Document de travail du LEM / Discussion paper LEM
2017- 23

Technological catching-up and growth convergence among US industries

Jean-Philippe BOUSSEMART
LEM UMR 9221 / jp.boussemart@ieseg.fr

Hervé LELEU
LEM UMR 9221 / h.leleu@ieseg.fr

Edward MENSAH
University of Illinois at Chicago and IÉSEG School of Management / dehasnem@uic.edu

Karina SHITIKOVA
LEM UMR 9221 / k.shitikova@ieseg.fr

http://lem.cnrs.fr/IMG/pdf/dp2017-23.pdf

http://lem.cnrs.fr/

Les documents de travail du LEM ont pour but d'assurer une diffusion rapide et informelle des résultats des chercheurs du LEM. Leur contenu, y compris les opinions exprimées, n'engagent que les auteurs. En aucune manière le LEM ni les institutions qui le composent ne sont responsables du contenu des documents de travail du LEM. Les lecteurs intéressés sont invités à contacter directement les auteurs avec leurs critiques et leurs suggestions.

Tous les droits sont réservés. Aucune reproduction, publication ou impression sous le format d'une autre publication, impression ou en version électronique, en entier ou en partie, n'est permise sans l'autorisation écrite préalable des auteurs.

Pour toutes questions sur les droits d'auteur et les droits de copie, veuillez contacter directement les auteurs.

The goal of the LEM Discussion Paper series is to promote a quick and informal dissemination of research in progress of LEM members. Their content, including any opinions expressed, remains the sole responsibility of the authors. Neither LEM nor its partner institutions can be held responsible for the content of these LEM Discussion Papers. Interested readers are requested to contact directly the authors with criticisms and suggestions.

All rights reserved. Any reproduction, publication and reprint in the form of a different publication, whether printed or produced electronically, in whole or in part, is permitted only with the explicit written authorization of the authors.

For all questions related to author rights and copyrights, please contact directly the authors.

Technological catching-up and growth convergence among US industries

Jean-Philippe BOUSSEMART
Univ. Lille, CNRS, IÉSEG School of Management, UMR 9221 - LEM, F-59000 Lille, France
3 rue de la Digue 59000 Lille, France
jp.boussemart@ieseg.fr
Phone : +33.3.20.545.892

Hervé LELEU
CNRS, IÉSEG School of Management, Univ. Lille, UMR 9221 - LEM, F-59000 Lille, France
3 rue de la Digue 59000 Lille, France
h.leleu@ieseg.fr
Phone : +33.3.20.545.892

Edward MENSAH
University of Illinois at Chicago and IÉSEG School of Management
757 Sphpi, M/c 923, 1603 W. Taylor St, Chicago, IL 60612, USA
Phone: +1.312-996-3001
dehasnem@uic.edu

Karina SHITIKOVA
IÉSEG School of Management, Univ. Lille, UMR 9221 - LEM, F-59000 Lille, France
3 rue de la Digue 59000 Lille, France
k.shitikova@ieseg.fr
Phone : +33.3.20.545.892

September 2017

ABSTRACT

Using a non-parametric programming framework, we analyze input-output ratio convergence and technical efficiency catching-up among 63 North American industries over the period 1987-2014. We first separate efficiency gaps into two components: a technical efficiency effect taking into account industry size heterogeneity and a structural component which highlights the impacts of an input-output deepening or expanding effect on technological transfer over time. Secondly, a panel data analysis is performed to link input and output price evolutions with changes in technical efficiencies and input-output mixes. Results clearly show that convergence is observed for both technical and structural components. The impact of these convergence processes on the US economy is estimated at around 0.64% of additional growth. Moreover, these two convergence processes have positive influence onto final demand prices and profitability but negative impact onto suppliers' prices while no effect can be established on employees or capital providers' remunerations.

Keywords: catching-up, convergence, directional distance function, productivity accounting, US industries

1. Introduction

Most of previous studies about productive performance simply highlight technical efficiency at the individual level, but pay less or no attention to a structural effect at a more aggregated level. Indeed, national productivity changes arises from two origins. First, a technological catching-up effect related to the fact that less productive industries put in extra effort to grow faster than the leading sectors. Second, a convergence process in output and input ratios through transfer of resources among industries do occur over time. The latter is connected to an output/input deepening or expending effect and diminishing returns of the production technology.

This paper attempts to analyze the efficiency convergence process within a group of 63 industries which cover the whole U.S. economy over the period of 1987−2014. We intend to bring an original decomposition for productive performance growth at the macro level by splitting overall efficiency evolution into two components: technical and structural changes. The structural effect measures the differences in the input and output mixes among industries impacting productivity ratios at the macro level. Over time, a decrease of this effect means that input and output combinations are becoming more homogenous among the different industries which contributes to improve the productivity level for the global economy. The technical effect measures an efficiency gap between the evaluated sector and its benchmark located on the production frontier. Its reduction over time discloses a technological catching-up process: the inefficient industry has reached the benchmark progressively.

Relying on the convergence literature, two simultaneous processes support income convergence between countries: a capital deepening effect and a technological transfer/diffusion related to Total Factor Productivity (TFP) gaps. Through the initial Solow's Model, the neoclassical standard theory devoted most attention to the first process. Assuming an exogenous and non-costly technological progress, technology adoption issues were not explicitly taken into account. For Solow (1994) this restrictive hypothesis was necessary at that initial step of progress of the growth theory. Later, the identical production technologies assumption was rejected by authors such as Jorgenson (1995) or Durlauf and Johnson (1995). In the same vein, a less drastic approach adopted by Abramovitz (1986) considers a common available technology among economies which may diverge in their capability to join and use it. As a result the concept of "social capabilities" was introduced to explain different productivity levels between countries and concern in cross-country TFP gaps has become a major issue to investigate economic growth (Islam, 2003).

As empirical measure of technology can be linked to TFP estimations, the concept of TFP-convergence investigates whether production plans such as industries are capable to catch up in terms of highest observed TFP levels. Most of empirical studies concerning TFP convergence have focused on international comparison of TFP and have shown that differences in technology are related to gaps in TFP levels. For example, through a regression of the productivity growth rates with the initial TFP levels of fifteen OECD nations, Dowrick and Nguyen (1989) analyzed TFP-convergence. Substantial signs of TFP catch-up among developed nations are established. However, their restraining hypothesis of a single capital-output ratio for all countries is a main issue. Wolff (1991) developed a TFP catching-up equation including a capital/labor ratio growth rate on the G-7 countries in order to study the relation between technical change and capital deepening effects. He found a positive influence of capital accumulation on TFP catch-up. Later, Dougherty and Jorgenson (1997) revealed a process of sigma-convergence of TFP levels among the G-7 through a significant reduction of their coefficients of variation over time.

TFP growth due to the interaction between technological adoption and capital accumulation was mainly studied for East Asian economies during the nineties. Several of authors (Young, 1992, 1994, 1995; Kim and Lau 1994) found that TFP growth did not play a major effect on their economic expansion. As a result, Krugman (1994) deduced that East Asian development should mainly result from factor accumulation. Nevertheless, Collins et al. (1996) and Klenow and Rodriguez (1997) showed more substantial role of TFP growth for some East Asian economies such as Singapore

While a huge literature was devoted to productivity convergence at country level, the sources of these aggregate productivity changes at the industry level remain largely unstudied. Through data on sectors, Bernard and Jones (1995) analyzed the sources of aggregate labor productivity convergence among the U.S. states over the period 1963-1989. They estimated the individual sectors' contribution to aggregate convergence. Their main result is that productivity growth in the manufacturing industries explained the main part of private non-farm productivity growth. Focusing on productivity changes by sector from 1963-1989, Barro and Sala-i-Martin (1991) pointed out that convergence was happening in all industries, although this process has been more significant in manufacturing than in other types of industries. They also established a break of macro-convergence after the early 70s mainly due to price changes in oil industry. More recently, Cardarelli and Lusinyan (2015) studied the aggregate US TFP slowdown using TFP estimators across U.S. states over the last two decades. They revealed that the deceleration of TFP growth was quite common among the states and not correlated to the presence of IT producing or using industries. Gaps in production efficiency across U.S. states are mainly explained by differences in investment rates of education and R&D.

Estimating productivity gains and their distribution among inputs and outputs for 63 American industries over the period 1987-2012, Boussemart and al. (2017) showed that TFP of US industries increased at an average trend of 0.8% and highlighted that employees and firms' profitability were the winners while clients and fixed capital providers were the losers in the distribution of productivity gains. Beyond these global results, TFP growth rates have been significantly different between the 63 industries over the last 26 years. Clearly, the computer and electronic products industry had the highest level of TFP growth (7.48%) followed by other sectors such as support activities for mining and wholesale trade (2.32% and 2.09%) while the oil and gas extraction industry registered the lowest performance (-1.22%).

Yet, most of studies about TFP growth present several caveats. First, they need to define a technological leader a priori (generally the US) instead of letting data choose the benchmark to reach. Second, the technology estimation requires a particular functional form (Cobb–Douglas, CES, Translog…). Third, the constant returns to scale assumption does not take into account size heterogeneity across production plans and may bias TFP indexes and the underlying catching-up process.

