A multi-sector nonparametric production-frontier analysis of the economic growth and the convergence of the European countries*

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Abstract

In this paper, I apply the recent nonparametric multi-sector production-frontier methodology of Walheer (2016), tailored to analyze the economic growth and convergence of countries taking the sector heterogeneity and interdependence into account, to the European countries from 1995 to 2014. Thanks to a simple rewriting of his initial model, I also give results on the sector level, which was not possible with the initial version of the methodology. My results confirm the non-neutrality of technological change and highlight that human capital accumulation plays the biggest role in the increase of labor productivity. Technological change and capital accumulation also play an important, if smaller, role in the increase of output-labor productivity. My results also confirm the presence of heterogeneity between sectors in Europe which gives credit to multi-sector analysis. Finally, my results confirm the presence of two groups, in terms of labor productivity, within the European counties: eastern and central European countries and the EU12. These two groups diverge over time. The results are not affected by robustness checks.

Keywords: growth, convergence, multi-sector, production-frontier analysis, Europe.

*I thank the anonymous referee for his comments that substantially improved the paper.

1 Introduction

In this introductory section, I motivate the relevance of sector-specific results when studying the economic growth and the convergence of countries, and position my contributions in the relevant literature

Nonparametric growth analysis. Typically, models used to study the economic growth and the convergence are based on the Solow (1956) (parametric) decomposition of the economic growth into two components attributable to capital deepening and technological progress; and the Baumol (1986) – Barro (1991) cross-sectional regressions used to determine if there is a tendency for the world's economies to converge over time. While these models have contributed to increase our understanding of the growth and convergence issues, the empirical growth studies based on these models have not led to many definitive conclusions.[1] This could be explained, as argued by Quah (1993, 1996, 1997) and others (e.g. Galor (1996), Jones (1997), Feyrer (2003) and Johnson (2005)) by the bimodal distribution of labor productivity; which implies that the world is divided into two categories[2] (the poor and the rich). As such, these models, that are focused on the first moment of the distribution, cannot address the growth and convergence issue properly.

Building on this issue in the growth and convergence analysis, Kumar and Russel (2002) have proposed a (deterministic) nonparametric production-frontier analysis method.[3] They see two main advantages to use their methodology. On the one hand, their technique reconstructs the world production frontier without relying on any particular (typically unverifiable) assumptions on the technology, market structure, technological change, market imperfections or other aspects of the growth process (by contrast to most of the references cited above that are model driven). On the other hand, their methodology allows for a tripartite decomposition of labor productivity growth into those attributable to (1) technological change, i.e. shifts in the world

[1] See, for example, Paap, Franses and Van Djik (2005), Higgins, Levy, Young (2006), Alfo, Trovato and Waldmann (2008), Battisti and Di Vaio (2008) and, Owen, Viderasa and Davis (2009) for recent works using regression based methodologies.

[2] The division of the world into two categories is a robust stylized fact that does not depend of the test used. See Henderson, Parmeter and Russell (2008) for more details.

[3] Refer to Fare, Grosskopf and Lovell (1994), Cooper, Seiford and Zhu (2004), Cooper, Seiford and Tone (2007), Fried, Lovell and Schmidt (2008) and Cook and Seiford (2009) for reviews; and to Gattou, Oral and Reisman (2004) and Emrouznejad, Parker and Tavares (2008) for extensive listings of papers.

production frontier, (2) technological catch-up, i.e. movements toward or away from the frontier, and (3) physical capital accumulation, i.e. movements along the frontier.

Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013), inspired by the endogenous growth models of Lucas (1988) and Romer (1990), extended the previous work of Kumar and Russell (2002) by incorporating human capital.[4] They used the human capital measure of Hall and Jones (1999), which is based on the summary of returns-to-education regressions by Psacharopoulos (1994). They obtained a quadripartite decomposition of the growth of labor productivity into (1) technological change, (2) technological catch-up, (3) physical capital accumulation and (4) human capital accumulation.

At this point, it is useful to emphasise that stochastic parametric and semiparametric frontier models, initiated by Aigner, Lovell, and Schmidt (1977), Meeusen and van den Broeck (1977), and Schmidt and Sickles (1984), have also been proposed to tackle the growth and convergence issues.[5] Contrary to the nonparametric production-frontier analysis used by Kumar and Russell (2002), Henderson and Russell (2005) and the followers, those stochastic models account for the possibility of errors in variables which could be due to errors in data or to uncontrollable external factors. As explained in detail in Sickles, Hao and Shang (2015), those methods allow also to decompose the productivity growth into different sources: (1) innovation (or technological change) and (2) technological catch-up. The convergence issue can also be considered with these stochastic frontier models.[6]

Methods have also been suggested to include the possibility of measurement errors in (deterministic) nonparametric production-frontier analysis. One of the first papers is due to Grosskopf (1996). More recently, procedures have been suggested to correct the frontier for the well-known downward bias in the construction of the production frontier (see Simar and Wilson (1998, 2000) amongst others) and to detect the presence of outliers which could influence the reconstructed frontier (see Simar (2003)

[4]Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013) used the same methodology. Badunenko, Henderson and Russell (2013) increase the sample (more countries and bigger period of time) used in Henderson and Russell (2005).

[5]In the context of panel data, see also Cornwell, Schmidt, and Sickles (1990) and Kumbhakar (1990), Adams, Berger and Sickles (1997,1999), Adams and Sickles (2007), and Parks, Sickles and Simar (1998, 2003, 2007).

[6]Applications using these stochastic methods to analyse the growth and convergence issues could be found, for example, in Koop, Osiewalski and Steel (1999), Hultberg, Nadiri, and Sickles (1999, 2004), Ahn and Sickles (2000), Wu (2001), Deliktas and Balcilar (2005), Kumbhakar and Wang (2005), Sickles, Hao, and Shang (2014), Cardoso and Ravishankar (2015).

and Daraio and Simar (2007)) amongst others).[7] These procedures give a robustness feature to the results obtained.

