Globalisation and Technological Convergence in EU*

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Abstract

We propose a simple practical approach to model dynamic interactions between common globalisation factors (proxied by FDI and imports) and common efficiency in EU. In particular, we follow recent developments in panel data studies on stochastic frontier that allow for cross-section dependence, and then implement a three dimensional factor VAR model. Empirical results based on the spectral decomposition and the impulse response analyses provide a strong evidence that these globalisation factors are an important transmission channel under which efficiency externalities diffuse across EU countries. Hence, our finding clearly indicates that any protection-oriented policy in response to the ongoing economic and financial crisis will be likely to be detrimental on technological convergence in European countries.

JEL: D24, O47, C13, C33.

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1 Introduction

For the first time since 1982, the world trade registers a decline in 2009 mainly owing to the global recession that has been triggered by the ongoing financial crisis. The contraction in trade also helps to spread further economic contractions initially originated from developed countries to emerging markets. Given the priority to tackle domestic economic problems, the policy makers are tempted towards protecting the national economy by imposing restrictions on imports, reserving government contracts for domestic firms and refusing to help companies who mainly invest abroad. Most countries tend to adopt existing technologies instead of inventing new ones. In a closed economy, new technology already in use in other countries has to be internally produced whereas in an open economy, technology can be transferred through importing of capital goods or the inflows of foreign direct investment (FDI). The issue of importance is whether technical progress is more likely to occur in a closed economy or in open economies.[1]

In this paper we aim to provide contributions to the debate on whether protectionism, that limits both FDI and imports, hampers production efficiency. If knowledge transfer made available by FDI and imports creates efficiency externalities, openness to FDI and imports should raise total factor productivity through increasing efficiency. The growth literature highlights that capital accumulation and technological diffusion should 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. In particular, Bernard and Jones (1996) clearly demonstrate that technological difference is a key factor in explaining income disparities across countries, suggesting that such technology catch-up will be a crucially dominant factor in reaching the steady-state level of per capita output growth.

However, the relationship between economic growth and technology diffusion still remains a conundrum. The issue of dynamic (partial) adjustments is at the centre of theoretical debates on efficiency. Most stochastic frontier models tend

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[1] The infant-industry argument posits that protection can help the domestic (import-substitution) industries such that there will be a dynamic productivity gain in the long-run, Nishimizu and Robinson (1984, 1986), Nishimizu and Page (1991), Pack (1992), Stokey (1991), Rodrik (1998a,b), Rodriguez and Rodrik (2000) and Matsuyama (1992). On the other hand, trade liberalisation is shown to increase the production of high-skill intensive (import-competition) industries, which mainly use the production technology and the capital goods imported, *e.g* Pack (1988), Tybout (1992), Coe and Helpman (1995), Coe *et al.* (1997), Robbins (1996), Levin and Raut (1997) and Pissarides (1997).

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 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 as analysed in 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 exists a transmission mechanism in which technological diffusion plays a significant role in spurring the productivity growth by lowering barriers to flows of foreign goods and investments. This paper aims to address this issue by analysing the dynamic interactions between technological catch-ups and two main transmission channels, FDI and imports, through which technology diffuses, e.g. Borensztein et al. (1998), Griffith et al. (2004) and Cameron et al. (2005). We define these two channels as globalisation factors and focus on the effects of those channels on dynamic adjustments of common EU efficiency.

In a cross-country framework, production inefficiencies can be identified as the distance of the individual production from the frontier as proxied by the maximum output of the reference country regarded as the empirical counterpart of an optimal boundary of the production set. Inefficiencies generally reflect a sluggish adoption of new technologies, and thus efficiency improvement will represent productivity catch-up via technology diffusion. In particular, we consider the factor model where time-varying inefficiency can be represented as a linear combination of observed and/or unobserved factors (Forni and Lippi 1997; Forni and Reichlin, 1998; Kneip et al., 2005), and employ the panel-based stochastic frontier model with unobserved time-varying factors. For consistent estimation, we follow the common correlated effects estimation procedure proposed by Pesaran (2006).[2] By allowing cross-section error dependency via heterogeneous factor loadings, inefficiency can be measured as time-varying common effects. Our approach is thus more general than existing stochastic frontier models that usually neglect the cross-section dependence.

Next, in order to deepen our understanding of the technological catching-up process, we apply a vector autoregressive (VAR) approach to model dynamic interactions between common FDI and import factors and efficiency. First, by applying

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[2] See also Ahn et al. (2007) for a similar approach that is valid only for the panels with a fixed T.

the spectral decomposition and the dynamic correlation analyses of Croux et al. (2001) and Mastromarco and Woitek (2007) to the VAR model, we find that the common efficiency of EU countries takes a cyclical pattern of 3 to 5 years. In particular, business cycles of common inefficiency have a higher co-movement with FDI than imports. The VAR approach also allows us to evaluate the impulse responses of efficiency with respect to (unexpected) shocks of the respective factor equation (FDI and import). We find that both FDI and import exert a positive impact in improving efficiency. Furthermore, the impulse responses of common EU inefficiency with respect to the import shocks reach a peak immediately whilst those with respect to FDI shocks are peaked after 3 years. As the horizon increases, both impacts approach monotonically to zero. In the short run the impacts of import shocks are significantly higher than those of FDI shocks although the latter remain significant over the medium-terms. This evidence is also coherent with the higher synchronization of the dominant cycles of 3-5 years displayed by FDI and inefficiency rather than by import and inefficiency. This finding on the significant lagged impacts of the FDI shocks provides a support for evidence that the knowledge embodied in FDI requires a substantial time period to be fully transferred for efficiency externalities, e.g. Cohen and Levinthal (1989, 1990), Tybout (1992) and Coe and Helpman (1995).