To avoid the first two drawbacks, the catching-up mechanism was re-examined with a new methodology by Kumar and Russell (2002) which did not impose any functional form on the production frontier, nor any hypothesis for the market structure. In addition, they did not choose a specific country as the world leader and allow for eventual technical and/or allocative inefficiencies for economies. Through productivity indexes estimated with a non-parametric method, the catching-up hypothesis across 57 poor and rich nations was investigated. More precisely, they decomposed variations of the cross-country distribution of labor productivity in dissimilarities in levels of technology and technical changes over time. They showed how much of income convergence was due to technological transfer or to alignment in capital/labor intensities. They settled an evident technological catch-up, as most of countries have moved closer to the production frontier, non-neutral technological progress and a dominant role of capital deepening effect compared to technological catch-up inducing both growth and income divergence between countries.

A Data Envelopment Analysis (DEA) approach was also used by Christopoulos (2007) to study the effect of human capital and international opening (i.e.: economic globalization) on efficiency within a group of 83 developed and less developed nations. He confirmed that more openness improves significantly countries' productive performances while human capital does not impact the efficiency to a great degree. Nonetheless, a constant returns to scale hypothesis still characterized the underlying technology.

Relaxing this restrictive constant returns to scale assumption for the technology, Färe et al. (1994) decomposed productivity growth in a technical progress effect and an efficiency change component that was referred to a catching-up process for 17 OECD countries over the period 1979-1988. Additionally, the catching-up component was split into two terms: a pure technical efficiency change and a scale efficiency change. Their results showed that Japan obtained the highest TFP growth rate.

Using such a non-parametric programming framework, our study analyzes both input-output ratio convergence and TFP catching-up among 63 North American industries over the period 1987-2014. Compared to most of studies on convergence cited above, one empirical contribution of our research is to analyze the catching-up process at the sectoral level within the US economy. We first separate efficiency gaps into two components: a technology effect taking into account industry size heterogeneity by relaxing the constant return to scale assumption and a structural element which highlights the impacts of an input-output deepening or expanding effect on technological transfer over time. The convergence processes on each of them are analyzed. Secondly, following Boussemart et al. (2017) who interrelated the distribution of TFP changes between inputs and outputs, we perform a panel data analysis to explain the input and output price evolutions by the changes of technical efficiencies and input-output mixes.

This paper is organized as follows. In the next section we use a directional distance function to define the production frontier and evoke the measures of technical and structural effects which may impact the convergence process within a set of units. Section 3 presents data and the underlying technology and discusses the results. Finally, we give the main conclusions in the last section.

2. Analyzing convergence process with directional distance functions

We aim at estimating both a technical catching-up effect between observed production plans of industries and their maximum achievable levels of TFP and a convergence process of input-output ratios among industries. A technical catching-up process reveals the ability to fit the current technology and a structural convergence process considers the diversity across industries regarding their respective input or output intensity evolutions. This latter can be related to an input/output deepening or expanding effect.

In the followings paragraphs, the concepts of technical catching-up and structural convergence are defined. Moreover, methodological tools to measure these effects are developed.

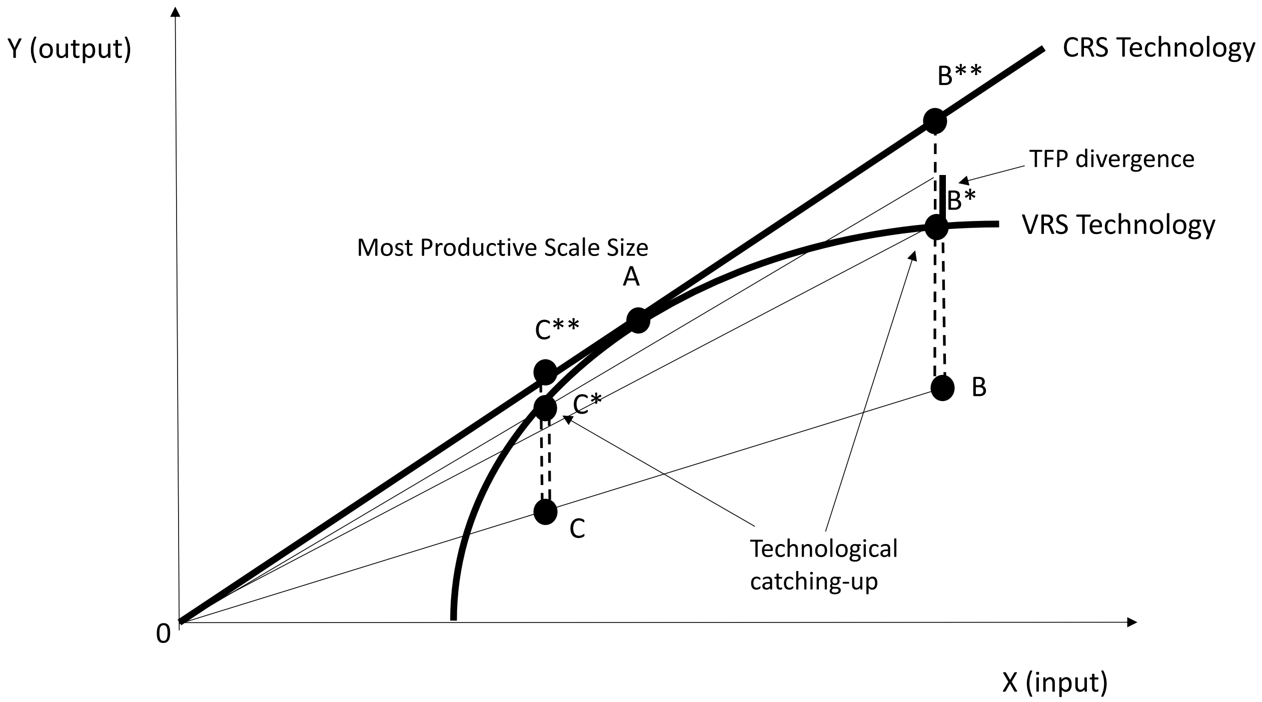
2.1 Definition and measure of a technical catching-up process

A technical catching-up process happens when less efficient industries tend to catch up more efficient ones over time. In this case, the inefficient industries are overtaking the efficient sectors which have retained leadership positions. Thus, one can observe a convergence process to the efficient frontier if the technical inefficiency level is decreasing over time. Less efficient industries can progressively adopt technological innovations, managerial procedures, or organizational capabilities from the most productive ones.

Traditionally, in the literature, technological adoption is viewed as comparison of TFP levels across sectors or countries and testing an inverse link between TFP growth rates and their original levels. Convergence process occurs if industries with the smallest TFP levels display the highest growth rates. The assumption of constant returns to scale (CRS) is necessary since the best production plan, set as a benchmark for all sectors, has the maximal observed productivity. Nevertheless, if the CRS assumption is not fulfilled and increasing and/or decreasing returns to scale (variable returns to scale, VRS) appear to be more appropriate, the maximal feasible productivity level may not correspond to the maximal observed productivity level and should be estimated for each sector relatively to its own size. Indeed, this size is constrained by the industry's scale of operations which can be considered as quasi-fixed in the short-run. In fact, if a CRS technology is retained while a VRS is more faithful to the data, the analysis of technological transfer can lead to substantial bias. Indeed, one can observe a divergence in productivity levels among industries when they achieve the production frontier and contribute to a technological catching-up process as it is shown in Figure 1.

Let us consider 3 sectors A, B and C which use one input (X) to produce one output (Y) under variable return to scale (Figure 1). One can observe that sectors B and C characterized by a similar productivity level are inefficient while industry A is efficient and has the most productive scale size (mpss). If we suppose that sector A is a benchmark for all industries, we implicitly assume a CRS technology. That is, if sectors B and C could achieve B** and C**, TFP convergence will occur as all industries will reach the same maximal productivity level. However, if the true VRS technology holds, sectors B and C will be only capable to achieve B* and C* for which productivity divergence is observed. Since B and C will never be able to achieve B** and C**, one can draw a conclusion about divergence of productivity levels between the industries even if they have reached their respective maximum feasible productivity levels located on the VRS production frontier. In that case, their technical inefficiencies have decreasing over time denoting a clear technical catching up process.