Multi-sector nonparametric growth analysis. Walheer (2016) extended the nonparametric production-frontier analysis model of Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013) by integrating the sector heterogeneity and interdependence. While he agreed that the economic growth analysis must be conducted at the country level since countries share common factors (such as the government, the legal system, the education system, etc), ignoring sector heterogeneity may give biased results. Building on this idea, Walheer (2016) proposed a multi-sector nonparametric growth model that has the same features as the previous models of Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013) (i.e. no assumption on the technology, one efficiency score for each country, and a quadripartite decomposition of labor productivity growth) and has the extra advantage of taking the specificities of the sectors into account. Consequently, his resulting methodology increases the realism of the growth analysis without making any extra assumption.

Contributions. In this paper, I extend the work of Walheer (2016) in several directions. Firstly, while taking the sector heterogeneity and interdependence into account, his model does not give any results on the sector level. By simply rewriting his multi-sector efficiency measurement as the result of an (non-trivial) aggregation of the sector-specific efficiency measurements, I obtain a model with such sector level results. Secondly, I extend his data, which ends at 2008, to the year 2014. Finally, I check for the presence of outliers and I correct the reconstructed frontier for the bias.

I apply the methodology to the European countries from 1995 to 2014. My results confirm the non-neutrality of technological change already found in all the previous works cited above. I also find that human capital accumulation has played the biggest role in the increase of labor productivity, while technological change and capital accumulation played also an important but smaller role. My results confirm two stylized facts already highlighted by Walheer (2016): the emergence of two groups, in terms of labor productivity, in the European countries (the eastern and central

[7]These procedures have also been used by Enflo and Hjertstrand (2008) and Badunenko, Henderson and Russell (2013) in a similar context.

European countries and the EU12); and the divergence of these groups over time. Those results are not affected by the robustness checks.

My sector-specific results confirm the presence of heterogeneity between sectors in Europe which gives credit to multi-sector analysis. The sector-specific results allow to better explain the role of each sector in the convergence/divergence between countries/groups. They allow also to understand in which sector each country/group perform better and in which sector an effort (in terms of investment for example) has to be made. I found that the Electricity, Gas and Water and the Health sectors have a bigger productivity change in the eastern and central European countries while it is the opposite for the other sectors.

Outline. The rest of the paper is structured as follows. In Section 2, I define the multi-sector output efficiency measurement and show how the labor productivity growth can be decomposed into four parts. In Section 3, I present the results. In Section 4, I conclude.

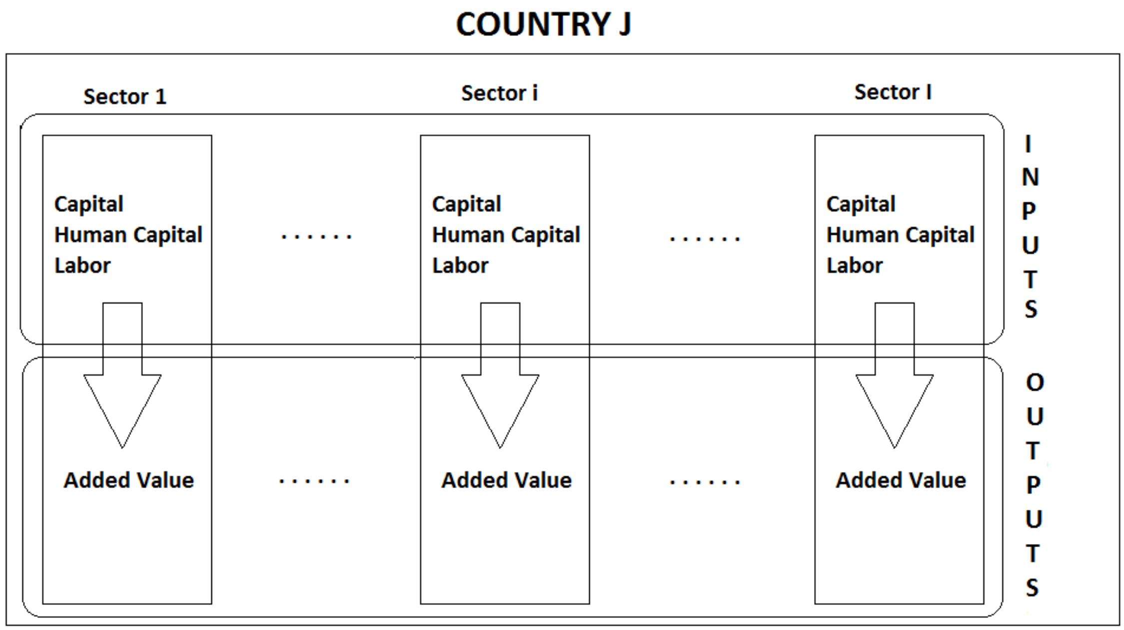
2 Methodology

This section is divided in two parts. In Section 2.1, I define and show how to measure the sector-specific and multi-sector output efficiency measurements. In Section 2.2, I show how the labor productivity growth can be decomposed into four parts.

2.1 Multi-sector production-frontier approach

Data set and technology sets. Assume I observe J countries during T periods of time. Assume also that each country j is composed by I sectors. Every sector i in country j at time t uses labor L_{ijt}, physical capital K_{ijt} and human capital H_{jt} to produce output Y_{ijt} (proxied by the added value, see Section 3.1 for more details). Capital and labor are completely allocated to the sectors since they are specific to each sector i. Human capital, which is computed with the average number of years of education in the country (see Section 3.1), is common to the sectors. As such, the sectors are interdependent since they share the country's education system, captured by human capital. This interdependence between the sectors is the main reason while the economic growth analysis must be conducted at the country level since countries share common factors as the government, the legal system, the education system. Figure 1 summarizes the multi-sector setting I consider.