In sum, globalisation factors proxied by imports and FDI, with different dynamics, clearly help EU countries improving their efficiency position relative to the frontier, suggesting that openness will be a vital factor in fostering the technology catch-up. Hence, our empirical results provide a support for positive externalities associated with openness, e.g. Edwards (1998), Frankel and Romer (1999), Barro (2001), Sachs and Warner (2001), and Barro and Sala-i-Martin (2004) and shed some light on the dynamics of these effects.

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.

2 Stochastic Frontier Modelling in Panels

The large literature on stochastic frontier modelling posits that the production frontier is common to all countries:

$$y_{it} = f\left(x_{it}\right)\tau_{it}\omega_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{1}$$

where τ_{it} is the efficiency measure with $0 < \tau_{it} < 1$, and ω_{it} captures the stochastic nature of the frontier. Supposing that the production frontier, $f\left(x_{it}\right)$, assumes the

Cobb-Douglas form, then we obtain the log-linear specification:

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

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

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

where $v_{it} = \ln \omega_{it}$ is an idiosyncratic noise and $u_{it} = -\ln \tau_{it} \geq 0$ (logged) technical inefficiency.[3] Then, technical efficiency of country i at time t can be easily obtained by

$$\tau_{it} = \exp\left(-u_{it}\right). \tag{2}$$

However, the above modelling approach is too restrictive to appropriately represent technical efficiency. Battese and Coelli (1995) propose a model that directly analyses 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 η_{it} a truncated random disturbance usually assumed to follow a truncated normal distribution.

Alternative specifications have been proposed by Cornwell et al. (1990), Kumbhakar (1990), Battese and Coelli (1992) and Lee and Schmidt (1993), suggesting the following model:

$$y_{it} = \alpha_{it} + \boldsymbol{\beta}' \mathbf{x}_{it} + v_{it}, \tag{3}$$

where

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

Assuming that α_{it}'s can be estimated consistently under sufficiently weak restrictions, then inefficiency can be estimated consistently as

$$\hat{u}_{it} = \hat{\alpha}_* - \hat{\alpha}_{it} \qquad \text{where} \quad \hat{\alpha}_* = \max_i(\hat{\alpha}_{it}). \tag{4}$$

In order to encompass the specifications proposed in the previous studies, Ahn et al. (2007) propose the following factor-based specification:

$$\begin{aligned} y_{it} &= \alpha_{it} + \mathbf{x}_{it}' \boldsymbol{\beta} + v_{it}, \\ \alpha_{it} &= \sum_{j=1}^{p} \theta_{jt} \alpha_{ij}, \end{aligned} \tag{5}$$

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[3] When $\tau_{it} = 1$, the country i produces on the full efficiency frontier. Inefficiency is ranked as $u_{Nt} \leq \ldots \leq u_{1t}$ such that country N produces with maximum efficiency.

where θ_{jt}, $j = 1, ..., p$, are unobservable factors. By estimating θ_{jt} directly as parameters, this approach does not need to impose any particular factor structure. Kneip et al. (2005) propose 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 that factors can play an important role in the stochastic frontier approach.

Following recent trends in the literature, this paper aims to explicitly investigate the dynamic interaction between time-varying efficiencies and the common global factors.[4] In particular, we wish to explicitly analyse the impacts of globalization factors on the diffusion of common technology efficiencies. To this end we turn to the alternative approaches advanced by Coakley et al. (2002) and Pesaran (2006). In particular, Pesaran (2006) considers a generalized panel data model:

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\pi}_i'\mathbf{s}_t + \varepsilon_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{6}$$

with the two-way error components structure,

$$\varepsilon_{it} = v_{it} - u_{it} = v_{it} - (\alpha_i + \varphi_i \theta_t), \tag{7}$$

where θ_t is the time-specific effects common to all cross section units, and α_i is an individual specific effect. We now have both observed and unobserved factors: $\mathbf{s}_t = (s_{1,t}, ..., s_{s,t})'$ is an $(s \times 1)$ vector of observed factors, regarded as proxies for common global shocks such as changes in oil prices, with the conformable parameter vector, $\boldsymbol{\pi}_i = (\pi_{1,i}, ..., \pi_{s,i})'$, whist θ_t is an unobserved common time-specific effect, that could arise as a result of unobserved global factors such as the diffusion of technological progress, with φ_i capturing heterogeneous individual responses with respect to θ_t. The distinguishing feature of the model given by (6) and (7) is that it allows us to accommodate certain degrees of cross section dependence of ε_{it} via heterogeneous factor loading coefficient, φ_i. It is easily seen that various econometric specifications proposed in the literature can be expressed as a variation of (6) and (7).

3 Analysis of Dynamic Efficiency

In this section we describe our estimation steps in details. First, we employ the generalised stochastic frontier specification described in Section 2, and obtain consistent estimates of unobserved global efficiency measures. Secondly, we apply a

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[4] Factors are defined as global variables that underlie common shocks, drive comovements of variables but are not explicitly specified in the baseline regression. Omitting factors may lead to serial and cross-section correlated residuals though those are usually neglected in stochastic frontier literature.

vector autoregressive (VAR) model to observed globalisation factors and global efficiency measures and investigate their dynamic interactions through the spectral analysis and the impulse response functions.

The modelling approach proposed in this section allows us to consider at least three fundamental issues related to the dynamic evolution of technology efficiencies: (i) to relax the restrictive assumption that efficiency is independent of the regressors (Schmidt and Sickles, 1984); (ii) to accommodate possibly nonstationary factors and nonstationary variables (Kapetanios et al., 2006); (iii) to study the effect of factors on efficiency and thus analyse technological catch-up effects over time through factors.

