is measured in millions of the US 2000 dollars, labour is measured as total employment, capital is measured as energy consumption (electric power consumption in KWh). All three are logged before estimating stochastic frontier. We also collect the data on trade and FDI for globalisation factor and education expenditure and patents for technology innovation factor. In details, trade is computed as the sum of imports and exports, FDI as net inflows of foreign direct investment, expenditure in education as government expenditure on education (adjustment savings). These variables are then transformed as percentage of GDP. Data sources are as follows: labour measurement is collected from OECD Labour Force Statistics; GDP, energy consumption, expenditure on education, trade and FDI from the World Bank *World Development Indicators*; and Total Number of Patents from OECD, *Statistical Compendium*, Main Economic Indicators, *Indicators of International cooperation*.

### 4.1 Stochastic Frontier and Inefficiency

We now discuss the estimation results of the stochastic frontier model given by (13) and (14).<sup>17</sup> Here some comments on the selected input measures are in order. Energy consumption is used as a measure of capital in order for us to take into account of the factor utilization over the cycle (Basu and Fernald, 1997)<sup>18</sup> and extrapolate the effectiveness of capital utilization simultaneously. Factor utilization of labour is typically measured by adjusting

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<sup>16</sup>The forecast error variance decomposition and/or the probability event forecasting exercises can be further easily implemented, see Garratt et al. (2006).

<sup>17</sup>Although constant elasticity of substitution may be too stringent, these restrictions turn out to be more or less suitable for industrialized countries (Blomstrom et al., 1994, Malley et al., 2005).

<sup>18</sup>Basu and Fernald (1997) state that to avoid the potential correlation between input growth and technology shocks, they use instruments uncorrelated with technology change.

the total employment by hours actually worked. Importantly, however, the data on working-hours (extracted from OECD Labour Force Statistics) reveal that annual working hours are considerably longer in the US and other non-European OECD countries than in Europe.<sup>19</sup> For these reasons we do not adjust labour input for factor utilization.<sup>20</sup>

Table 1 summarises the estimation results for alternative estimations; namely Pooled OLS (POLS), Fixed Effect (FE) and PCCE estimators. Both labour and capital elasticities are all statistically significant at the 1% level, and labour's contributions are significantly higher as expected. The POLS and FE estimates turn out to be surprisingly high, also showing that labor elasticities are greater than unity, a finding inconsistent with most empirical studies on production function.<sup>21</sup> This may be an indication of biases stemming from neglecting cross-section error dependency across OECD countries that is highly likely to be present in our sample data. Indeed the PCCE estimates provide much more sensible values of labor and capital elasticities respectively at 0.53 and 0.36, though they are slightly lower than implied by constant returns to scale. There may be a few reasons for this slight underestimation. First, we recall that, differently from other studies, our strategy takes allows for cross-section, second the time span we consider is longer than in most of the empirical studies which usually do not include the 70s in the estimation sample.

Table 1: Estimates of inputs elasticity

	$\beta_k$	$\beta_l$
POLS	0.6*	1.03*
FE	0.45*	1.5*
PCCE	0.36*	0.53*

Notes: Labour is measured by total labour force and Capital is measured as energy consumption, PCCE estimates have been performed using unobserved factor ( $\bar{y}_t, \bar{x}_t$ ) and observed factors ( $\bar{s}_t$ = FDI, trade, government expenditure on education and number of patents); \* denotes significance at 1% level.

<sup>19</sup>There are a few reasons. First, European working week and year are shorter especially for women. Secondly, working time regulations are less constrained in the US and other non-European OECD countries. Finally, employment protection legislation and product market regulations are more stringent on average in European countries (OECD, 2008)

<sup>20</sup>We expect that this nonadjustment will make the labor elasticity somewhat underestimated.

<sup>21</sup>On average technology based on constant returns to scale has been confirmed for OECD countries, e.g. Iyer et al. (2008).

Once obtained a consistent estimation of the elasticities  $\beta$  we compute inefficiency,  $\hat{e}_{it}$ , as explained in subsection 3.1.

## 4.2 Descriptive and Spectral Analysis of Efficiency

We now investigate the descriptive stylised features of the country-specific inefficiency estimates,  $\hat{e}_{it}$ , and the associated common global efficiency measure,  $\bar{\hat{e}}_t \left( = N^{-1} \sum_{i=1}^N \hat{e}_{it} \right)$  through graphic representations, convergence tests and spectral analyses.