Figure 1: Multi-sector setting of country j in period t



I assume that human capital H_{jt} enters the technology as a multiplicative augmentation of labor input, i.e. $\hat{L}_{jt} = H_{jt}L_{jt}$. This assumption is adopted in the previous works of Henderson and Russell (2005) and the followers (Badunenko, Henderson and Russell (2013), Walheer (2016), etc). They argue that it is a standard assumption in macroeconomic theory that human capital enters the technology as a multiplicative augmentation of labor input.[8] Taking together, I observe the following data set D

$$D = \{(Y_{ijt}, \hat{L}_{ijt}, K_{ijt}) \mid i = 1, \ldots, I; j = 1, \ldots, J; t = 1, \ldots, T\} \tag{1}$$

where $\hat{L}_{ijt} = H_{jt}L_{ijt}$, as explained previously.

The data set D allows to characterize each sector in every country by its own production technology set. Formally, using the sequential production set formulation of Diewert (1980), I construct monotone (or free-disposal), convex and constant returns-to-scale technology sets for every sector in each country for all periods. In

[8]The following can easily be adapted to obtain a multi-sector version of the nonparametric growth model of Kumar and Russell (2002), i.e. a version of Henderson and Russell (2005) without human capital. Just replace $\hat{L}_{jt}$ by L_{jt} in the whole paper.

particular, the technology set for sector i in country j at period t is given by[9]

$$T_t^i = \left(\begin{array}{c} (Y, \hat{L}, K) \mid Y \leq \sum_{\tau=1}^{t} \sum_{j=1}^{J} \lambda_{ij\tau} Y_{ij\tau}, \\ \hat{L} \geq \sum_{\tau=1}^{t} \sum_{j=1}^{J} \lambda_{ij\tau} \hat{L}_{ij\tau}, \\ K \geq \sum_{\tau=1}^{t} \sum_{j=1}^{J} \lambda_{ij\tau} K_{ij\tau}, \\ \lambda_{ij\tau} \geq 0 \ \forall i, \forall j, \forall \tau. \end{array} \right). \tag{2}$$

Nonparametric sector-specific output efficiency measurement. In order to construct the multi-sector (country level) efficiency measurement, I first define the efficiency measurement for each sector i. Following the previous works of the papers cited before, I use a Debreu (1951)−Farrell (1957) output efficiency measure to compute the maximal expansion of the output (keeping the inputs constant) for each sector i in country j at time t, which is defined as

$$TE_{ijt}(Y_{ijt}, \hat{L}_{ijt}, K_{ijt}) = \min \left\{ \eta \mid \left(\frac{Y_{ijt}}{\eta}, \hat{L}_{ijt}, K_{ijt} \right) \in T_t^i \right\}. \tag{3}$$

$TE_{ijt}(Y_{ijt}, \hat{L}_{ijt}, K_{ijt})$ is the inverse of the maximal amount that output Y_{ijt} can be expanded while keeping the inputs ($\hat{L}_{ijt}$ and K_{ijt}) constant. $TE_{ijt}(Y_{ijt}, \hat{L}_{ijt}, K_{ijt}) \leq 1$ and $TE_{ijt}(Y_{ijt}, \hat{L}_{ijt}, K_{ijt}) = 1$ means that sector i in country j produces the maximal amount of output at time t. A smaller value of $TE_{ijt}(Y_{ijt}, \hat{L}_{ijt}, K_{ijt})$ implies more inefficient behavior.

Besides computing the multi-sector (country level) efficiency measurement as explained in the next paragraph, the sector-specific efficiency measurements give also valuable extra information. Namely, ranking the sectors within a specific country; identifying the cause of the (in)efficiency within each country; looking which sectors is the most/least (in)efficient in Europe; identifying the sectors which has the most/least numbers of (in)efficient countries; etc. I refer to Section 3.2 for the practical use of these sector-specific efficient measurements.

[9]See Cherchye et al. (2016) for a rigorous definition of the monotonicity (or free-disposability) and convexity of the production set T_t^i. I remark that assuming monotonicity, convexity, and constant return-to-scales of the country-specific technology set (used for example by Kumar and Russel (2002), Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013)) is stronger than assuming monotonicity, convexity, and constant return-to-scales of the sector-specific technology sets T_t^i (for $i = 1, \ldots, I$). See Cherchye et al. (2013) for a formal proof.

Nonparametric multi-sector (country level) output efficiency measurement. I now explain how to obtain the multi-sector efficiency measurement using the sector-specific efficiency measurements TE_{ijt}. A first observation is that, for given country j and time t, the multi-sector efficiency measurement lies between the minimum and maximum of the sector-specific efficiency scores TE_{ijt}. Let TE^L_{ijt} and TE^U_{ijt} be the minimal and the maximal efficiency measurements of the sector $i = 1, \ldots, I$ in country j at time t. Then, the following holds

$$MSTE_{jt} \in \left[TE^L_{ijt}; TE^U_{ijt}\right] \tag{4}$$

No aggregation procedure is known at this stage. Moreover I prefer to follow the nonparametric spirit of the procedure and consequently give a 'benefit of the doubt' to the countries by evaluating each country by its least inefficient sector. In the absence of a known aggregation procedure, it is the most favorable way to aggregate the sector efficiency measurements in order to obtain the country efficiency measurements, or in other words, the measure of country efficiency represents the upper bound of the sector-specific efficiency measurements.[10] The multi-sector efficiency score is therefore given for each county j at time t by

$$MSTE_{jt} = TE^U_{ijt}. \tag{5}$$

Attractively, the multi-sector efficiency measurement, for each country j at time t, could be obtained in one step by adapting the standard Debreu (1951)−Farrell (1957) output efficiency measure to the multi-sector setting (with I production sets T^i_t)

$$MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt}) = \min\left\{\theta \mid \forall i : \left(\frac{Y_{ijt}}{\theta}, \hat{L}_{ijt}, K_{ijt}\right) \in T^i_t\right\}. \tag{6}$$

$MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt})$ is the inverse of the maximal amount that output Y_{jt} can be expanded in all sectors while keeping the input $(\hat{L}_{jt}, K_{jt})$ constant. $MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt}) \leq 1$ and $MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt}) = 1$ means that country j produces the maximal amount of output at time t in at least one sector. A smaller value of $MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt})$ implies more inefficient behavior.