3.1 Estimation of Time-varying Efficiency

We now consider the model, (6) with only unobserved factors:

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \varepsilon_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{8}$$

$$\varepsilon_{it} = \alpha_i + u_{it},\ u_{it} = \varphi_i\theta_t + v_{it}. \tag{9}$$

The conventional panel data estimation such as the fixed or the random effects estimator of $\boldsymbol{\beta}$ obtained from (8) would be seriously biased without properly accommodating the error component structure given by (9), as confirmed by Monte Carlo studies by Kapetanios and Pesaran (2005). Hence, in order to obtain consistent estimates of $\boldsymbol{\beta}$, α_i and $f_{it} = \varphi_i\theta_t$, we consider the transformed specification by augmenting (8) with cross-sectional averages of y_{it} and $\mathbf{x}_{it}$:[5]

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\pi}_i'\mathbf{f}_t + \alpha_i^* + v_{it}, \tag{10}$$

where $\mathbf{f}_t = (\bar{y}_t, \bar{\mathbf{x}}_t')'$. Pesaran (2006) shows that as $N, T \to \infty$, $\boldsymbol{\beta}$, $\boldsymbol{\pi}_i$ and α_i^* can be consistently estimated by the Pooled Common Correlated Effects (hereafter, PCCE) estimator, denoted $\hat{\boldsymbol{\beta}}_{PCCE}$, which is simply the pooled OLS estimator obtained from (10).[6]

It is easily seen from (8) and (9) that inefficiency can be measured with respect to $\max_i (\alpha_i + \varphi_i\theta_t)$ at each point of time, namely

$$e_{it} = u_{it} - \max_i u_{it} = (\alpha_i + \varphi_i\theta_t) - \max_i (\alpha_i + \varphi_i\theta_t), \tag{11}$$

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[5] We assume: (i) $v_{it} \sim iid\left(0, \sigma_v^2\right)$. (ii) $\alpha_i \sim iid\left(\alpha, \sigma_\alpha^2\right)$. (iii) $E\left(\alpha_i v_{jt}\right) = 0$ and $E\left(\theta_t v_{it}\right) = 0$ for all i, j, t. (iv) $E\left(\mathbf{x}_{it} v_{js}\right) = \mathbf{0}$, $E\left(\mathbf{s}_t v_{is}\right) = \mathbf{0}$ 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.

[6] Furthermore, Pesaran (2006), Kapetanios et al. (2006) show that the PCCE estimator is consistent even when the variables and/or factors are non-stationary. This provides an additional advantage over the method proposed by Kneip et al. (2005) who assume that factors are stationary.

showing that we need to obtain consistent estimates of heterogeneous parameters of α_i and $\boldsymbol{\pi}_i$ for $i = 1, ..., N$ in (10). Replacing $\boldsymbol{\beta}$ by $\hat{\boldsymbol{\beta}}_{PCCE}$ in (10) and rearranging the result, we have:

$$\tilde{y}_{it} = \alpha_i^* + \boldsymbol{\pi}_i' \mathbf{f}_t + \tilde{u}_{it},\ i = 1, ..., N,\ t = 1, ..., T, \tag{12}$$

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

$$\hat{e}_{it} = \hat{u}_{it} - \max_i \hat{u}_{it} = \left(\hat{\boldsymbol{\pi}}_i' \mathbf{f}_t + \hat{\alpha}_i^*\right) - \max_i \left(\hat{\boldsymbol{\pi}}_i' \mathbf{f}_t + \hat{\alpha}_i^*\right). \tag{13}$$

Once consistent estimates of $\hat{e}_{it}$ are obtained, the global efficiency measure can be constructed as the cross-sectional average:

$$\bar{e}_t = N^{-1} \sum_{i=1}^{N} \hat{e}_{it}. \tag{14}$$

This measure will provide a valid proxy under the common production frontier assumption maintained by stochastic frontier models.

3.2 VAR Analysis of Efficiency and Factors

We now employ the VAR analysis and examine the dynamic evolution of common EU efficiency with respect to main factors or determinants that proxy for globalization effects. We consider an aggregate VAR(p) model for the $(m+) \times 1$ vector, $\bar{\mathbf{z}}_t = (\bar{\mathbf{g}}_t, \bar{e}_t)'$,

$$\bar{\mathbf{z}}_t = \sum_{j=1}^{p} \boldsymbol{\Phi}_j \bar{\mathbf{z}}_{t-j} + \boldsymbol{\varepsilon}_t,\ \boldsymbol{\varepsilon}_t \sim iid\left(\mathbf{0}, \boldsymbol{\Sigma}\right), \tag{15}$$

where $\bar{\mathbf{g}}_t$ is an $m \times 1$ vector of common effects proxied by the cross-section average of the globalization factors, $\bar{e}_t$ the common inefficiency measures defined by (14), $\boldsymbol{\Phi}_i$'s a $(m+1) \times (m+1)$ matrix of unknown coefficients, p is the lag order selected on the basis of the information criteria, and it is assumed that $E\left(\boldsymbol{\varepsilon}_{it}\right) = \mathbf{0}$ and $E\left(\boldsymbol{\varepsilon}_{it} \boldsymbol{\varepsilon}_{is}'\right) = \boldsymbol{\Sigma}$ for $t = s$ with $\boldsymbol{\Sigma}$ being a $m \times m$ symmetric positive definite matrix.