Figure 1 displays country-specific efficiency and common efficiency factor over the sample period, 1970-2005. Remarkably, the US and Japan are two most efficiency countries over the full period. Typically, efficiency remains stagnant at relatively low levels for almost all other countries, though this evidence of poor efficiency performance is consistent with previous studies. Furthermore, efficiency levels show similar pattern to the ones estimated by Koop et al. (2000).

A stylised finding since the 1980s, well-established in the growth literature, is that labour productivities in the US, Japan and many emerging economies such as China and India are significantly higher than other countries. The EU KLEMS productivity report (van Ark et al., 2007) show that labour productivity in the US has been growing at 3% per annum over 1980-1995 and remarkably at 3.7% from 1995 to 2004. On the other hand the growth rates of most EU countries are substantially lower, e.g. 1.7% and 2.5% in France and 2.5% and 3.3% in the UK. In particular, performances of Italy and Spain are much more unsatisfactory with a marked slowdown in productivity appearing at the beginning of the new century. Average annual growth rate in Italian labor productivity (excluding agriculture) has dropped from 1.9% over 1980-1995 to a meagre 1.4% during 1995-2004. It is generally agreed that the recent decline in EU productivity has largely been a result of the weak growth in TFP. Our findings also provide a support that the efficiency is constant or slightly declining for all European countries over the period, 1970-2005, except Ireland that experiences weak efficiency improvement.

Slow technological catch-up often causes the lack of convergence in per capita output levels (Mankiw et al., 1992, Barro and Sala-i-Martin, 1995). Technological catch-up or increases in efficiency represents a movement towards the frontier, though efficiency increase does not necessarily imply that there is a tendency for technology transfer to reduce the gap between outperforming and underperforming countries, since relatively outperforming countries may benefit from efficiency improvements as much as or even more

than underperforming countries.

The close reading of the figure 1 does not support the growth theories emphasising that poorer countries can grow faster than richer ones because they only need to copy the technology. There is no clear signs of inefficiencies being eliminated. Several poorer countries - in terms of GDP per capita - in 1970 (e.g. Austria, Ireland, Greece, Norway and Portugal) achieved the below-average efficiency improvements whilst Italy and Spain only achieved the above-average improvement. These findings, combined together, may suggest that the technological catch-up process is not the driving force behind output growth during the sample period, the result in line with Koop (2001).

To better evaluate the technological catching-up process of the OECD countries, we now turn to synchronisation of the business cycle of the country-specific efficiency,  $e_{it}$  and the common global factor,  $\bar{e}_t$ .<sup>22</sup> To identify the relative importance of the relationship between the components in the 3-10 years range, we now employ spectral analysis described in subsection 3.2. In particular we fit the bivariate VAR models for  $(e_{it}, \bar{e}_t)$  for each country, evaluate the spectra of the fitted VAR model and derive the in-phase component of explained variance as a measure of synchronisation.

The results clearly indicate that cycles in the 3 – 10 year range dominate. We further decompose this range and focus on traditional business cycle frequencies such as the Kitchin cycle with a length of 3 – 5 years and the Jugular cycle with a length of 7 – 10 years (Zarnowitz, 1992). Tables 3, 4, 5 report the proportion of share variances, explained variances and in-phase explained variances in the frequency bands (i.e. the cycles of length 3-5, 5-7 and 7-0 years). Table 3 shows that shortest cycle of 3-5 years dominates efficiency in all countries except for Canada where the 5-7 years cycle prevails. The explained variance (Table 4) suggests that the cyclical structure of inefficiency common factor is predominated by the fluctuations in the efficiency of Austria, France, Germany, Italy, Japan, Norway, Spain, Sweden. National inefficiency business cycles and common factor show co-movement for Austria, France, Germany, Italy, Japan, Norway, Spain, Sweden; to less extent, for Belgium, Iceland, Korea, and United Kingdom (see Table 5). Australia, Canada, Denmark and the United States turn out to be special cases, with very low synchronization between common factor and national inefficiency.

We attribute the synchronization in the business cycles of common factor and country-specific inefficiencies to converging best “business practices” among European countries who have similar economic structures. This convergence process would include an improvement of financial market structures (Ahmed et al., 2002), expanding trade flows (Frankel and Rose, 1998) and

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<sup>22</sup>See also Bai and Ng (2002) and Forni et al. (2000) for a similar approach.

converging inventory technologies and management standards.