[10]See, for example, Cherchye et al. (2007) for a detailed discussion of the 'benefit of the doubt' interpretation of nonparametric efficiency models and Cherchye et al. (2013, 2014, 2015, 2016) and Walheer (2016) for measures close to mine which adopt this 'benefit of the doubt' spirit.

The common θ in the definition reflects the 'benefit of the doubt' spirit of the measure as explained before. Indeed, imposing a common efficiency measurement to the sectors implies that $MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt})$ is equal to the upper bound of the sector efficiency measurements.

As a final remark, I point that $MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt})$ gives a more complete and more realistic analysis by taking the multi-sector setting into account (i.e. heterogeneity and interdependence) than the country-level efficiency measure used in the previous work of Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013) and others, which is based on aggregated data; but keep the same advantages as their measure (i.e. no assumption on the technology and one efficiency score for each country).

Linear programs. In the following, I show how the sector-specific output efficiency scores $TE_{ijt}(Y_{ijt}, \hat{L}_{ijt}, K_{ijt})$ and the the multi-sector output efficiency scores $MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt})$ are easily obtained in practice by means of linear programs.

- The sector-specific output efficiency scores $TE_{ijt}(Y_{ijt}, \hat{L}_{ijt}, K_{ijt})$ for $i_0 \in (1, \ldots, I)$, $j_0 \in (1, \ldots, J)$ and $t_0 \in (1, \ldots, T)$ are obtained by solving the following linear program **(LP-S)**:

$$TE_{i_0j_0t_0}(Y_{i_0j_0t_0}, \hat{L}_{i_0j_0t_0}, K_{i_0j_0t_0}) = \min_{\lambda_{i_0j\tau}\ (j\in\{1,\ldots J\},,\tau\in\{1,\ldots t_0\})} \eta$$

$$\text{(S-1)}\ \frac{Y_{i_0j_0t_0}}{\eta} \leq \sum_{\tau=1}^{t_0} \sum_{j=1}^{J} \lambda_{i_0j\tau} Y_{i_0j\tau}$$

$$\text{(S-2)}\ \hat{L}_{i_0j_0t_0} \geq \sum_{\tau=1}^{t_0} \sum_{j=1}^{J} \lambda_{i_0j\tau} \hat{L}_{i_0j\tau}$$

$$\text{(S-3)}\ K_{i_0j_0t_0} \geq \sum_{\tau=1}^{t_0} \sum_{j=1}^{J} \lambda_{i_0j\tau} K_{i_0j\tau}$$

$$\text{(S-4)}\ \forall j, \forall \tau : \lambda_{i_0j\tau} \geq 0$$

$$\text{(S-5)}\ \eta \geq 0.$$

- The multi-sector output efficiency scores $MSTE_{jt}(Y_{jt}, \hat{L}_{jt}, K_{jt})$ for $j_0 \in (1, \ldots, J)$

and $t_0 \in (1, \ldots, T)$ are obtained by taking the maximum of the TE's

$$MSTE_{j_0t_0}(Y_{j_0t_0}, \hat{L}_{j_0t_0}, K_{j_0t_0}) = \max_{i=1,\ldots,I}\Big(TE_{ij_0t_0}(Y_{ij_0t_0}, \hat{L}_{ij_0t_0}, K_{ij_0t_0})\Big) \tag{7}$$

or in one step by solving the following linear program **(LP-MS)**:

$$MSTE_{j_0t_0}(Y_{j_0t_0}, \hat{L}_{j_0t_0}, K_{j_0t_0}) = \min_{\lambda_{ij\tau}\ (i\in\{1,\ldots I\}, j\in\{1,\ldots J\},, \tau\in\{1,\ldots t_0\})} \theta$$

$$\text{(MS-1) } \forall i: \frac{Y_{ij_0t_0}}{\theta} \leq \sum_{\tau=1}^{t_0}\sum_{j=1}^{J}\lambda_{ij\tau}Y_{ij\tau}$$

$$\text{(MS-2) } \forall i: \hat{L}_{ij_0t_0} \geq \sum_{\tau=1}^{t_0}\sum_{j=1}^{J}\lambda_{ij\tau}\hat{L}_{ij\tau}$$

$$\text{(MS-3) } \forall i: K_{ij_0t_0} \geq \sum_{\tau=1}^{t_0}\sum_{j=1}^{J}\lambda_{ij\tau}K_{ij\tau}$$

$$\text{(MS-4) } \forall i, \forall j, \forall \tau: \lambda_{ij\tau} \geq 0$$

$$\text{(MS-5) } \theta \geq 0.$$

As a final remark, I point that the following can easily be adapted when some data are not perfectly measured, as it could be the case for sector level data. See Walheer (2016) for more details.

2.2 Quadripartite Decomposition of Labor Productivity Growth

In this section, I show how the growth of labor productivity can be decomposed into four parts: (1) efficiency change, (2) technological change, (3) capital deepening (increases in the capital−labor ratio), and (4) human capital accumulation, for each country and each sector in every country. This section is directly inspired by the decompositions suggested by Kumar and Russell (2002) and extended by Henderson and Russell (2005) with human capital. I refer to their papers for more details. The only difference with this paper is that the efficient output levels are computed with the multi-sector country level model instead of the standard country level model used in their papers. In the rest of this section, I drop the subscript j (referring to a specific country) for better readability.

Country-level Quadripartite Decomposition. Before explaining the decomposition, one important remark must be made. Thanks to the constant returns-to-scale assumption of the technology, I can move from a representation in three dimensions $\langle Y, \hat{L}, K\rangle$ to a representation in two dimensions $\langle \hat{y}, \hat{k}\rangle$, by defining $\hat{y}_t = Y_t/\hat{L}_t$ and $\hat{k}_t = K_t/\hat{L}_t$. The technology is then characterized by the function $\hat{y}_t(\hat{k}_t)$.

The decomposition of labor productivity $y_t = Y_t/L_t$ is done in five main steps.