Figure1. Maximal observed productivity level under CRS assumption versus maximal feasible productivity level under VRS assumption



In order to measure technical inefficiency, we develop an activity analysis model assuming that all industries face the same VRS technology in the sense that they are able to produce a common output such as gross output from similar resources such as fixed capital, labor and intermediate inputs:

In a more general way, let us consider a vector of inputs $\mathbf{x} \in R_+^N$ and a vector of outputs $\mathbf{y} \in R_+^M$ for an observed industry or DMU (decision making unit). At time *t*, the technology can be simply defined by the production set which includes all the feasible production plans:

$$T_{VRS}^t = \left\{ (\mathbf{x}^t, \mathbf{y}^t) : \mathbf{x}^t \text{ can produce } \mathbf{y}^t \right\} \qquad (1)$$

To better structure and clarify the definition of T_{VRS}^t, we consider two assumptions on the production possibility set: free disposability of inputs and outputs and convexity. Now from a sample of K observed DMUs, we achieve an operational definition of T_{VRS}^t as:

$$T_{VRS}^t = \left\{ (\mathbf{x}^t, \mathbf{y}^t) : \mathbf{x}^t \in R_+^N, \mathbf{y}^t \in R_+^M, \sum_{k=1}^{K} \mu_k y_k^{m,t} \geq y^{m,t}, m = 1, \ldots, M, \right.$$
$$\left. \sum_{k=1}^{K} \mu_k x_k^{n,t} \leq x_k^{n,t}, n = 1, \ldots, N, \sum_{k=1}^{K} \mu_k = 1, \mu_k \geq 0, k = 1, \ldots, K \right\}. \qquad (2)$$

We measure the gaps between any DMU and the technology frontier at time *t* using a directional distance function:

$$\vec{D}_{T^t}(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}^t_{\mathbf{x}},\mathbf{g}^t_{y}) \;=\; \sup_{\lambda^t}\left\{\ \lambda^t \in \Re_+ :\ (\mathbf{x}^t+\lambda^t\cdot\mathbf{g}^t_{\mathbf{x}},\mathbf{y}^t+\lambda^t\cdot\mathbf{g}^t_{y}) \in T^t_{VRS}\ \right\}, \qquad (3)$$

where $\mathbf{g}^t = (\mathbf{g}^t_{\mathbf{x}};\mathbf{g}^t_{\mathbf{y}}) \in (-R^N_+;R^M_+)$ characterizes the direction of the projection onto the annual production frontier. In our analysis we define $\mathbf{g}^t_{\mathbf{x}} = 0$ and $\mathbf{g}^t_{\mathbf{y}} = \sum_{k=1}^{K}\mathbf{y}^t_k$. Therefore, the technical inefficiency for any evaluated DMU "*a*" can be estimated with the following linear program:

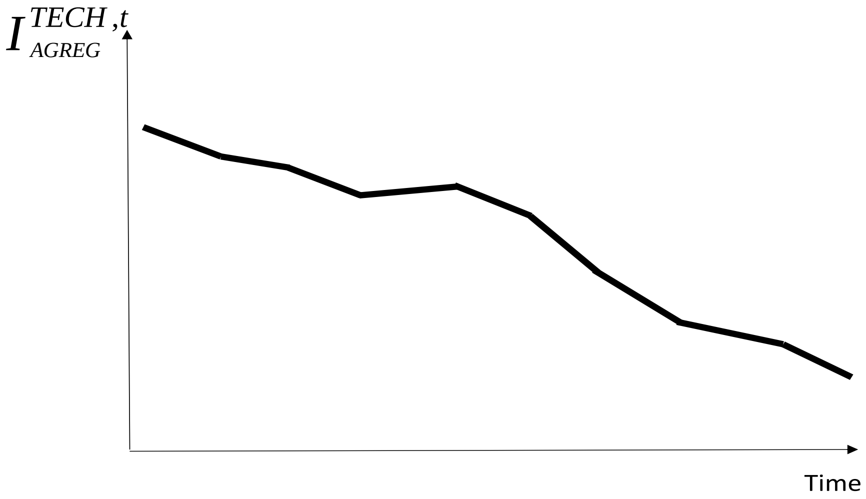
$$\begin{aligned}
&I_a^{TECH,t} = \vec{D}_{T^t_{VRS}}(\mathbf{x}^t_a,\mathbf{y}^t_a;\mathbf{g}^t_{\mathbf{x}},\mathbf{g}^t_{\mathbf{y}}), \forall a \in \{1,2,...,\mathrm{K}\}\\
&\vec{D}_{T^t_{VRS}}(\mathbf{x}^t_a,\mathbf{y}^t_a;\mathbf{g}^t_{\mathbf{x}},\mathbf{g}^t_{\mathbf{y}}) = \max_{\mu,\lambda^t_a}\ \lambda^t_a\\
s.t.\ &\sum_{k=1}^{K}\mu_k y_k^{m,t} \geq y_a^{m,t} + \lambda^t_a \mathbf{g}^t_{\mathbf{y}}\quad \forall m = 1,\cdots,M\\
&\sum_{k=1}^{K}\mu_k x_k^{n,t} \leq x_a^{n,t} + \lambda^t_a \mathbf{g}^t_{\mathbf{x}}\quad \forall n = 1,\cdots,N \qquad\qquad \text{(LP1)}\\
&\sum_{k=1}^{K}\mu_k = 1\\
&\lambda^t_a \geq 0\\
&\mu_k \geq 0\ \forall k = 1,...,K
\end{aligned}$$

Considering the group of K industries or DMUs called "AGREG", all individual technical inefficiencies can be summed up to obtain the technical inefficiency score at the aggregate level:

$$I_{AGREG}^{TECH,t} = \sum_{a=1}^{K}\vec{D}_{T^t_{VRS}}(\mathrm{x}^t_a,\mathrm{y}^t_a;\mathrm{g}^t_{\mathrm{x}},\mathrm{g}^t_{\mathrm{y}})\,. \qquad (4)$$

Thus, a decrease with time of $I_{AGREG}^{TECH,t}$ will denote a general catching-up process to the maximal feasible productivity levels for the majority of industries (Figure 2).

Figure 2. Illustration of a technological catching-up process



2.2 Definition and measure of a structural convergence process

If we consider a multi outputs-inputs technology, diversity in input and output allocations among industries can cause structural inefficiency (Ferrier et al. 2010). As we can observe at Figure 3, efficient sectors A and B which produce the same output level but with different input mixes, create technical inefficiency at the aggregate level. Related structural effects in the output and input-output spaces are displayed in Figures 4 and 5. Thus, differences in relative input and output endowments between the two technically efficient industries induce such a structural inefficiency.