### 4.3 Dynamic Transmission Channels between Factors and Efficiency

Using the VAR methodologies described in subsection 3.3, we now turn to analyse the impulse response of efficiency to unexpected shocks to both globalisation and technology factors. We first conduct this exercise using the country-specific VAR. We comply with the usual procedure for determining the lag order and checking for stability conditions of each of the  $N$  country-specific VAR models. Depending on the proxies selected for globalisation and technology factors, we have estimated the country-specific VAR for four different combinations; namely,  $(g_{it}, t_{it}) = \{ (Trade_{it}, EducExp_{it}), (Trade_{it}, Patents_{it}), (FDI_{it}, EducExp_{it}), (FDI_{it}, EducExp_{it}) \}$ . Our main interests lie in the impulse response function of  $e_{it}$  (inefficiency) to a shock in the different proxies of  $g_{it}$  and  $t_{it}$  for each country  $i$ . Here we provide our main empirical findings using the generalized impulse response functions for the case with  $(Trade_{it}, EducExp_{it})$ .<sup>23</sup> Table 2 shows the lag order and the deterministic specification chosen for each country. The responses of  $u_t$  (inefficiency) to one standard deviation shock to each of the  $g_{it}$  and  $t_{it}$  proxies are shown in Figure 2. Considering that inefficiency is measured in terms of the distance from the frontier, a negative impact indicates the catching-up. Our evidence can be summarized as follows:

The impulse responses with respect to  $EducExp_{it}$  are negative for most of the countries whereas Germany, Ireland, Luxembourg, the Netherlands and Spain display (nonnegligible) positive impacts. Impacts are mostly prominent over the short horizons but eventually die out to zero after 10-12 years. Notable exceptions are observed for Italy, Luxembourg and Spain. In particular, there is no sign of convergence for Luxembourg even after 30 years after an initial shock. Interestingly, the impulse responses for Italy display a big swing from an initially negative impact to a large positive value after 3-4 years. Turning to the aggregated or average impulse responses of inefficiency to the shock in  $EducExp_{it}$  provided respectively by AGIRF and MGIRF, we find that their impacts are clearly negative for 4 to 6 years and relatively negligible thereafter. This finding clearly provides evidence in favour of a significant role that the human capital investment proxied by

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<sup>23</sup>The results obtained using the orthogonalised impulse response functions are qualitatively similar. Overall results obtained using other combinations of  $(g_{it}, t_{it})$  are also qualitatively similar, though a notable difference is that technology factors proxied by  $Patents_{it}$  do not always improve efficiencies. Detailed estimation results are available upon request.

education expenditures play in improving the efficiency position on a global scale. A large body of the literature has emphasized the central role played by externalities associated with human capital accumulation (see, e.g. Barro and Sala-i-Martin (2004), Barro (2001), Barro (1991), de la Fuente A. and R. Domenech (2001)). The importance of externalities in this context is highlighted by Lucas (2002), who states that “the existence of important external effects of investment in human capital — in knowledge — has long been viewed as an evident and important aspect of reality”.

The impulse responses with respect to  $Trade_{it}$  are mostly negative for Denmark, Finland, Ireland, the New Zealand Norway and Sweden while they are mostly positive for Australia, Canada, Germany, Greece, Iceland, Luxembourg, Portugal and Spain. Notably, it takes a longer period (about 15-16 years) for the impacts to die out to zero, and there is no sign of convergence for Australia, Canada, Greece and Luxembourg even after 30 years. Turning to AGIRF and MGIRF of trade shocks, we find that their impacts are initially positive and become negative after 5-8 years. Interestingly, MGIRF shows a slightly long-run negative impacts. This suggests that the role of globalisation proxied by trade in promoting efficiency is less clear-cut. Such evidence may reflect that the relative benefit implications of the global trade expansions will be different for trade surplus and deficit countries, though its overall negative impacts on efficiency is somewhat surprising. In this regard, the results of responses to trade shocks may be better summarized by providing the summary statistics for two heterogeneous groups of countries: trade surplus and trade deficit countries. Figure 3 shows that in countries where the current account balance is on average on surplus, trade shock has negative impacts on efficiency over the short-run followed by positive impacts in the long-run. This evidence is in line with theories that highlight the role of export in enhancing productivity though the initial negative impacts may be due to non-negligible initial adjustment costs.<sup>24</sup> Conversely, in the cases where current account balance is on average on deficit, the impact of trade on efficiency is positive and approaches to zero in the long run, confirming the positive effect of openness in boosting productivity only in the short-medium period. In the long-run the positive effect of trade on efficiency of net importers will be compensated by the negative effect of holding a current account deficit. This argument is largely accepted in the literature. Referring to the US current account deficit, for example, Obstfeld and Rogoff (2004) claim that large current deficits cannot be sustained indefinitely.