3.2.1 Spectral analysis

We briefly describe how the relative importance of efficiency cycle in EU can be analysed by employing the spectral analysis. Consider the bivariate spectrum of two stationary time series x_t and y_t which is defined as the Fourier transform of the covariance function, $\mathbf{\Gamma}_{xy}$:

$$\mathbf{F}_{xy}(\omega) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{\infty} \mathbf{\Gamma}_{xy}(\tau) e^{-i\omega\tau}, \ \omega \in [-\pi, \pi], \tag{16}$$

where the off-diagonal cross-spectrum at frequency ω is given by

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

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

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

which assesses the degree of a linear relationship between x_t and y_t at each frequency.[7]

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 and unexplained parts as follow:

$$\int_{\omega_1}^{\omega_2} f_y(\omega) d\omega = \int_{\omega_1}^{\omega_2} sc(\omega) f_x(\omega) d\omega + \int_{\omega_1}^{\omega_2} f_u(\omega) d\omega. \tag{17}$$

This decomposition enables us to compare the degree of a linear relationship between cycles of different series over frequency intervals of interest. Furthermore, we decompose the explained variance into the in-phase component and the out-of-phase component respectively by (Mastromarco and Woitek, 2007)

$$\int_{\omega_1}^{\omega_2} sc(\omega) f_x(\omega) d\omega = \int_{\omega_1}^{\omega_2} \frac{[c_{xy}(\omega)]^2}{f_x(\omega) f_y(\omega)} f_x(\omega) d\omega + \int_{\omega_1}^{\omega_2} \frac{[q_{xy}(\omega)]^2}{f_x(\omega) f_y(\omega)} f_x(\omega) d\omega, \tag{18}$$

where we use $|f_{xy}(\omega)|^2 = [c_{xy}(\omega)]^2 + [q_{xy}(\omega)]^2$. (18) clearly shows that the importance of the phase shift in a frequency interval is now explicitly incorporated to (17). Notice that information about co-movement or synchronisation in the frequency bands of interest are provided by the in-phase component of explained variance.

From the VAR(p) model, (15), we can obtain the $m \times m$ spectral density matrix by

$$\mathbf{F}_{\mathbf{z}}(\omega) = \frac{1}{2\pi} \mathbf{\Phi}(\omega)^{-1} \mathbf{\Sigma} \mathbf{\Phi}(\omega)^{-1*}, \ \omega \in [-\pi, \pi], \tag{19}$$

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[7] This has a similar interpretation to R^2 obtained from linear regressions in time domain.

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 common globalization factors and the common efficiency term. Using (19), we then derive the cross-spectra and the in-phase explained variance. This enables us to judge the extent to which cycles of globalization factors and of the efficiency move together.

3.2.2 Impulse response analysis

Using the flexible impulse response analysis, we will be able to uncover the important transmission channels through which technology diffuses.[8] Following the standard derivations (Pesaran and Shin, 1998), we obtain the $(m+1) \times 1$ vector of the orthogonalized impulse response function of a unit shock to the jth equation's orthogonalised innovation on $\bar{\mathbf{z}}_{t+h}$ as

$$\mathbf{o}_j(h) = (\mathbf{\Theta}_h \mathbf{P})\, \mathbf{e}_j,\ h = 0, 1, 2, ..., \tag{20}$$

where $\mathbf{\Theta}_h$ is a $(m+1) \times (m+1)$ VMA coefficient matrix obtained from (15), $\mathbf{P}$ a $(m+1) \times (m+1)$ lower triangular matrix obtained from the Cholesky decomposition of $\mathbf{\Sigma} = \mathbf{PP}'$, and $\mathbf{e}_j$ a $(m+1) \times 1$ selection vector with unity as its jth element and zeros elsewhere. Similarly, we obtain the generalized impulse response function by

$$\mathbf{g}_{,j}(h) = \sigma_{jj}^{-\frac{1}{2}} \mathbf{\Theta}_h \mathbf{\Sigma} \mathbf{e}_j,\ h = 0, 1, 2, ... \tag{21}$$

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

4 Empirical Results

The data used cover 18 countries of the EU members (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK) over the period, 1970-2004 (35 years). GDP is measured in million dollars (2000 = 100), labour measured as total employment, and capital constructed using the perpetual inventory method (PIM).[9] All three variables are logged before estimating

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[8] The forecast error variance decomposition and/or the probability event forecasting exercises can be further easily implemented, see Garratt *et al.* (2006).

[9] PIM is common and 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;

stochastic frontier. For globalization factors we identify two most important channels: import and FDI inflow, and collect the data on import and FDI, measured as net inflows of foreign direct investment. These variables are then transformed as percentage of GDP. Data sources are as follows: capital is sourced from PWT 6.2, labour measurement from OECD Labour Force Statistics; GDP, import and FDI from the World Bank World Development Indicators.

Table 1 shows descriptive statistics. FDI is much more volatile than imports. Looking at individual countries, imports of Belgium, Ireland, Luxembourg and the Netherlands are much larger than rest of countries. FDI of Belgium, Ireland and Luxembourg are large whereas Germany shows a very tiny figure. Also imports and FDI of Italy are relatively smaller. Notably, as documented in official figures, the tiny country of Luxembourg is on average the largest recipient of FDI and largest trade oriented.[10]

[Table 1 about here]

4.1 Stochastic Frontier and Inefficiency

Table 2 summarises the estimation results of the stochastic frontier model given by (8) and (9) by alternative estimations; namely Pooled OLS (POLS), Fixed Effect (FE) and PCCE estimators. Both labour and capital elasticities are all statistically significant and labour's contributions are significantly higher as expected. The POLS and FE estimates turn out to be surprisingly high, which is generally inconsistent with most empirical studies.[11] This may suggest that both POLS and FE estimates are biased upward owing to neglecting cross-section error dependency across the European countries, that is highly likely to be present in our sample. This suspicion is confirmed by applying the general diagnostic test

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Bernanke and Gurkaynak, 2003; 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 1950, we set the initial stock, $K_{1949} = K_{1949}/(g+\theta)$, where g is the 10-year output growth rate from 1950 to 1960. The estimated capital stock includes both residential and nonresidential capital.

[10] These figures are due to 'trans-shipped' FDI, *i.e.* how companies transfer funds between affiliates within the same group located in different countries, or channel funds to acquire companies in different countries through a holding company established in Luxembourg. This country offers very favorable conditions such as tax exemptions for holding companies and corporate headquarters. For those reasons, Luxembourg is often treated as an outlier in studies that focus on openness, see Daniels et al. (2005) and Edwards (1998) among others. Following this reasoning we also dropped Luxembourg out of the sample and obtained qualitatively similar results.