Figure 3. Structural inefficiency and convergence in the input space

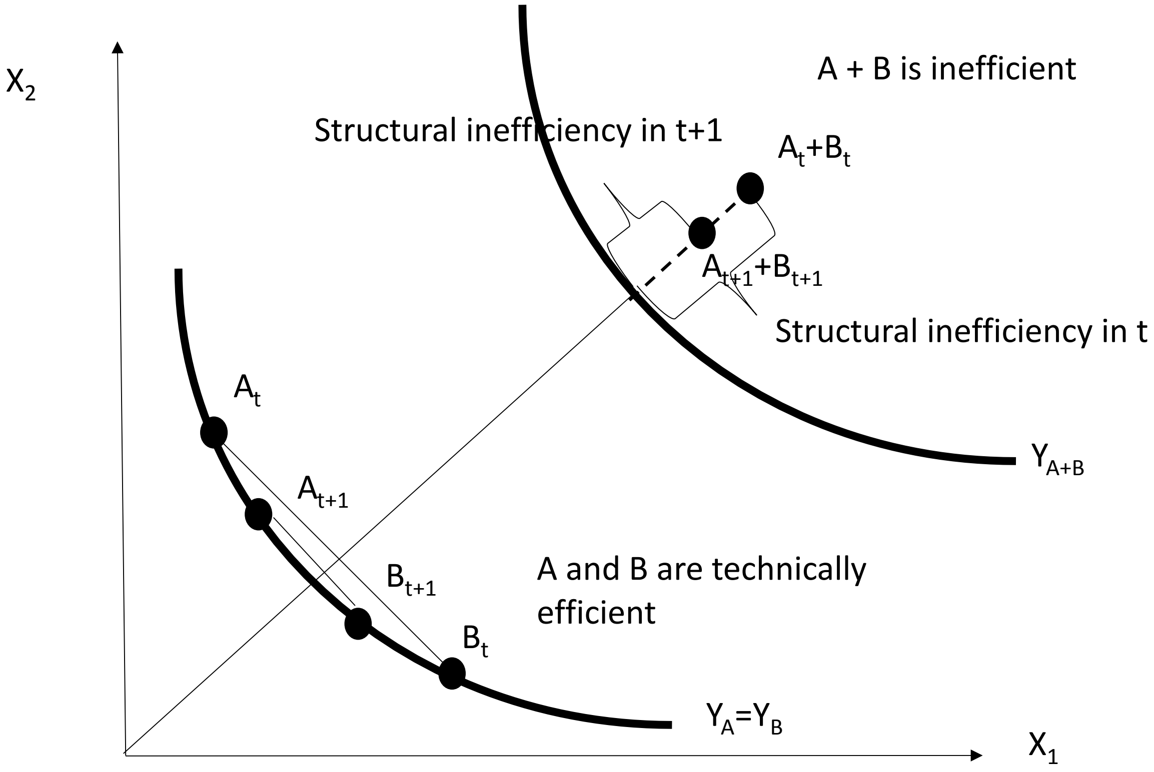


Figure 4. Structural inefficiency and convergence in the output space

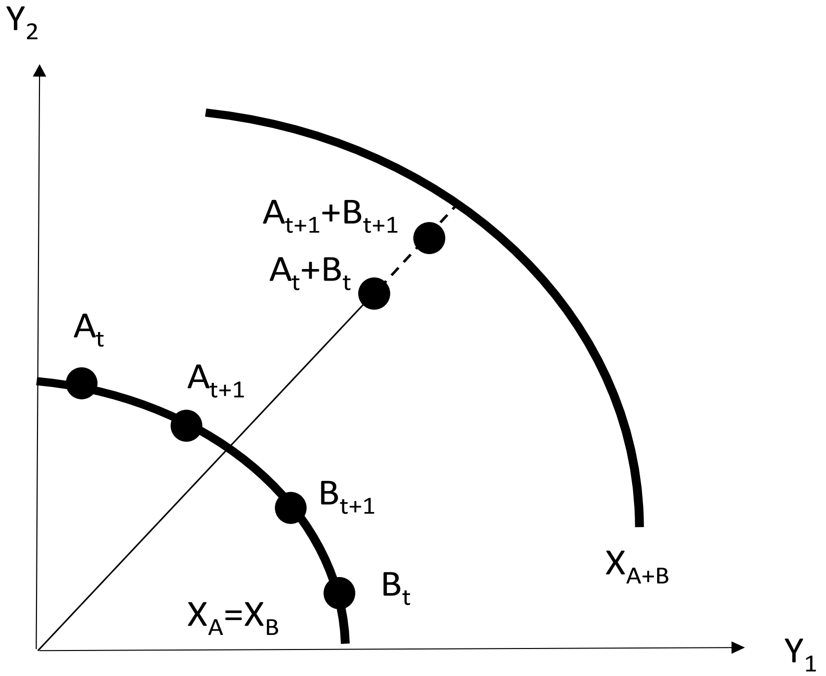
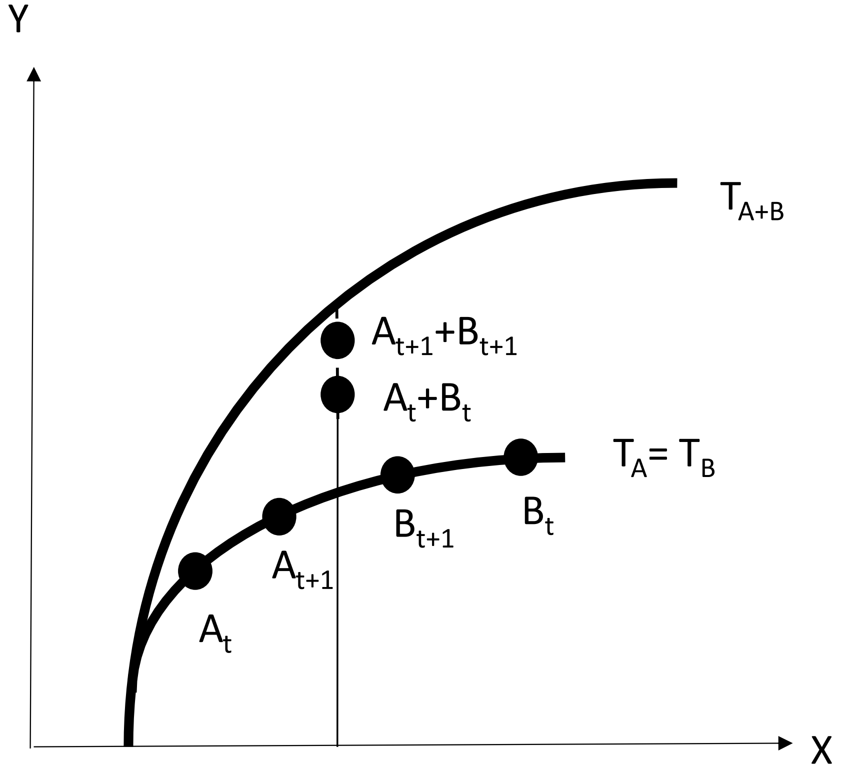


Figure 5. Structural inefficiency and convergence in the input-output space



In a perfect competitive market, a common given input-output price vector leads to industries to adopt identical input-output allocations. As a result, less resistances in the reallocation process reduce misallocation of resources and improve aggregate productivity. Consequently, in the spirit of Debreu's (1951) concerning coefficients of resource utilization, market allocation inefficiency can be revealed through the structural inefficiency. Thus, the decrease of this component over time is correlated to aggregate productivity growth at the group level since sectors homogenize their input-output allocations gradually disclosing a structural convergence process.

We intend to estimate structural inefficiency scores for all industries at the group and individual levels. To obtain the inefficiency scores at individual level, we first estimate structural inefficiency at the group level. As previously, we consider K industries or DMUs which constitute the total group AGREG and we suppose, in a formal way, that the group technology is the sum of the K DMUs technologies:

$$T^{AGREG,t} = \sum_{k=1}^{K} T^{t}. \qquad (5)$$

Li and Ng (1995) proved that under convexity assumption the VRS aggregate technology $T_{VRS}^{AGREG,t}$ is equal to K times the individual technology:

$$T_{VRS}^{AGREG,t} = \sum_{k=1}^{K} T_{VRS}^{t} = K \times T_{VRS}^{t}. \qquad (6)$$

We estimate first the overall inefficiency as the technical inefficiency for AGREG with the following linear program:

$$\begin{aligned}
&\vec{D}_{T_{VRS}^{AGREG,t}}\Big(\sum_{\mathbf{k=1}}^{\mathbf{K}} \mathbf{x}_k^t, \sum_{\mathbf{k=1}}^{\mathbf{K}} \mathbf{y}_k^t; \mathbf{g}_\mathbf{x}^t, \mathbf{g}_\mathbf{y}^t\Big) = \max_{\mu,\lambda_{AGREG}^t} \ \lambda_{AGREG}^t \\
&s.t.\ K\sum_{k=1}^{K} \mu_k y_k^{m,t} \ge \sum_{k=1}^{K} y_k^{m,t} + \lambda_{AGREG}^t \mathbf{g}_\mathbf{y} \quad \forall m = 1,\cdots,M \\
&K\sum_{k=1}^{K} \mu_k x_k^{n,t} \le \sum_{k=1}^{K} x_k^{n,t} + \lambda_{AGREG}^t \mathbf{g}_\mathbf{x} \quad \forall n = 1,\cdots,N \qquad \text{(LP2)} \\
&K\sum_{k=1}^{K} \mu_k = K \Leftrightarrow \sum_{k=1}^{K} \mu_k = 1 \\
&\lambda_{AGREG}^t \ge 0 \\
&\mu_k \ge 0 \quad \forall k = 1,\dots,K
\end{aligned}$$

The linear program given above allows us to identify overall inefficiency which measures the technical efficiency of the aggregated production plan merging the K DMUs.

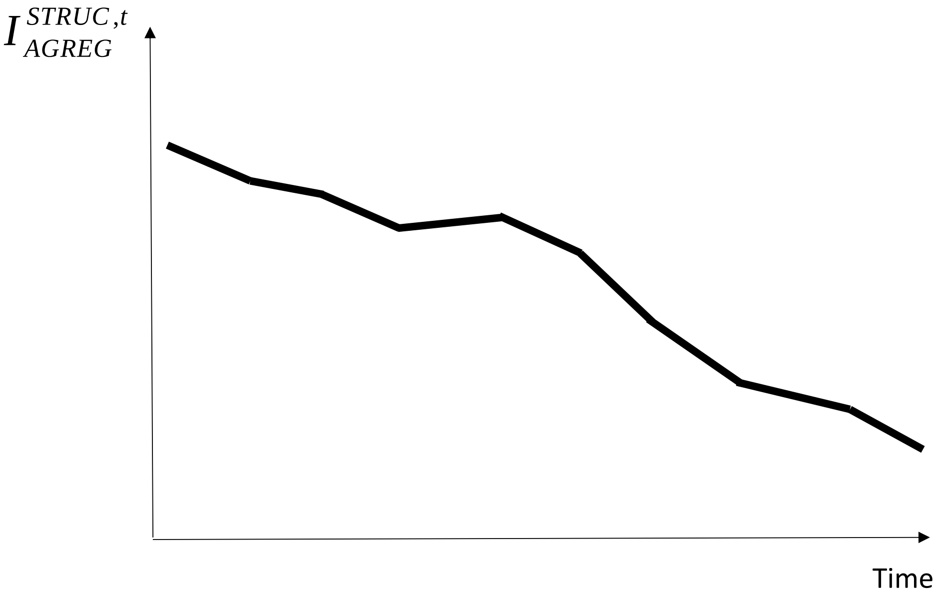
$$I_{AGREG}^{OVERALL,t} = \vec{D}_{T_{VRS}^{AGREG,t}}\Big(\sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{x}_k^t, \sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{y}_k^t; \mathrm{g}_\mathrm{x}^t, \mathrm{g}_\mathrm{y}^t\Big) \qquad (7)$$

The difference between the overall component and the sum of individual technical scores defines the structural inefficiency coming from the heterogeneity in relative input/output allocations among the K DMUs. Thus, structural inefficiency is defined at the group level:

$$I_{AGREG}^{STRUC,t} = I_{AGREG}^{OVERALL,t} - I_{AGREG}^{TECH,t} = \vec{D}_{T_{VRS}^{AGREG,t}}\Big(\sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{x}_k^t, \sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{y}_k^t; \mathrm{g}_\mathrm{x}^t, \mathrm{g}_\mathrm{y}^t\Big) - \sum_{a=1}^{K} \vec{D}_{T_{VRS}^{t}}(\mathrm{x}_a^t, \mathrm{y}_a^t; \mathrm{g}_\mathrm{x}^t, \mathrm{g}_\mathrm{y}^t) \quad (8)$$

As a result, if structural inefficiency decreases over time, we observe an input/output mixes convergence process among the K DMUs(Figure 6).