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<sup>24</sup>Indeed, exporting generally involves fixed costs in the form of establishing distribution networks, creating transport infrastructure, learning about consumers’ tastes, regulatory arrangements and so on in overseas markets.

In sum we find evidence that technology proxied by education expenditure clearly helps countries to improve efficiency position relative to the frontier, suggesting that human-capital investments will be a vital factor in fostering the technology catch-up. On the other hand, our results do not provide any evidence in favour of the positive impacts of globalisation on efficiency on average, although we also show that the implications are significantly different for two heterogeneous groups of trade surplus and deficit countries.<sup>25</sup> Hence, we may conclude that, although there is not an unambiguous evidence across the countries examined, countries' efficiency reacts to shocks to common factors in a significant manner especially in the short run. In particular, our results support the theories that highlight technology innovations as leading factors in spreading efficiency across countries (Pack, 1988, Tybout, 1992, Coe and Helpman, 1995, Coe et al., 1997, Robbins, 1996, Levin and Raut, 1997, Pissarides, 1997, Lichtenberg and van Pottelsberghe de la Potterie, 1998)

## 5 Conclusion

In this paper we estimate a stochastic production frontier and explicitly take into account dynamic technological diffusion. Our motivation stems from the need of better understanding partial dynamic adjustments of efficiency and technological convergence among OECD countries.

The issue of partial dynamic adjustments is at the centre of theoretical debate in the literature on efficiency. The inclusion of short-term economic fluctuations is relevant to a stochastic frontier approach as it arises in an intertemporal context. The stochastic frontier model estimates a long-term equilibrium relationship between output and production factors, without considering the dynamic adjustments which take place in an attempt by agents to achieve equilibrium. Due to time delays, delivery lags and installation costs, the adjustment from current input use to desired future input use is imperfect. This partial adjustment process continues through a number of periods, and is not encapsulated by the estimation of a frontier model based

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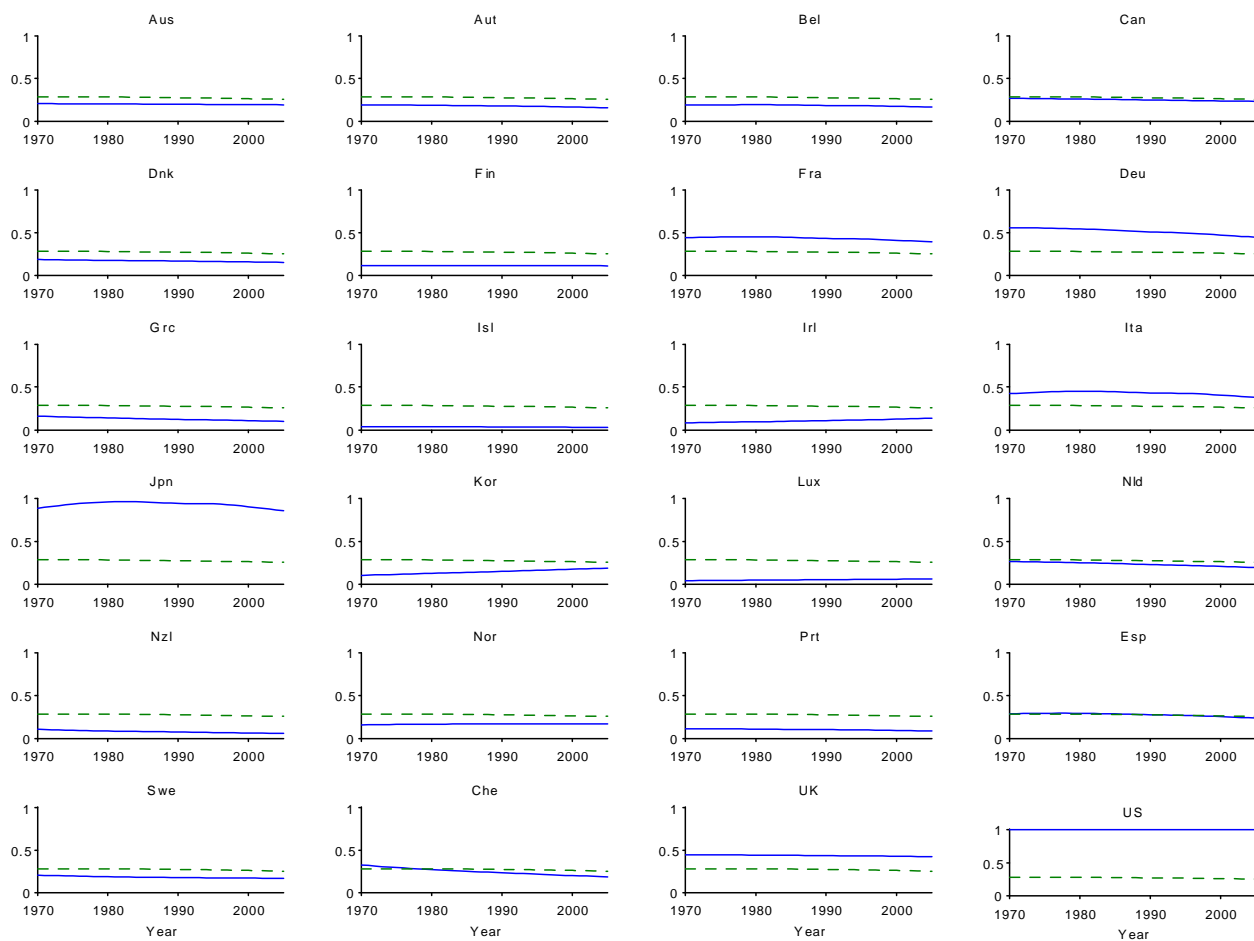
<sup>25</sup>The most relevant relates to: (i) misallocation of labour from research to production of final goods, (ii) disincentives to R&D due to imitation in technology, (iii) the possibility of negative spillover when they are national rather than international in scope. On the other hand, Harrison (1996), Edwards (1998), Frankel and Romer (1999), Sachs and Warner (2001) and Alcalà and Ciccone (2004) document a positive association between openness and economic growth. In particular, Wacziarg and Welch (2003) point to two problematic issue: (i) the vast amount of heterogeneity across country in the regression analysis and (ii) the non-adequacy of a simple dichotomous indicator of openness to discriminate between slow and fast growing countries.