Step 1. I decompose the growth of labor productivity, y_t for $t = \{b, c\}$ (b and c denote the base and the current periods), into the growth of human capital and the growth of output per efficiency unit of labor.

$$\frac{y_c}{y_b} = \frac{H_c}{H_b}\frac{\hat{y}_c}{\hat{y}_b}. \tag{8}$$

Step 2. In order to isolate the effect of pure efficiency and technical change, I denote the efficient output at time b and c by $\hat{y}_b(\hat{k}_b) = \hat{y}_b/\theta_b$ and $\hat{y}_c(\hat{k}_c) = \hat{y}_c/\theta_c$, where $\theta_t = MSTE_t(Y_t, \hat{L}_t, K_t)$ for $t = \{b, c\}$. It allows to define the following equality

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{\theta_c}{\theta_b}\frac{\hat{y}_c(\hat{k}_c)}{\hat{y}_b(\hat{k}_b)}, \tag{9}$$

Step 3. In order to isolate the effect of capital-labor ratio and of human capital in labor productivity growth I denote $\tilde{k}_c = K_c/(L_c H_b)$ as the ratio of capital to labor measured in efficiency units under the counterfactual assumption that human capital has not changed from its base period; and $\tilde{k}_b = K_b/(L_b H_c)$ as the ratio of capital to labor measured in efficiency units under the counterfactual assumption that human capital is equal to its current-period level. Multiplying equation (8) by $\frac{\hat{y}_b(\hat{k}_c)}{\hat{y}_b(\hat{k}_c)}$ and $\frac{\hat{y}_b(\tilde{k}_c)}{\hat{y}_b(\tilde{k}_c)}$ gives

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{\theta_c}{\theta_b}\frac{\hat{y}_c(\hat{k}_c)}{\hat{y}_b(\hat{k}_c)}\frac{\hat{y}_b(\tilde{k}_c)}{\hat{y}_b(\hat{k}_b)}\frac{\hat{y}_b(\hat{k}_c)}{\hat{y}_b(\tilde{k}_c)}; \tag{10}$$

and by $\frac{\hat{y}_c(\hat{k}_b)}{\hat{y}_c(\hat{k}_b)}$ and $\frac{\hat{y}_c(\tilde{k}_b)}{\hat{y}_c(\tilde{k}_b)}$ gives

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{\theta_c}{\theta_b}\frac{\hat{y}_c(\hat{k}_b)}{\hat{y}_b(\hat{k}_b)}\frac{\hat{y}_c(\hat{k}_c)}{\hat{y}_c(\tilde{k}_b)}\frac{\hat{y}_c(\tilde{k}_b)}{\hat{y}_c(\hat{k}_b)}. \tag{11}$$

Step 4. Combining all the previous equations gives

$$\frac{y_c}{y_b} = \frac{\theta_c}{\theta_b} \frac{\hat{y}_c(\hat{k}_b)}{\hat{y}_b(\hat{k}_b)} \frac{\hat{y}_c(\hat{k}_c)}{\hat{y}_c(\tilde{k}_b)} \left(\frac{\hat{y}_c(\tilde{k}_b)}{\hat{y}_c(\hat{k}_b)} \frac{H_c}{H_b} \right) \tag{12}$$

$$= EFF \times TECH^b \times KACC^c \times HACC^c. \tag{13}$$

and

$$\frac{y_c}{y_b} = \frac{\theta_c}{\theta_b} \frac{\hat{y}_c(\hat{k}_c)}{\hat{y}_b(\hat{k}_c)} \frac{\hat{y}_b(\tilde{k}_c)}{\hat{y}_b(\hat{k}_b)} \left(\frac{\hat{y}_b(\hat{k}_c)}{\hat{y}_b(\tilde{k}_c)} \frac{H_c}{H_b} \right) \tag{14}$$

$$= EFF \times TECH^c \times KACC^b \times HACC^b. \tag{15}$$

Equations (13) and (15) decompose labor productivity growth over the two periods b and c into the change in efficiency (EFF), i.e. shifts in the world production frontier; technological change ($TECH$), i.e. movements toward or away from the frontier; the change in the capital-labor ratio ($KACC$); and the human capital accumulation ($HACC$), i.e. movements along the frontier.

Step 5. The decompositions of equations (13) and (15) do not yield the same results.[11] To overcome the path dependence of the decomposition, Kumar and Russell (2002) and Henderson and Russell (2005) have suggested to adopt the Fisher Ideal decomposition introduced by Caves et al. (1982) and Fare et al. (1993). In particular, top and bottom of Equation (8) are multiplied by $\left(\hat{y}_b(\hat{k}_c)\hat{y}_b(\tilde{k}_c)\right)^{1/2} \left(\hat{y}_c(\hat{k}_b)\hat{y}_c(\tilde{k}_b)\right)^{1/2}$ which yields

$$\frac{y_c}{y_b} = EFF \times \left(TECH^b TECH^c\right)^{1/2} \times \left(KACC^b KACC^c\right)^{1/2} \times \left(HACC^b HACC^c\right)^{1/2} \tag{16}$$

$$= EFF \times TECH \times KACC \times HACC. \tag{17}$$

The labor productivity change can be decomposed into the efficiency change (EFF), the geometric averages (over the base and current periods) of technological change ($TECH$), the change in the capital-labor ratio ($KACC$), and human capital accumulation ($HACC$).

[11] The two decompositions are equal only if the neutrality of technological change is assumed (as in Solow (1957) and in the many studies building on his pioneering article).