Figure 6. Illustration of a structural convergence process



While technical inefficiency can be retrieved directly at individual level through LP1, structural inefficiency is computed as a part of the overall inefficiency for the whole group. Nevertheless, we can allocate the overall inefficiency across DMUs by using the shadow prices derived in LP2 (Briec and al., 2003) in order to deduce the individual structural inefficiency:

$$I_{AGREG}^{OVERALL,t} = \sum_{a=1}^{K} I_a^{OVERALL,t} \Rightarrow I_a^{STRUC,t} = I_a^{OVERALL,t} - I_a^{TECH,t}$$
$$\text{and } I_{AGREG}^{STRUC,t} = \sum_{a=1}^{K} I_a^{STRUC,t} \qquad (9)$$

3. Data and results

In order to analyze the technological catching-up and structural convergence processes among the industries, the previous models are now applied to a dataset on 63 different sectors covering the whole US economy over the period 1987-2014. In a second step, a panel data analysis is performed to explore the link between the changes in both technical catching-up and structural inefficiencies and the distribution of productivity gains among the different retained inputs and output.

3.1. Data

Data was collected from the Bureau of Economic Analysis (BEA) website (http://www.bea.gov/). For each industry, we have the current values (expressed in current U.S. dollars) and the quantity indexes (base year 100=2009) of their gross output net of taxes on production-less subsidies, intermediate inputs, labor (compensation of employees), and consumption of fixed capital (equipment, structures, and intellectual property products). The volume of taxes and subsidies on production directly link to their related quantity output indexes. The labor quantity is estimated in a full-time equivalent employee. The volume of capital consumption (the sum of equipment, structure, and intellectual property products) is calculated by the cost depreciation at a constant price. Thus, for each sector, we can compute both the value and the volume for each variable stated. Finally, the underlying technology is defined as a production function of one output (gross output) which depends on 3 inputs (intermediate inputs, labor and fixed capital).

3.2. Technical catching-up and structural convergence processes among US industries

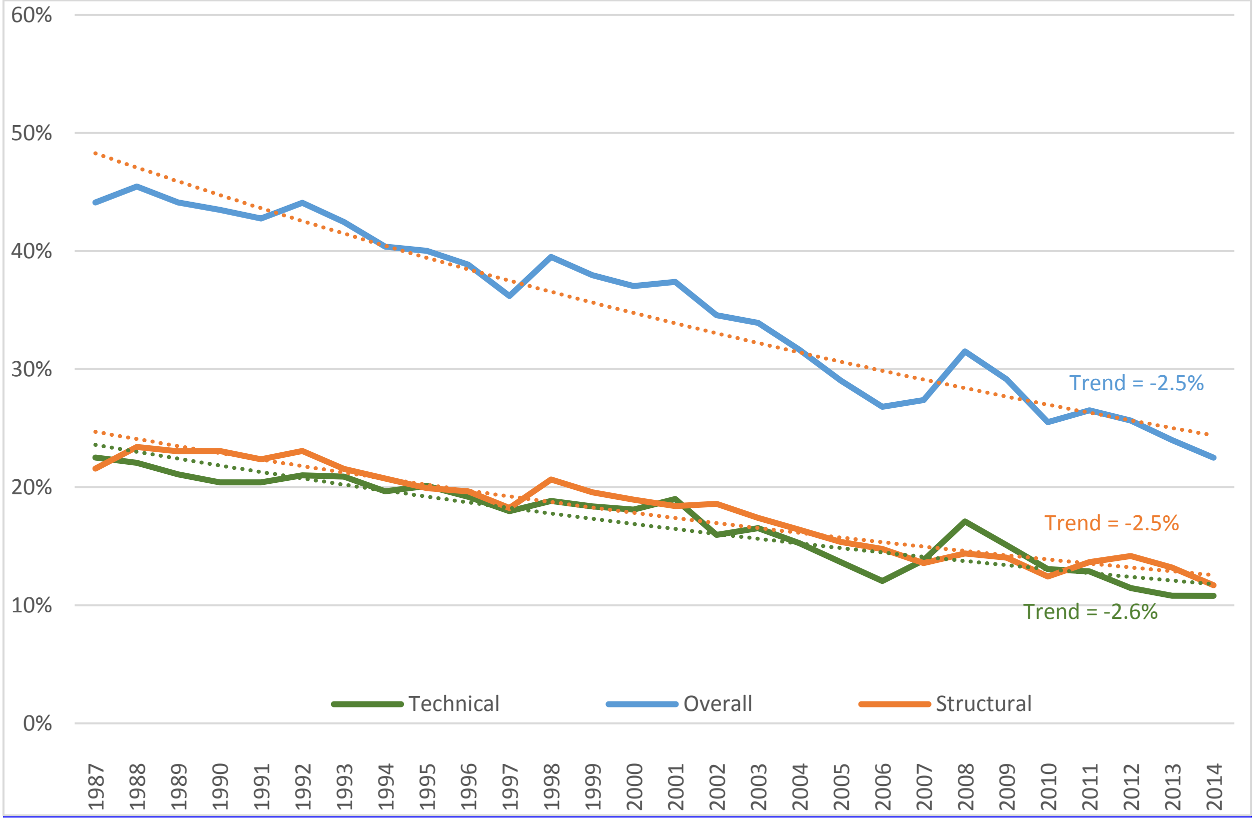
Production frontiers are estimated year by year over the whole period. In a first step, we compute technical inefficiency scores at industry level using a directional distance function. The direction is defined as the sum of gross outputs of all industries. For each evaluated industry, efficiency scores reveal potential growth computed in terms of percentages of the total US gross output. Based on this common direction, the individual efficiency scores can be directly aggregated to each other. In a second step, we estimate overall inefficiency for all industries at the aggregate level. Finally, for each sector, the structural component is deduced through the difference between individual overall and technical inefficiencies. As the production frontier is year-specific, the number of efficient industries can change over time. Although some of them are always located on the production frontier. Table 1 list these stable efficient sectors over the whole period.

Table 1. Technically efficient industries over the period 1987-2014

Industry	**Sum of inefficiency scores over 1987-2014**
Legal services	0,00%
Funds, trusts, and other financial vehicles	0,00%
Real estate	0,00%
Construction	0,00%
State and local	0,00%
Petroleum and coal products	0,00%
Food and beverage and tobacco products	0,00%

The respective evolutions of technical, structural and overall inefficiencies for the sum of 63 industries are presented in Figure 7. All three types of inefficiencies demonstrate convergence processes over the period 1987-2014 at the macro level. The technical and structural inefficiency dynamics follow a similar pattern with average annual decrease rate of respectively 2,6% and 2,5%. The technical inefficiency evolution seems to be more fluctuated over the period 2006-2011. As a result, the overall inefficiency is decreasing over time with a trend of -2.5%.

Figure 7. Evolution of the overall, technical and structural inefficiencies for the sum of 63 US industries over the period 1987-2014



Individual industries contribute to the technical catching-up and structural convergence processes differently. For instance, compared to computer systems design, chemical products and hospitals and nursing facilities, textile, electrical equipment industries and food services face significant and regular technical inefficiency decreases. Concerning the homogenization of input-output mixes, the individual effects seem more irregular. Examples of industries with ones of the most important convergence rates of technological catching-up effect and homogenization of input-output mixes over the considering period are given in Figures 8 and 10 respectively. Examples of industries without technological catching-up effect and input-output mixes homogenization are presented respectfully in Figures 9 and 11.

Figure 8. Examples of industries with significant technological catching-up effects