on the implicit assumption of complete adjustment. The failure to incorporate such partial adjustment into the model can lead to the inappropriate classification of an intertemporally efficient producer as being inefficient during the adjustment period. The main scope of this paper is to properly address this issue.

Moreover, growth theory emphasizes the importance to analyze the process of convergence. On this respect our study presents an important attempt to shed some light on the cause of technological convergence which has been stated as playing an important role in determining the productivity growth.

Our methodology implements factor models techniques which allow us to model correlation between factors and regressors. By means of factors we are able to capture the common time variation of efficiency across countries, which we interpret as sluggish adoption of new technology. As a further contribution, we study the dynamic properties of factors by analysing the influence of factors on countries' efficiency over time. We believe that this methodology is an important step to better understand the process of technology diffusion and convergence towards the frontier. Our findings prove the existence of a slow technological adjustment towards the best technology practice (technological frontier) among 24 OECD countries over the observed period 1970-2005. This technology convergence process shows a cyclical pattern of 3-5 year. The VAR analysis illustrates that efficiency is generally affected by common factors over time which act as channels to diffuse common technology, confirming the importance of considering dynamic factors in the analysis of efficiency. Our findings, in particular, highlight that technology innovations as leading factors in spreading efficiency across countries. The spectral analysis indicates that the efficiency and common factor are dominated by short cycles of 3-5 years; there is synchronization and comovement of common efficiency factor and efficiency of European OECD countries and Japan. This result sheds more light on the correlation between common technological shocks and business cycles (Basu, 1996, Basu and Kimball, 1997, Basu and Fernald, 2001).

Figure 1 Country Specific Efficiency and Common Efficiency Factor



Notes: The solid line is the country specific efficiency; the dashed line is the common efficiency factor.

Table 2: Country- VAR specification

	Var orders	trend	quadratic trend
AUS	1	x	
AUT	1	x	
BEL	1	x	
CAN	1		x
DNK	1		x
FIN	1		
FRA	1	x	
DEU	1		x
GRC	1		
ISL	1	x	
IRL	1	x	
ITA	2		x
JPN	1	x	
KOR	1		x
LUX	1		x
NLD	1	x	
NZL	1		
NOR	2		x
PRT	1	x	
ESP	1		
SWE	1		
CHE	1		
GBR	1		x
USA	2		x

Notes: The lag-order selection is conducted on the basis of the Akaike, Schwarz Bayesian and Hannan and Quinn information criteria.