[11] Constant-returns-to-scale technology has been generally accepted for OECD countries, *e.g.* Iyer et al. (2008).

for cross-section dependency (CD) advanced by Pesaran (2004) and finding evidence of cross-section dependence at 1% significance level. The PCCE estimates provide more reliable estimates of labor and capital elasticities respectively at 0.58 and 0.40, supporting the widely accepted empirical evidence that technology in European countries follows constant returns to physical capital and labour, as also confirmed by an insignificant t-ratio for the sum of elasticities being equal to unity.

[Table 2 about here]

Hence, we employ more reliable estimates of both labour and capital elasticities given by PCCE estimation, and use (12), (13) and (14) to evaluate individual and common inefficiency measures, $\hat{e}_{it}$ and $\bar{e}_t$.

4.2 Dynamic Analysis of Common Efficiency and Factors

We now examine the dynamic interaction between the common time-varying efficiencies in EU proxied by $\bar{e}_t$, and the two common global factors, import and FDI, that have been identified as most important channels of technology diffusion in the literature (Romer, 1990; Barro and Sala-i-Martin, 1995; Borensztein et al., 1998). After complying with the usual procedure for determining the lag order and checking for stability conditions, we fit the following trivariate VAR(1) model:[12]

$$\bar{\mathbf{z}}_t = a + \mathbf{\Phi}_j \bar{\mathbf{z}}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{22}$$

where $\bar{\mathbf{z}}_t = \left(\overline{FDI}_t, \overline{M}_t, \bar{e}_t\right)'$, $\overline{FDI}_t$, $\overline{M}_t$ are cross-section averages of the logged ratios of FDI and import to GDP.

Figure 1 gives a visual impression of the change of common efficiency $(\bar{e}_t)$ and the global factors $\left(\overline{FDI}_t \text{ and } \overline{M}_t\right)$ over time. Over the whole sample period from 1970 to 2004, efficiency and total imports grow positively by 9% and 37%, respectively, whilst FDI negatively by 75%. If we split the sample in two subperiods - 1970-1998 and 1999-2004 -, we then find that all three variables grow positively in the first subperiod: namely, efficiency by 6% , FDI by 52% and total imports by 30%. On the other hand in the second period (1999-2004), efficiency and imports grow of around the 2% and the 5% respectively, while FDI registers a decline of the 126%. This descriptive analysis provides some preliminary insights on the interaction of the sources of the EU productivity over time. Indeed the slowdown of EU productivity and FDI in the last years of our analysis are somehow related. Taylor (2007) describes how the peak in 1999-2000 in European FDI flows might be attributable both to the favourable conditions created by the single

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[12] To save the space we do not report the estimation results of (22), which will be available upon request, though displaying that there is no serious misspecification.

currency and to merge and acquisition operations that largely involved the services sectors' companies (telecommunications and capital intense fields suche as oil, gas production and banking). As a matter of facts the crises that hit those sectors after 2000 mostly accounts for the decline in both productivity (see van Ark et al., 2007) and FDI flows.

[Figure 1 about here]

4.2.1 Spectral analysis of efficiency

We now investigate the stylised features of the common inefficiency estimates, $\bar{e}_t$ and two common factors, $\overline{FDI}_t$, $\overline{M}_t$, by spectral analysis. Our efficiency measure, by capturing the effects of globalisation factors, differs from what commonly used in the literature and it is expected to shed further light on the issue as to how globalisation shocks affect productivity.

It is generally accepted that the recent decline in EU productivity has largely resulted from weak growth in total factor productivity (TFP). Slow technological catch-up often causes the lack of convergence in output levels, *e.g.*, Mankiw et al. (1992) and Barro and Sala-i-Martin (1995). Technological catch-up or an increase in efficiency represents movement towards the frontier, though it does not necessarily imply that technology transfer will reduce the gap between outperforming and underperforming countries, since the former may benefit from efficiency improvements as much as or even more than the latter.

To better evaluate the technological catching-up process of the European countries under analysis, we turn to synchronisation of the business cycle of the common efficiency and the globalization factors.[13] To identify the relative importance of the relationship between these components over the 3 to 10 years range, we evaluate the spectra of the VAR model, (22), and then derive the in-phase component of explained variance as a measure of synchronisation.[14]

Table 3 reports the proportion of share variances, explained variances and in-phase explained variances in the frequency bands of interests (*e.g.* Zarnowitz (1992)), *i.e.* the cycles with a length of 3-5 years (the Kitchin cycle), of 5-7 years and 7-10 years (the Jugular cycle). We find that common inefficiency is dominated by the shortest cycles of 3-5 years.

[Table 3 about here]

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[13] See Bai and Ng (2002) and Forni et al. (2000) for a similar approach.

[14] The partial squared coherency can be used to calculate the proportion of variance in a certain frequency band due to a specific variable, with the influence of the other variables removed, see Koopmans (1974). This measure enables us to consider isolated effects of fluctuations in imports and FDI on common efficiency.

This result is also confirmed by Figure 2 that reports the variance of inefficiency, the explained and in-phase variance at each frequency band of imports and FDI. The dominant cycle of efficiency is of around 4 years and it shows somewhat weak co-movements with both imports and FDI. Especially, weak co-movements with FDI can be explained by the adjustment costs involved in FDI before spurring efficiency externalities, e.g. Tybout (1992) and Coe and Helpman (1995). Indeed the knowledge embodied in FDI requires a substantial time period to be fully transferred and absorbed. This result is in accordance with Cohen and Levinthal (1989, 1990), who observe that the competence to evaluate and utilize outside knowledge is largely a function of prior related knowledge. Notice also that common inefficiency shows higher synchronization with FDI rather than with imports both in the dominant cycles and in higher frequency cycles, providing evidence of higher persistence of the FDI shocks on efficiency in the short-medium periods, as presented in the impulse response results (see Figures 3a and 4a).