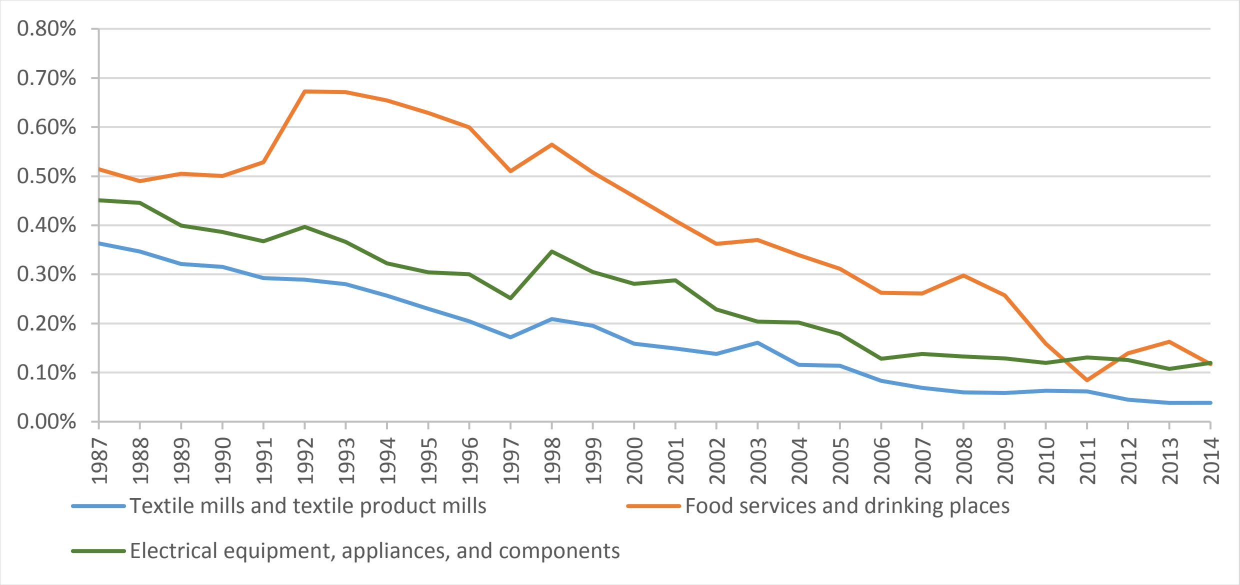


Figure 9. Examples of industries without technological catching-up effects

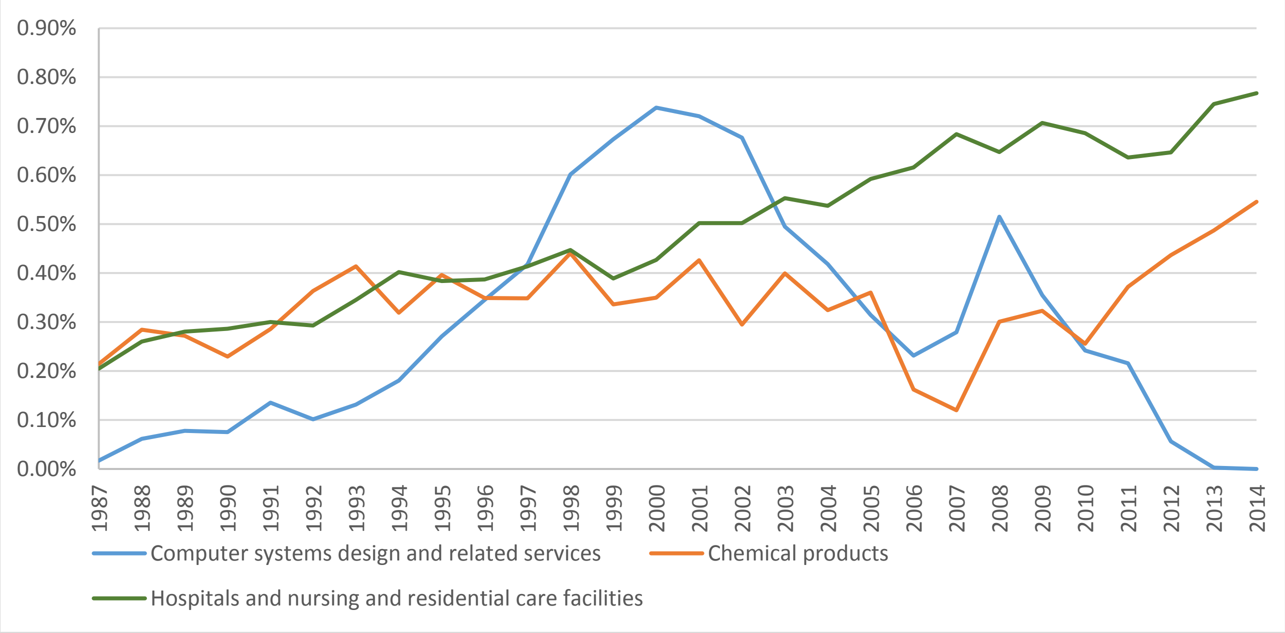


Figure 10. Examples of industries with homogenization of input-output mixes

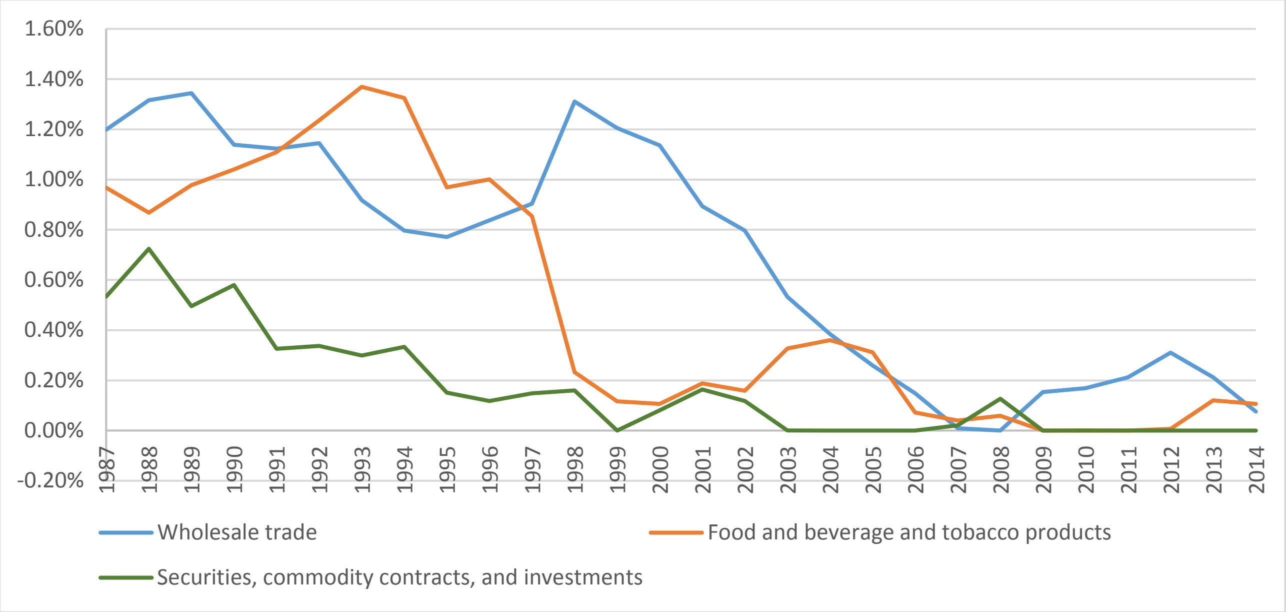
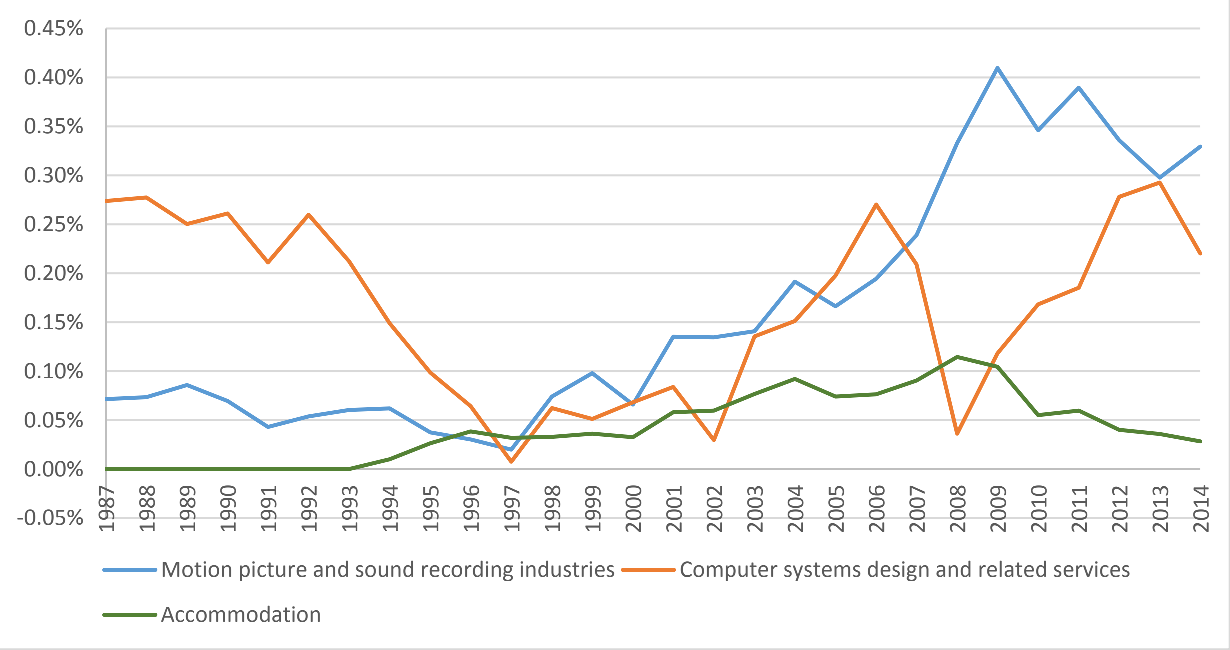
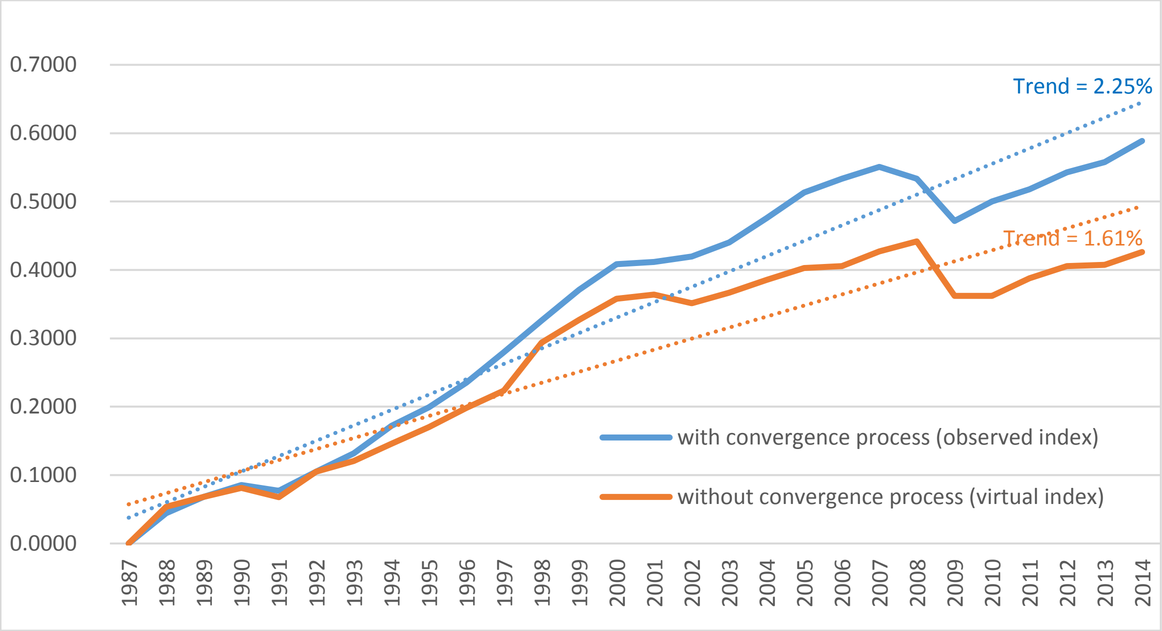