Table 3: Share of Total Variance

	7-10 years	5-7 years	3-5 years
Aus	0.07	0.29	0.39
Aut	0.07	0.26	0.56
Bel	0.07	0.29	0.51
Can	0.09	0.34	0.33
Dnk	0.10	0.34	0.35
Fin	0.08	0.28	0.40
Fra	0.06	0.29	0.54
Deu	0.06	0.24	0.56
Grc	0.08	0.14	0.38
Isl	0.08	0.32	0.50
Irl	0.08	0.22	0.43
Ita	0.06	0.29	0.56
Jpn	0.06	0.28	0.56
Kor	0.05	0.29	0.54
Lux	0.09	0.30	0.40
Nld	0.09	0.33	0.46
Nzl	0.08	0.30	0.43
Nor	0.06	0.27	0.57
Prt	0.08	0.25	0.48
Esp	0.06	0.28	0.56
Swe	0.04	0.23	0.61
Che	0.04	0.28	0.48
UK	0.07	0.28	0.48
US	0.02	0.06	0.34

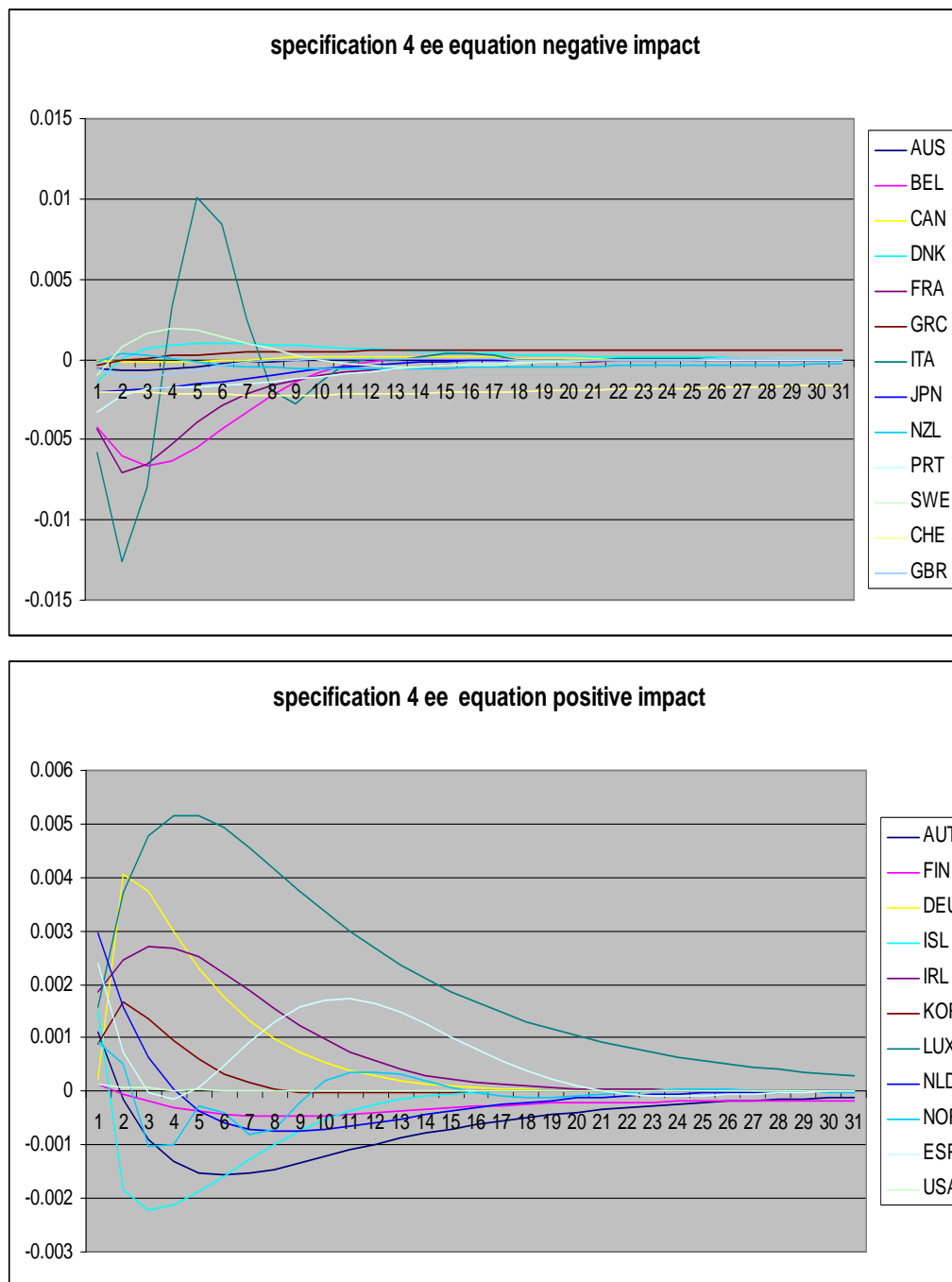
Table 4: Explained Variance

	7-10 years	5-7 years	3-5 years
Aus	0.05	0.21	0.08
Aut	0.06	0.25	0.54
Bel	0.06	0.28	0.48
Can	0.07	0.28	0.11
Dnk	0.07	0.27	0.10
Fin	0.06	0.22	0.16
Fra	0.06	0.28	0.53
Deu	0.06	0.24	0.56
Grc	0.02	0.04	0.04
Isl	0.07	0.31	0.48