[Figure 2 about here]

4.2.2 Dynamic transmission channels between common factors and efficiency

Using the VAR model, (22), we turn to analyse the impulse response of common EU efficiency, $\bar{e}_t$, to unexpected shocks to two globalisation factors, $\overline{FDI}_t$ and $\overline{M}_t$. Figures 3 and 4 show the impulse responses of $\bar{e}_t$ to one standard deviation shock to each of the $\overline{FDI}_t$ and $\overline{M}_t$ equations.[15]

The impulse responses of common EU inefficiency with respect to the FDI shocks are mostly negative, and therefore FDI is proved to be important in promoting efficiency. Interestingly, we find that the impulse responses are peaked at 3 years after the initial shock, and then gradually approach zero as the horizon increases. In particular, we find that, at the peak, 1% increase in FDI will cause a 0.019 increase in efficiency.[16] The cumulative IRFs also show that FDI has a positive effect on efficiency in the medium- and the long-run.

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[15] Since inefficiency is measured in terms of the distance from the frontier, a negative impact indicates the catching-up.

[16] In order to facilitate the interpretation of the IRFs and to render them broadly comparable to the dynamic multipliers derived under the traditional ARDL models, we consider prudent to re-normalise them such that the impact effect of a shock to the j-th equation on the j-th variable is unity. Namely, we divide the IRFs of FDI shocks by the impact effect of FDI shock on FDI and the IRFs of import shocks by the impact effect of import shock on import. Thus we are able to evaluate the effect on efficiency relative to 1% increase in FDI and import, respectively. In what follows we calculate the marginal effect of efficiency with respect to log of FDI as $\left(\frac{\partial \exp(-\bar{e}_t)}{\partial \overline{log(FDI)}_t}\right)$ and with respect to log of imports as $\left(\frac{\partial \exp(-\bar{e}_t)}{\partial \overline{log(M)}_t}\right)$

Next, we also find that the impulse responses of common EU inefficiency with respect to import shocks are negative, reach a peak immediately and approach monotonically zero as the horizon increases. At the peak, 1% increase in import will cause a 0.023 increase in efficiency. The responses are significantly different form zero in the first two years at the 5% significance level, and the cumulative effects show that the import shocks have a long run positive effect on efficiency. This result provides support for the beneficiary implication of the global trade expansion, documented by Harrison (1996), Edwards (1998), Frankel and Romer (1999), Sachs and Warner (2001) and Alcal'a and Ciccone (2004), and thus confirm the positive effect of openness in boosting productivity.

This evidence provides a general support for an earlier result obtained by the spectral analysis where 3-5 years business cycles of efficiency and FDI display higher synchronization than those of efficiency and imports, demonstrating the higher persistence of FDI shocks on efficiency.

[Figures 3 and 4 about here]

In sum, globalisation factors proxied by import and FDI clearly help EU countries improving their efficiency position relative to the frontier, suggesting that openness will be a vital factor in fostering the technology catch-up. The impulse response analysis demonstrates that the positive impact of import on efficiency is much quicker and less persistent than that of FDI, confirming that technology catch-up in response to foreign direct investments may require a substantial time period before take-off. Hence, our findings provide a strong support for the theory that highlights globalisation as leading factor in spreading efficiency across countries.

5 Conclusion

This paper aims to address an important policy issue on whether there exists a transmission mechanism under which technological diffusion plays a significant role in spurring the productivity growth by lowering barriers to flows of foreign goods and investments. To this end we propose a practical two-step approach: in the first step we estimate the panel-based stochastic frontier model with unobserved time-varying factors, and obtain consistent estimates of individual and global time-varying inefficiency measures in EU. Next, we apply a trivariate VAR approach to model dynamic interactions of common efficiency and two globalisation factors, FDI and imports.

The methodology implemented allows us to study the dynamic properties of common efficiency and factors, and to further investigate the influence of such factors on global efficiency in a dynamic setting. Our main empirical findings are summarised as follows: (i) the European technology efficiency process shows a cyclical pattern of 3-5 year; (ii) both imports and FDI appear to be weakly synchronised with the common efficiency cycles; (iii) the impulse response analysis illustrates that global efficiency is affected positively by the shocks to FDI and import factors, both of which act as channels to diffuse common technology in the medium- and the long-run; (iv) the responses of common EU inefficiency with respect to the import shocks reach a peak immediately whilst those with respect to the FDI shocks are peaked after 3 years. This result is in line with the evidence provided by spectral analysis (higher synchronization of the dominant cycles of 3-5 years of efficiency and FDI) and proves that the knowledge transfer associated with FDI requires a substantial time period to diffuse efficiency externalities and drives more persistent effects.

Hence, our findings stress the importance to consider time delay in evaluating the effects of external factors on efficiency. Our evidence strongly supports the studies that highlight globalisation as a leading factor in spreading efficiency across countries, suggesting that the effects of protectionist policy will be more detrimental on technology efficiency and catch-up in the European Union, which will be likely to exert further negative impacts on the global economy under the current financial turbulence and global recession.