Figure 11. Examples of industries without homogenization of input-output mixes



Furthermore, the impacts of overall convergence process (technical + structural effects) on the US output growth can be estimated. By correcting all observed output levels with their respective annual inefficiency scores, one can compute the virtual output growth along the production frontier. Considering that technical and structural inefficiency reductions over time denote additional productivity gains for the US economy, the difference of the observed and the previous virtual growth rates gives an estimation of the impact of overall convergence process on the US growth which is around 0.64% (2.25% - 1.61%). These virtual and observed output changes are displayed in figure 12.

Figure 12. Gross-output in logarithm terms for all industries (100 =1987)



3.3. The linkage between stakeholder's price advantages and convergence processes

Technological catching-up and structural convergences processes by implying productivity gains at the industry and macro levels should be transferred to the different stakeholders (namely clients, intermediate input suppliers, employees, fixed capital suppliers and profitability). These productivity transfers may be related or not to the input/output price evolutions reflecting financial advantages or disadvantages that the stakeholders have benefitted or suffered over time. In this perspective, we investigate the long-run relationship between real output/input price evolutions and technical/structural efficiency scores at the industry level for the panel of 63 US industries over the period 1987-2014.

a) Definition of price advantages

Considering that a value change of any input n between two periods t and $t+1$ can be split into Bennet price and quantity effects as:

$$\Delta(w^n x^n) = \left[\frac{1}{2}\left(x_t^n + x_{t+1}^n\right)\Delta w^n\right] + \left[\frac{1}{2}\left(w_{t+1}^n + w_t^n\right)\Delta x^n\right] \qquad (10)$$

with x_t^n = quantity of input n at period t and w_t^n = price of input n at period t.

On the right hand side, the first bracket measures a price effect called the price advantage of the stakeholder related with input *n*. The price advantage or remuneration change over the two periods for any stakeholder is equal to the difference between the quantity weighted changes in its related input price. If $\Delta w^n > 0$ (price increasing between the two periods), the price advantage gives a positive remuneration change to the stakeholder. The second bracket measures a quantity effect related to the considered input. As a result, the combination of the price and quantity effects allows to retrieve the value change over the two periods.

In a similar way, a value change of any output *m* between periods t and t+1 is decomposed into Bennet price and a quantity effects as:

$$\Delta(p^m y^m) = \left[\frac{1}{2}\left(y_t^m + y_{t+1}^m\right)\Delta p^m\right] + \left[\frac{1}{2}\left(p_{t+1}^m + p_t^m\right)\Delta y^m\right] \qquad (11)$$

with $\mathrm{y}_t^m =$ quantity of output *m* at period *t* and $p_t^m =$ price of output *m* at period *t*.

From equation (11), the price advantage related to the stakeholder or purchaser *m* is defined by $-\left[\frac{1}{2}\left(y_t^m + y_{t+1}^m\right)\Delta p^m\right]$ where the negative signs indicates a positive price advantage in case of a selling price decrease over the two periods.

b) Price advantages and TFP growth

Adopting a productivity accounting approach outlined by Grifell-Tatjé and Lovell (2015), we estimate productivity gains and their distribution among inputs and output for the US industries. In this perspective the traditional surplus accounting approach, initially developed by CERC[1] (1980), is performed in order to compute the respective stakeholders' price advantages related to the corresponding input and output price changes. These price advantages allow us to determine which stakeholders benefit or do not benefit from productivity gains over time.

Furthermore, considering that the total output value is distributed into returns to the *n* different inputs, the following accounting identity holds for any particular industry:

---

[1] Centre d'Etudes des Revenus et des Coûts

$$\sum_{m=1}^{M} p_t^m y_t^m = \sum_{n=1}^{N} w_t^n x_t^n \qquad (12)$$

Given the previous equation, changes in output and input values between periods t and t+1 can be measured in terms of changes in quantity and price components. Denoting that $p_{t+1}^m = (p_t^m + \Delta p^m)$, $y_t^m = (y_t^m + \Delta y^m)$, $w_{t+1}^n = (w_t^n + \Delta w^n)$ and $x_{t+1}^n = (x_t^n + \Delta x^n)$, after simplification and re-arrangement, equation (12) leads to equation (13):

$$\sum_{m=1}^{M} \frac{p_t^m + p_{t+1}^m}{2} \Delta y^m - \sum_{n=1}^{N} \frac{w_t^n + w_{t+1}^n}{2} \Delta x^n = -\sum_{m=1}^{M} \Delta p^m \frac{y_t^m + y_{t+1}^m}{2} + \sum_{n=1}^{N} \Delta w^n \frac{x_t^n + x_{t+1}^n}{2} \qquad (13)$$
$$PS = PA$$

In equation (13), the left hand side characterizes a productivity surplus (PS) defined as the difference between price weighted changes in output and input quantities while the right hand side aggregates the different stakeholders' price advantages (PA). Such price variations result in reallocations among stakeholders that are constrained by the productivity surplus level. More precisely, equation (13) ensures that the total amount of remuneration changes shared among the different agents (PA) cannot surpass the total productivity growth (PS).

Through equation (13), *PS* estimates productivity gains expressed in level terms (i.e. in dollars) which can also be directly linked to the usual Solow technical change residual as a measure of TFP changes defined in terms of relative growth rates (%).

Departing from the multi-output and multi-input production function:

$$F(\mathrm{y},\mathrm{x},t) = 0$$

with t a time trend

and x, y input and output vectors respectively (14)

$$\mathrm{x} = (x_1, x_2, ..., x_n, ..., x_N)$$
$$\mathrm{y} = (y_1, y_2, ..., y_m, ..., y_M).$$

Supposing output prices equal to marginal costs and associating input prices to the marginal productivity levels, the Solow residual computed as a Törnqvist index of the TFP change over time is equal to the weighted output variations not explained by weighted input changes:

$$\frac{\Delta TFP}{TFP} = \sum_{m=1}^{M} \alpha_m \frac{\Delta y^m}{y^m} - \sum_{n=1}^{N} \beta_n \frac{\Delta x^n}{x^n} \qquad (15)$$

where $\boldsymbol{\alpha}$ represents the vector of *M* output shares in total revenue and $\boldsymbol{\beta}$ the vector of *N* input shares in total cost.

Substituting $\alpha^m \frac{\Delta y^m}{y^m}$ by $\frac{p^m \Delta y^m}{\sum_{m=1}^{M} p^m y^m}$ and $\beta^n \frac{\Delta x^n}{x^n}$ by $\frac{w^n \Delta x^n}{\sum_{n=1}^{N+1} w^n x^n}$ and seeing that the total revenue equals the total cost ($\sum_{m=1}^{M} p^m y^m = \sum_{n=1}^{N+1} w^n x^n$), TFP growth rate can be measured as:

$$\frac{\Delta TFP}{TFP} = \frac{\sum_{m=1}^{M} p^m \Delta y^m - \sum_{n=1}^{N+1} w^n \Delta x^n}{\sum_{m=1}^{M} p^m y^m} \qquad (16)$$

As a result, the TFP growth rate is just equal to the productivity surplus rate defined by the ratio between *PS* and the total output value. Additionally, an interesting link between TFP growth rate and price advantage changes can be proven. From the equality *PS* = *PA*, TFP growth rate is equivalent to the aggregation of price advantage ratios defined as the percentages between price advantages and the total output value):

$$\frac{\Delta TFP}{TFP} = \frac{PS}{\sum_{m=1}^{M} p^m y^m} = \frac{PA}{\sum_{m=1}^{M} p^m y^m} = \frac{-\sum_{m=1}^{M} \Delta p^m y_t^m + \sum_{n=1}^{N+1} \Delta w^n x_t^n}{\sum_{m=1}^{M} p^m y^m} \qquad (17)$$

c) The model linking price advantages and technical and structural inefficiency scores

For each industry and each year, available data enable the establishment of the following balanced production account

Gross output value

=

Intermediates inputs + Compensation of employees + Depreciation of capital + Net operating Surplus

In this accounting identity, the net operating surplus can be equated to a cost which remunerates a virtual X^N including dividends, interest costs or managers' remunerations before tax. This specific cost gauges the capacity of an industry to achieve a financial surplus after covering the costs of intermediate consumptions and primary inputs (labor and fixed capital). Therefore, one can associate 5 different stakeholders: clients, suppliers of intermediate inputs, employees, suppliers of fixed capital and managers who are remunerated through the net operating surplus.