Sector-level Quadripartite Decomposition. The decomposition of the labor productivity $y_{it} = Y_{it}/L_{it}$ for every sector $i \in \{1, \dots, I\}$ is done in an analogous way as done previously for the country level decomposition. Indeed, it suffices to follow the five main steps by using the sector-level output y_{it} instead of the country-level output y_t. Given this direct similarity and for the sake of compactness, I do not repeat the five steps here but directly give the main results (compare with (16) and (17)):

$$\frac{y_{ic}}{y_{ib}} = EFF_i \times \left(TECH_i^b TECH_i^c\right)^{1/2} \times \left(KACC_i^b KACC_i^c\right)^{1/2} \times \left(HACC_i^b HACC_i^c\right)^{1/2} \tag{18}$$

$$= EFF_i \times TECH_i \times KACC_i \times HACC_i. \tag{19}$$

where EFF_i is the efficiency change of sector i (i.e. using the score $\theta_{it} = TE_{it}(Y_{it}, \hat{L}_{it}, K_{it})$ for $t = \{b, c\}$); $TECH_i$, $KACC_i$ and $HACC_i$ are respectively the geometric averages (over the base and current periods) of technological change, change in the capital-labor ratio, and human capital accumulation of sector i.

3 Application

To present my application, I first explain how the sector-level data are selected and give some descriptive statistics. Subsequently, I give the results of the empirical analysis.

3.1 Data and descriptive statistics

In this section, I first explain how I measure the four variables and then present some descriptive statistics.

Data. I use the OECD Detailed National Accounts database for the data of output (Y), capital (K), labor (L), inflation and purchasing power parity (PPP). The database proxies output for the sectors by the Gross Added Value (measured in millions of the current national currency); and capital by the Gross Capital Formation (measured in millions of the current national currency). I correct output and capital by inflation and by purchasing power parity (PPP) to obtain comparable data. Consequently, output and capital are measured in constant PPP prices (I choose 1995 as reference year since it is the starting data of my sample). Labor is measured in thousands of people employed. No correction is needed for this variable. For human capital (H), I follow the construction of Hall and Jones (1999)

$$H_{jt} = e^{\phi(e_{jt})}. \tag{20}$$

where ϕ is a piecewise-linear function, with a zero intercept and a slope of 0.134 through the fourth year of education, 0.101 for the next 4 years, and 0.068 for education beyond the eighth year; and e_{jt} is the average number of years of education of the adult population in country j at time t. I used the most recent available database given by Barro and Lee (2013) for e_{jt}.

I select the biggest sample possible which consists of 19 European countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Slovakia, Slovenia, Spain, and Sweden; 10 sectors: Agriculture, Mining, Manufacturing, Electricity, Gas and Water, Construction, Wholesale, Transport, Public Administration , Education, and Health. The time period is 1995-2014.

Descriptive statistics. Table 1 contains the relative shares of output, labor, output/labor (i.e. labor productivity) and capital for the EU during the period 1995-2014. Manufacturing is the most output-, labor- and capital- intensive sectors but not the most output-per-labor-intensive sector, which is Mining. Wholesale has also big relative shares of output, labor and capital but does not perform in the output-per-labor relative share. Electricity, Gas and Water has a high output-per-labor relative share, which is due to a low labor relative share with respect to the output share. It is the opposite story for the Health sector. The Transport and Public Administration sectors have high capital relative shares. Finally, the available data for the sectors represent more than 75% of the total of output, labor and capital during the period 1995-2014 for the 19 countries. It is an acceptable rate which gives credit to the results of this analysis.

Table 1: Relative shares of output, labor, output/labor and capital(%)

Sector	Y	L	Y/L	K
Agriculture (A)	2.36	5.30	2.53	4.55
Mining (Mi)	1.17	0.42	23.03	1.64
Manufacturing (Ma)	20.90	19.59	5.34	24.66
Electricity, gas and water (EGW)	2.46	0.867	16.10	5.61
Construction (C)	6.64	7.89	3.92	4.38
Wholesale (W)	13.06	16.47	3.85	8.42
Transport (T)	7.10	6.33	5.37	11.81
Public administration (PA)	7.77	7.92	4.37	12.40
Education (E)	5.66	7.28	3.67	4.04
Health (H)	8.00	10.78	3.24	5.42
Total	75.11	82.85	71.62	82.93

3.2 Results

This section is divided into seven parts. In the first two parts, I present the results of the sector-specific and multi-sector output efficiency scores. In the next three parts, I give the quadripartite decomposition for the countries, I discuss the emergence of two groups within the European countries; and I give the quadripartite decomposition for the sectors. After, I compare my results to existing similar analysis. Finally, I use two procedures to check the robustness of my results.

Sector-specific output efficiency scores. I calculate efficiency scores for the endpoint years 1995 and 2014 for the 19 countries in the 10 sectors. Columns 2 to 11 of Tables 2 and 3 contain the results for the 10 sectors for 1995 and 2014 respectively. On the bottom of the two Tables, I report some descriptive statistics of the sector-specific efficiency scores for each sector (minimum, median, maximum and standard deviation) as well as the number of efficient countries.

In 1995, some interesting observations can be made from Table 2. Firstly, the expected heterogeneity between sectors is really present. Indeed, the minimum (between 0.16 and 0.27), the median (between 0.52 and 0.84) and standard deviation (between 0.18 and 0.26) of the scores; as well as the numbers of efficient countries (between 1 and 4) are significantly different between the 10 sectors. I give below the most importantly results. The Public Administration sector has the highest median (0.84) and the biggest number of efficient countries (4). This is the opposite story for Mining which has the smallest median efficiency score (0.52). Agriculture, Construc-