Table 1: Descritive statistics for variables used in estimations

		y	k	l	M	FDI
AUT	mean	25.65	15.79	8.11	35.67	0.85
	sd	0.25	0.28	0.09	4.89	0.97
BEL	mean	25.87	15.68	8.24	63.87	7.62
	sd	0.23	0.23	0.04	9.50	1.19
DNK	mean	25.52	15.93	7.84	34.57	1.99
	sd	0.19	0.15	0.05	3.35	3.96
FIN	mean	25.17	16.03	7.74	28.02	1.26
	sd	0.26	0.13	0.06	2.77	2.17
FRA	mean	27.6	15.77	10.02	21.87	1.07
	sd	0.24	0.22	0.05	3.03	1
DEU	mean	27.97	15.96	10.32	24.49	0.16
	sd	0.23	0.15	0.15	4.35	2.13
GRC	mean	25.2	15.49	8.19	25.80	0.87
	sd	0.22	0.1	0.1	4.11	0.4
ISL	mean	22.48	15.74	4.8	36.38	0.94
	sd	0.33	0.29	0.2	3.73	1.19
IRL	mean	24.54	15.13	7.12	57.99	4.37
	sd	0.5	0.34	0.17	11.46	6.76
ITA	mean	27.43	15.72	9.94	20.90	0.45
	sd	0.24	0.19	0.04	2.85	0.34
LUX	mean	23.11	16.06	5.23	91.6	77.94
	sd	0.43	0.31	0.23	16.5	42.1
NLD	mean	26.32	16.01	8.68	52.66	2.94
	sd	0.25	0.1	0.19	4.94	3.68
NOR	mean	25.41	16.12	7.59	34.68	1.12
	sd	0.34	0.21	0.11	4.35	1.16
PRT	mean	25.01	15.11	8.36	33.62	1.52
	sd	0.33	0.27	0.11	4.44	1.51
ESP	mean	26.7	15.36	9.49	20.30	1.73
	sd	0.28	0.27	0.11	5.47	1.48
SWE	mean	25.93	15.92	8.33	31.19	2.37
	sd	0.2	0.11	0.04	4.50	4.47
CHE	mean	26.02	16.4	8.18	33.35	0.9
	sd	0.15	0.12	0.12	3.42	2
GBR	mean	27.67	15.38	10.15	26.93	2.09
	sd	0.23	0.25	0.04	2.56	1.6

Table 2: Estimates of inputs elasticity

	β_k	β_l
POLS	0.69*	0.98*
	(0.02)	(0.01)
FE	0.99*	0.57*
	(0.02)	(0.04)
PCCE	0.40*	0.58*
	(0.18)	(0.13)
t_{crs}	-0.12	$p-value$ 0.89
CD	13.3	$p-value$ 0.00

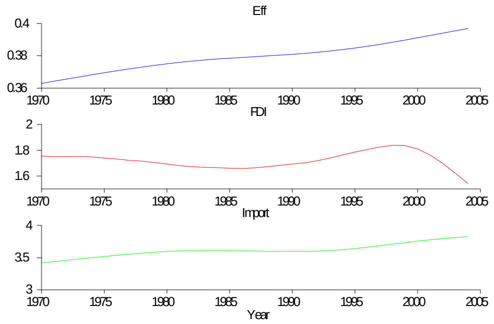
Notes: Labour is measured by total employment and Capital is measured as stock of capital, PCCE estimates have been performed using the following sets of observed and unobserved factors: unobserved factor $\left(\bar{k}_t\right)$ and observed factors ($\bar{s}_t$= M, FDI); t_{crs} denotes t-test for the hypothesis of constant return to scale in the case of PCCE estimates; CD denotes the general diagnostic test for cross-section dependency described in Pesaran (2004); * denotes significance at 1 per cent level; standard errors in parenthesis. Some omissis in the number of factors included in the estimation have been made on the basis of statistical significance.

Table 3: Average Group spectral analysis

	7-10 years	5-7 years	3-5 years
share of total variance	0.011	0.258	0.354
$\bar{M}_{t-1}$			
explained	0.004	0.225	0.248
in-phase	0.004	0.013	0.176
$F\bar{D}I_t$			
explained	0.006	0.245	0.255
in-phase	0.005	0.128	0.214

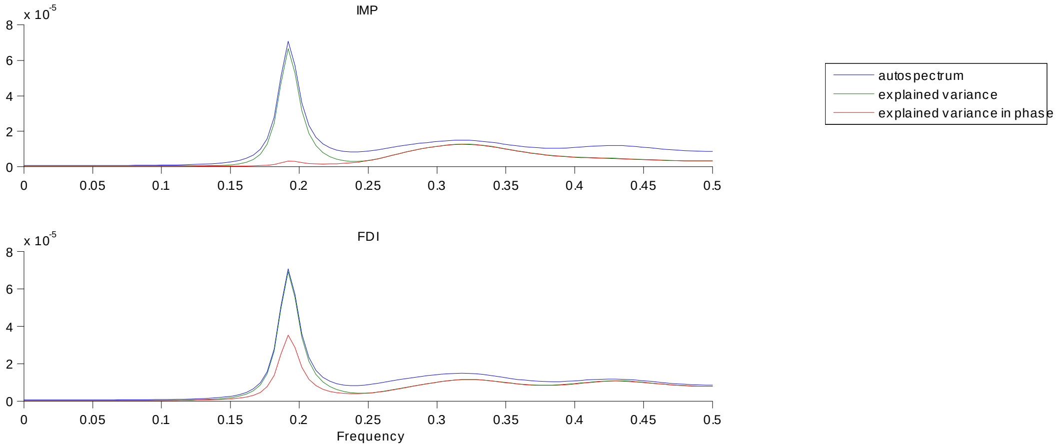
Notes: Columns 1 to 3 report: i) the estimates of variance shares in frequency ranges; ii) fraction of these variance shares that can be explained by the cycles of import and FDI; iii) the in-phase component.