In this context, our model combines six equations. The first five equations are related to output/input price advantages. The sixth one refers to the previous equation (17) by linking the distribution of TFP gains between the five stakeholders. Consequently, the model can be described through the following simultaneous equations:

- one equation related to the gross output :

$$\left(-\frac{\Delta py}{py}\right)_a^{t+1/t} = \alpha \; \Delta I_a^{TECH,t+1/t} + \beta \; \Delta I_a^{STRUC,t+1/t} + d_a + f^{\,t} + \varepsilon_a^t \tag{18}$$

- four equations related to the inputs including the profitability:

$$\left(\frac{\Delta w^n x^n}{py}\right)_a^{t+1/t} = \alpha^n \; \Delta I_a^{TECH,t+1/t} + \beta^n \; \Delta I_a^{STRUC,t+1/t} + d_a^n + f^{\,n,t} + \varepsilon_a^{n,t} \tag{19}$$

- one equation linking the TFP growth rate to the different price advantages

$$\left(\frac{\Delta TFP}{TFP}\right)_a^{t+1/t} = \left(\frac{-\Delta py}{py}\right)_a^{t+1/t} + \sum_{n=1}^{4}\left(\frac{\Delta w^n x^n}{py}\right)_a^{t+1/t} \tag{20}$$

with:
$a = 1, 2, ..., 63$ industries
t = 1987, 1988, ..., 2014
$n =$ 1,2,3,4 inputs.

In case of technical catching-up and structural convergence processes, productivity gains occur. As a result, if the coefficients $\alpha, \alpha^n, \beta, \beta^n$ are negative, the productivity gains (derived from inefficiency decreases) exert positive effects on the stakeholders' price advantages.

From the last TFP identity, the error terms are assumed to be correlated across the other equations. This justifies to estimate them simultaneously through the seemingly unrelated regression procedure, proposed by Zellner (1962). The econometric results are presented in Table 2.

Results show that both technical and structural efficiency scores have positive effects on clients' price advantages and profitability besides negative effects on supplier's price advantages. Labor and fixed capital stakeholders seem to be not dependent on structural and technical efficiency scores. We also notice that compared to the structural component, technical inefficiency score has higher impact on buyers' price advantages and profitability. According to these results, it is obvious that over the last 28 years, industries with significant inefficiency decreases have profited clients and firms through lower output prices or higher profitability rates while relative compensations of the other inputs do not seem to be impacted by inefficiency changes over time. Intuitively, the price and cost convergence process related to the global mobility of production resources among industries could explain this point. Indeed, price changes for these inputs are mainly determined by their specific national market structure and their own availability in accordance with the macroeconomic business cycle. As a result, inefficiency reductions produced in a certain industry do not significantly impact the labor and fixed capital market prices. On the contrary, they should influence considerably final demand prices and profitability rates of the considered sector.

Table 2. SUR procedure results

Equation	**Stakeholders**	**Coef.**	**T-stat**	**R2**	**DW**
Output	***Clients***				
Tech. catching-up	□	**-18,72**	**-11,35**	**0,24**	1,83
Convergence process	□	**-4,03**	**-3,11**		
Intermediate inputs	***Suppliers***				
Tech. catching-up	□	**3,09**	**3,48**	**0,32**	2,06
Convergence process	□	**2,73**	**3,92**		
Labor	***Employees***				
Tech. catching-up	□	-0,40	-0,89	0,28	2,18
Convergence process	□	-0,48	-1,37		
Fixed Capital	***Capital providers***				
Tech. catching-up	□	-0,26	-1,56	0,15	0,77
Convergence process	□	0,00	0,01		
Profitability	***Managers***				
Tech. catching-up	□	**-13,21**	**-9,97**	**0,11**	2,20
Convergence process	□	**-5,65**	**-5,44**		

4. Conclusion

In this paper we propose to evaluate two types of inefficiency: technical inefficiency between an industry and its benchmark on the production frontier and structural inefficiency seen as heterogeneity between input-output mixes among sectors. We define these two inefficiencies both at individual and at group levels. Finally, we link these two inefficiency measures to the stakeholders' price advantages.

This analysis was applied to US industries from 1987-2014. The results clearly show that convergence is observed for both technical and structural efficiencies. This reveals that technological transfer and reallocation process among sectors generate significant productivity gains at the country level. We estimate the impact of these convergence processes on the US economy at around 0.64% of additional growth.

Then, a panel data analysis performed for 63 US industries over the considering period relates positive influence of the two convergence processes onto final demand prices and profitability and negative influence onto suppliers' prices. The clients and managers get significant benefit from efficiency gains which occur in their specific industries which is not the case for the suppliers. Finally, no link can be established between technological catching-up process and input-output mixes homogenization and employees or capital providers' remunerations. For these two stakeholders, it seems that their price changes essentially result from the macro business cycle and do not take benefit or disadvantage from sectoral efficiency gains.

References

Abramovitz, M., (1986), Catching Up, Forging Ahead, and Falling behind, The Journal of Economic History, 46(2), 385–406

Barro, R. J.; Sala-i-Martin, X., (1991), Convergence across States and Regions, Center Discussion Paper, No. 629, 72p.

Bernard, A.B., Jones, C.I., (1996), Productivity and Convergence across U.S. States and Industries, Empirical Economics, 21(1), 113–135.

Boussemart, J.-P., Leleu, H., Mensah, E., (2017), Generation and Distribution of the Total Factor Productivity Gains in US Industries, Applied Economics, 49(24), 2379–93

Briec, W., Dervaux, B., Leleu, H., (2003), Aggregation of Directional Distance Functions and Industrial Efficiency, Journal of Economics, 79(3), 237–61

Cardarelli, R., Lusinyan, L., (2015), U.S. Total Factor Productivity Slowdown: Evidence from the U.S. States, IMF working paper, WP 15/116, 23p.

CERC (1980), Productivité globale et compte de surplus, documents du centre d'étude des revenus et des coûts, la documentation française, n°55/56, 218 p

Christopoulos, D. K., (2007), Explaining Country's Efficiency Performance, Economic Modelling, 24(2), 224–35

Collins, S. M., Bosworth, B. P., Rodrik, D., (1996), Economic Growth in East Asia: Accumulation versus Assimilation, Brookings Papers on Economic Activity, 2, 135-203

Debreu, G., (1951), The Coefficient of Resource Utilization, Econometrica, 19(3), 273-292

Dougherty C., Jorgenson D.W., (1997), There Is No Silver Bullet: Investment and Growth in the G7, National Institute Economic Review, 162, 57-74

Dowrick, S., Nguyen, D.-T., (1989), OECD Comparative Economic Growth 1950-85: Catch-up and Convergence, The American Economic Review, 79(5), 1010–1030

Durlauf, S. N., Johnson, P. A., (1995), Multiple Regimes and Cross-Country Growth Behaviour, Journal of Applied Econometrics, 10(4), 365–384

Färe, R., Grosskopf, S., Norris, M., Zhang, Z., (1994), Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries, American Economic Review, 84(1), 66-83

Ferrier, G. D., Leleu, H., Valdmanis, V. G., (2010), The Impact of CON Regulation on Hospital Efficiency, Health Care Management Science, 13(1), 84–100

Grifell-Tatjé E., Lovell C.A.K. (2015), Productivity Accounting, The Economics of Business Performance, Cambridge University Press, 386 p.

Islam, N. (2003). What Have we Learnt from the Convergence Debate? Journal of Economic Survey, 17(3), 310- 362.

Jorgenson D.W., (1995), Productivity: International comparisons of economic growth, 2, MIT Press

Kim, J-I., and L. Lau, (1994), The sources of growth in East Asian newly industrialized countries, Journal of the Japanese and International Economies, 8, 235-271.

Klenow, P., Rodriguez-Clare, A., (1997), Economic growth: A review essay, Journal of Monetary Economics, 40 (1997), 597 617

Krugman P., (1994), The Myth of Asia's Miracle, Foreign Affairs, 73(6), 62-78

Kumar, S., Russell, R., (2002), Technological change, technological catch-up, and capital deepening: Relative contributions to growth and convergence, American Economic Review, 92, 527–548

Li, S. K., Ng, Y. C. (1995), Measuring the Productive Efficiency of a Group of Firms, International advances in Economic Research, 1, 377–390

Solow, R. M., (1994), Perspectives on Growth Theory, The Journal of Economic Perspectives, 8(1), 45–54

Wolff, E. N., (1991), Capital Formation and Productivity Convergence over the Long Term, The American Economic Review, 81(3), 565–579

Young, A., (1992), A Tale of Two Cities: Factor Accumulation and Technical Change in Hong Kong and Singapore, NBER Macroeconomics Annual 1992, 7, 13 – 64

Young, A., (1994), Lesson from the East Asians NICS: A contrarian view, European Economic Review, 38, 964 – 973

Young, A., (1995), The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience, The Quarterly Journal of Economics, 110(3), 641–80

Zellner, A., (1962), An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias, Journal of the American Statistical Association, 57(298), 348-368