Table 2: Efficiency scores in 1995

Country	**MSTE**	**A**	**Mi**	**Ma**	**EGW**	**C**	**W**	**T**	**PA**	**E**	**H**
Austria	1	0.42	0.52	0.80	0.78	1	0.84	0.81	1	0.92	0.78
Belgium	1	0.91	0.99	0.96	1	0.91	0.86	0.87	0.91	1	0.79
Czech Republic	0.71	0.49	0.45	0.32	0.34	0.34	0.38	0.71	0.41	0.38	0.35
Denmark	0.91	0.84	0.30	0.62	0.74	0.67	0.67	0.67	0.91	0.65	0.84
Estonia	0.45	0.26	0.45	0.19	0.17	0.31	0.23	0.27	0.22	0.18	0.16
Finland	0.98	0.69	0.52	0.84	0.84	0.80	0.94	0.82	0.76	0.66	0.98
France	1	1	0.73	0.92	0.86	1	1	1	0.97	0.81	0.92
Germany	0.86	0.59	0.71	0.71	0.62	0.77	0.84	0.86	0.81	0.70	0.71
Hungary	1	0.88	0.51	0.44	0.40	0.41	0.56	0.50	1	0.37	0.38
Ireland	1	0.77	0.50	1	0.59	0.79	0.61	0.61	1	0.71	0.93
Italy	1	0.83	0.72	0.84	0.75	0.89	1	1	0.98	0.94	1
Luxembourg	1	0.88	0.96	0.96	0.63	0.83	0.91	1	1	1	0.90
Netherlands	1	0.94	1	0.76	0.65	0.82	0.75	0.79	0.90	0.66	0.57
Norway	1	0.55	0.52	0.70	1	1	1	0.76	0.61	0.52	0.62
Poland	0.99	0.99	0.92	0.48	0.41	0.40	0.68	0.91	0.82	0.30	0.32
Slovakia	1	0.77	0.27	0.46	0.43	0.27	0.50	0.70	0.33	0.38	1
Slovenia	1	0.48	1	0.53	0.45	0.44	0.43	0.75	0.53	0.48	0.52
Spain	1	0.84	0.71	0.79	1	0.83	0.73	0.82	0.84	0.69	1
Sweden	1	1	0.44	0.71	0.97	0.74	0.71	0.77	0.62	0.47	0.78
Minimum	0.45	0.26	0.27	0.20	0.17	0.27	0.23	0.27	0.22	0.18	0.16
Median	1	0.83	0.52	0.71	0.65	0.79	0.73	0.79	0.84	0.66	0.78
Maximum	1	1	1	1	1	1	1	1	1	1	1
Standard Dev.	0.14	0.22	0.24	0.23	0.25	0.25	0.22	0.18	0.25	0.24	0.26
# Efficient	13	2	2	1	3	3	2	3	4	2	3

A: Agriculture; Mi: Mining; Ma:Manufacturing; EGW:Electricity, Gas & Water; C: Construction; W: Wholesale; T: Transport;

PA: Public Administration; E: Education; H: Healt.

tion, Transport and Health have also good performances with median around 0.80 and 3 efficient countries. Electricity, gas and water has also 3 efficient countries but a smaller median (0.65). Manufacturing, which is the most output-, labor- and capital-intensive sector (see Table 1) has 2 efficient countries and an average median (0.71).

On the country level, the number of efficient sectors per country is between 0 and 4. France is the only country with 4 efficient sectors while Luxembourg, Italy and Norway have 3 efficient sectors. Czech Republic, Denmark, Estonia, Finland, Germany, and Poland have 0 efficient sectors but the sector-specific scores are very different between those countries. Indeed, Czech Republic and Estonia have scores smaller in almost all sectors than Denmark, Finland and Germany. The same story holds for Slovenia, Slovakia and Hungary that have 1 efficient sector. Comparing those countries with the other countries that have 1 efficient sector (the conclusion holds also if the comparison is done with country with 0 efficient sector), clearly show that they have smaller efficient scores in almost all sectors. These observations show already that two groups are present in Europe in term of output (in)efficiency: the eastern and central European countries (Czech Republic, Estonia, Hungary, Poland, Slovakia and Slovenia) and the EU12 (the twelve other countries).

Table 3: Efficiency scores in 2014

Country	**MSTE**	**A**	**Mi**	**Ma**	**EGW**	**C**	**W**	**T**	**PA**	**E**	**H**
Austria	0.97	0.45	0.55	0.57	0.46	0.84	0.64	0.64	0.97	0.82	0.76
Belgium	0.98	0.75	0.79	0.59	0.57	0.94	0.79	0.59	0.98	0.90	0.72
Czech Republic	0.55	0.55	0.21	0.28	0.32	0.33	0.41	0.25	0.46	0.37	0.53
Denmark	0.83	0.69	0.58	0.55	0.83	0.68	0.73	0.60	0.82	0.62	0.72
Estonia	0.40	0.39	0.39	0.28	0.14	0.33	0.40	0.27	0.29	0.18	0.26
Finland	0.81	0.81	0.13	0.51	0.57	0.76	0.67	0.58	0.71	0.66	0.72
France	0.91	0.84	0.37	0.54	0.54	0.83	0.77	0.56	0.85	0.91	0.85
Germany	0.89	0.53	0.57	0.50	0.61	0.82	0.68	0.48	0.87	0.66	0.61
Hungary	0.46	0.46	0.34	0.20	0.34	0.20	0.36	0.18	0.22	0.29	0.45
Ireland	1	0.43	1	0.88	0.57	0.65	0.53	0.50	0.82	0.85	0.93
Italy	1	0.80	0.47	0.40	0.67	0.70	0.74	0.64	1	0.85	0.92
Luxembourg	1	0.47	0.65	0.39	0.28	0.98	1	0.47	1	1	0.93
Netherlands	0.94	0.94	0.64	0.55	0.59	0.69	0.80	0.57	0.87	0.70	0.62
Norway	1	0.28	0.30	0.45	0.70	0.71	1	0.52	0.68	0.60	0.66
Poland	0.67	0.44	0.67	0.30	0.32	0.43	0.59	0.32	0.36	0.37	0.61
Slovakia	0.98	0.98	0.84	0.25	0.26	0.60	0.72	0.26	0.39	0.45	0.64
Slovenia	1	0.13	1	1	0.15	0.43	0.60	0.37	0.38	0.34	0.57
Spain	1	0.84	0.32	0.47	0.42	0.72	0.46	0.45	0.95	0.75	0.93
Sweden	0.97	0.84	0.13	0.61	0.60	0.80	0.69	0.57	0.77	0.69	0.97
Minimum	0.40	0.13	0.13	0.20	0.14	0.20	0.36	0.18	0.22	0.18	0.26
Median	0.97	0.55	0.55	0.50	0.54	0.70	0.68	0.50	0.82	0.66	0.72
Maximum	1	0.98	1	1	0.83	0.98	1	0.64	1	1	0.97
Standard Dev.	0.20	0.24	0.26	0.20	0.19	0.22	0.18	0.15	0.27	0.24	0.19
# Efficient	6	0	2	1	0	0	2	0	2	1	0

The results for 2014 given are given in Table 3. Clearly, the efficiency scores are on average smaller in every sectors than those of 1995 which implies a decrease of efficiency in 15 years. This is also confirmed by the presence of sectors with 0 efficient countries, implying that the efficient benchmark partner is before 2014. The conclusions made for 1995 using the minimum, maximum, median, standard deviation of the scores and number of efficient countries are confirmed for 2014: the sectors are heterogeneous.