Figure 1: Common efficiency and global factors ($\overline{M}_t$ and $\overline{FDI}_t$) over time



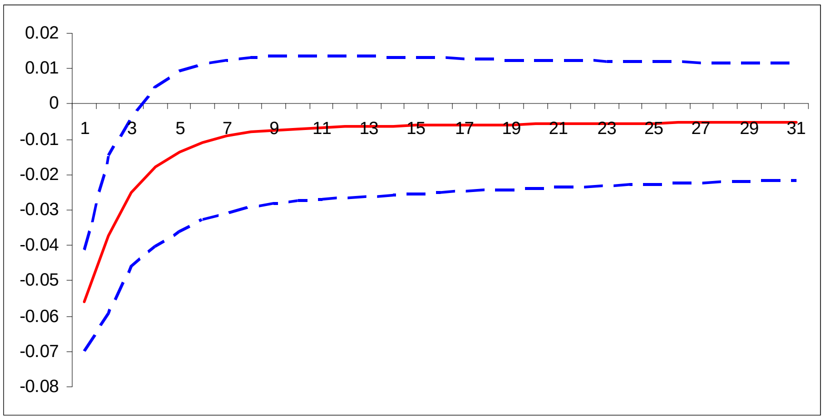
Notes: The first graph presents common efficiency, $E\bar{F}F_t = exp(-\bar{e}_t)$, the second log of $\overline{FDI}_t$, and the third log of Imports, $\overline{M}_t$.

Figure 2 Comovement of business cycles of common inefficiency and $\overline{M}_t$ and $\overline{FDI}_t$ factors.



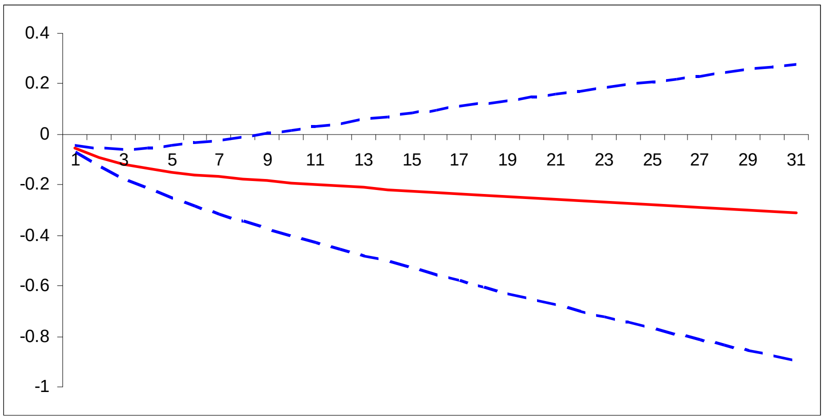
Notes: The first line (autospectrum) is the variance of common inefficiency at each frequency, the second line is the explained variance of $\overline{M}_t$ and $\overline{FDI}_t$ respectively, the third line is the explained variance in phase.

Figure 3a



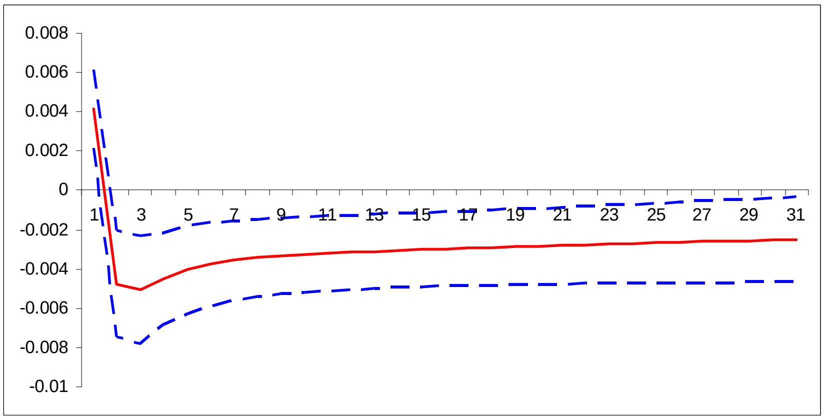
Notes: Ortohogonalized response of inefficiency to one standard deviation shock in $\overline{M}_t$ in VAR(1) $\left(\overline{M}_t, \overline{FDI}_t, \bar{e}_t\right)$. The dashed lines represent the 95% confidence interval.

Figure 3b



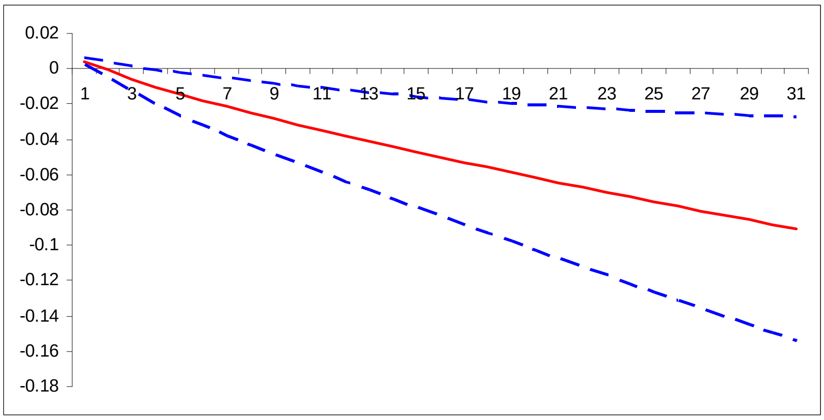
Notes: Cumulative orthogonalized response of inefficiency to one standard deviation shock in $\overline{M}_t$ in VAR(1) $\left(\overline{M}_t, \overline{FDI}_t, \bar{e}_t\right)$. The dashed lines represent the 95% confidence interval.

Figure 4a



Notes: Ortohogonalized response of inefficiency to one standard deviation shock in $\overline{FDI}_t$ in VAR(1) $\left(\overline{M}_t, \overline{FDI}_t, \bar{e}_t\right)$. The dashed lines represent the 95% confidence interval.

Figure 4b



Notes: Cumulative orthogonalized response of inefficiency to one standard deviation shock in $\overline{FDI}_t$ in VAR(1) $\left(\overline{M}_t, \overline{FDI}_t, \bar{e}_t\right)$. The dashed lines represent the 95% confidence interval.

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