Irl	0.05	0.16	0.24
Ita	0.06	0.28	0.55
Jpn	0.06	0.28	0.55
Kor	0.04	0.25	0.42
Lux	0.06	0.23	0.12
Nld	0.09	0.33	0.43
Nzl	0.05	0.23	0.17
Nor	0.06	0.26	0.56
Prt	0.06	0.20	0.31
Esp	0.06	0.28	0.55
Swe	0.03	0.22	0.57
Che	0.02	0.20	0.30
UK	0.06	0.26	0.41
US	0.01	0.02	0.06

Table 5: In-Phase Explained Variance

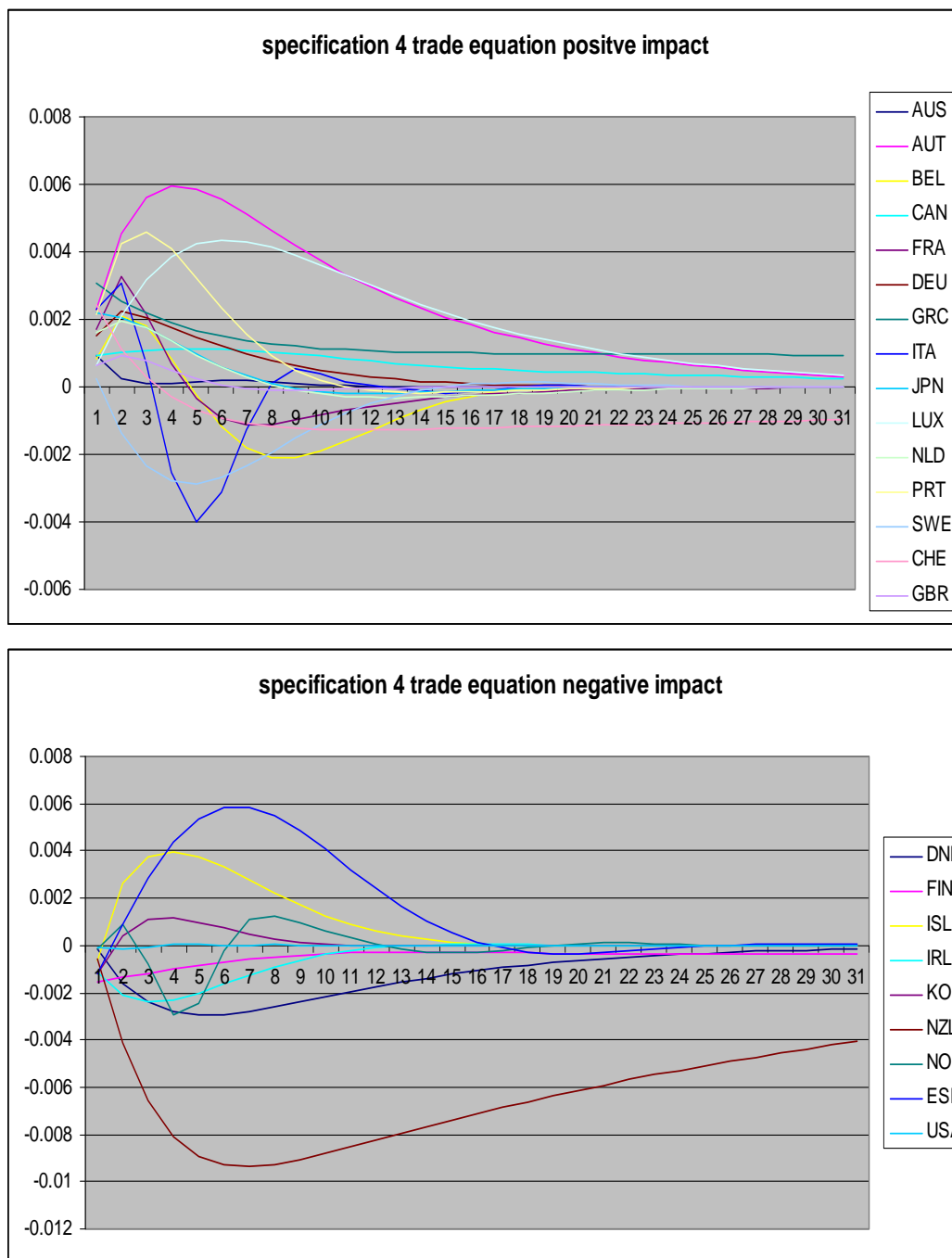
	7-10 years	5-7 years	3-5 years
Aus	0.00	0.00	0.03
Aut	0.06	0.25	0.54
Bel	0.06	0.27	0.47
Can	0.04	0.06	0.05
Dnk	0.02	0.06	0.03
Fin	0.02	0.10	0.13
Fra	0.06	0.28	0.53
Deu	0.06	0.24	0.56
Grc	0.02	0.04	0.02
Isl	0.07	0.30	0.48
Irl	0.05	0.16	0.24
Ita	0.06	0.28	0.54
Jpn	0.06	0.28	0.55
Kor	0.00	0.09	0.36
Lux	0.00	0.00	0.05
Nld	0.08	0.30	0.42
Nzl	0.00	0.02	0.11
Nor	0.05	0.25	0.55
Prt	0.03	0.12	0.29
Esp	0.06	0.28	0.55
Swe	0.03	0.21	0.56
Che	0.00	0.04	0.25
UK	0.05	0.22	0.40
US	0.01	0.02	0.05

Figure 2a



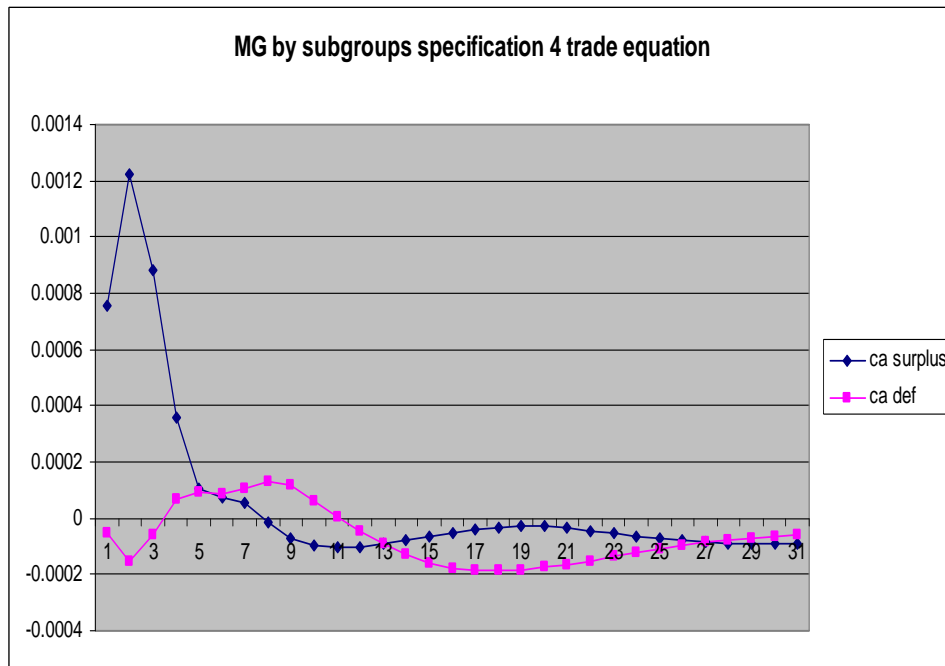
Notes: Country-specific response of inefficiency to one standard deviation shock in  $EducExp_{it}$  in VAR specification 4, i.e.  $(Trade_{it}, EducExp_{it}, e_{it})$ .

Figure 2b



Notes: Country-specific response of inefficiency to one standard deviation shock in  $Trade_{it}$  in VAR specification 4, i.e.  $(Trade_{it}, EducExp_{it}, e_{it})$ .

Figure 3



Notes: MG by subgroups response of inefficiency to one standard deviation shock in  $Trade_{it}$  in VAR specification 4, i.e.  $(Trade_{it}, EducExp_{it}, e_{it})$ . Countries are divided according to current account deficit or surplus.

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