On the sector level, Public Administration has still the biggest median (0.82) with 2 efficient countries. The performances of Construction and Health are still high while those of Agriculture and Transport have really decrease. Indeed, Transport and Manufacturing, have the smallest median. Mining has still a bad median performance but 2 efficient countries.

On the country level, the story of the two groups within the European countries holds also for 2014. Indeed, the eastern and central European countries (Czech Republic, Estonia, Hungary, Poland, Slovakia and Slovenia) have, on average, smaller sector output efficiency scores than the EU12 (the twelve other countries).

Multi-sector output efficiency scores. The results are available in the first column of Table 2 and 3. The efficient countries in 1995 are: Austria, Belgium, France, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Slovenia, Spain, and Sweden. In 2014, the efficient countries are: Ireland, Italy, Luxembourg, Norway, Slovenia and Spain. The median is 1 in 1995 and 0.97 in 2014, the minimum is 0.45 in 1995 and 0.40 in 2014, the maximum is 1 for both years, the number of efficient countries is 13 in 1995 and 6 in 2014. All these numbers confirm a decrease of the efficiency level between the two periods observed previously with the sector-specific efficiency scores. The standard deviation is bigger in 2014 (0.20) that in 1995 (0.14) which indicates a bigger dispersion of the scores in 2014.

Table 2 and 3 indicate that the biggest drops are in central and eastern European economies (due perhaps to disorganization and instability): Hungary (-0.54), Poland (-0.33) and Czech Republic (-0.16). The other countries have stable efficiency scores or a small decrease (between -0.02 and -0.08; except Finland: -0.17). This confirmed the previous observations made with the sector-specific efficiency scores that two groups are present within the European countries. This indicates also that the two groups seem diverging over time.

Country-level quadripartite decomposition. The decomposition of labor productivity per country is available in Table 4. I give the decomposition in percentages by subtracting 1 from the index and multiplying by 100. The median productivity change is 18.89%, which is attributed to efficiency change; i.e. shifts in the world production frontier (-9.54%); technical change, i.e. movements toward or away from the frontier (5.14%); capital accumulation (9.14%); and human capital accumulation (16.73%), i.e. movements along the frontier. The median efficiency change is negative, that of human capital accumulation is positive and bigger than those of capital accumulation and technological change. It implies that human capital accumulation plays the biggest role in the increase of labor productivity, while technological change and human capital accumulation play an important, if smaller, role.

Table 4: Quadripartite decomposition

Country	**Productivity change**	**EFF**	**TECH**	**KACC**	**HACC**
Austria	19.46	-10.12	5.54	9.14	24.02
Belgium	15.22	-1.76	0.89	9.92	12.59
Czech Republic	18.89	-33.49	39.56	27.64	6.53
Denmark	38.05	-5.35	2.79	16.52	24.38
Estonia	33.20	-28.16	81.68	12.48	0.75
Finland	22.06	-9.54	5.14	7.58	28.65
France	4.90	-5.75	3.00	-2.41	27.97
Germany	17.83	-18.44	27.87	7.04	27.61
Hungary	-38.77	-14.19	6.85	3.81	-29.82
Ireland	25.84	0	0	13.05	16.73
Italy	-4.97	0	0	-4.97	10.02
Luxembourg	7.46	-2.16	1.10	8.64	5.45
Netherlands	24.82	-11.62	6.37	25.74	10.44
Norway	61.25	-12.97	7.19	39.87	36.75
Poland	2.21	-22.40	13.52	14.00	8.19
Slovakia	29.82	0	0	-12.86	53.11
Slovenia	6.73	-19.53	12.50	-12.67	39.38
Spain	-2.26	-9.05	4.85	-3.40	27.92
Sweden	52.59	0	0	52.59	7.84
Median	18.89	-9.54	5.14	9.14	16.73

Some countries clearly perform better than the others in term of labor productivity growth: Austria, Denmark, Estonia, Finland, Ireland, the Netherlands, Norway, Slovakia and Sweden. The main reasons is different for these countries. Scandinavian economies (Denmark, Finland, Norway, and Sweden) and the Netherlands have high labor productivity growth probably because of fewer labor market rigidities, which allows lower costs to adopt or develop a new technology (see Scarpetta, Hemmings, Tressel, and Woo (2002)). Ireland also have great performance probably because of the high-tech manufacturing sector (see Fare, Grosskopf and Margaritis (2007)). Finally, the great performances of the central and eastern European economies (Austria, Estonia, and Slovakia) could be due to successfully passed key economic and political reforms.

Table 5 gives the median of the quadripartite decomposition for Central and eastern Europe and the EU12 (the twelve other European countries). Those numbers highlight one more time the existence of two groups (Central and eastern Europe and EU12). Central and eastern European countries have a smaller productivity change on the period. The smaller change is due to a bigger negative efficiency change (already observed in Tables 2 and 3) and a smaller positive human capital accumulation. This is compensated by a bigger technological change. These results are based on medians. More detailed results, i.e. using all the observations, are given in Figure 5.

Table 5: Quadripartite decomposition: median per group

Group	**Productivity change**	**EFF**	**TECH**	**KACC**	**HACC**
Central and eastern Europe	12.81	-20.96	13.01	8.15	7.36
EU12	20.76	-5.55	2.89	9.53	20.37
EU19	18.89	-9.54	5.14	9.14	16.73

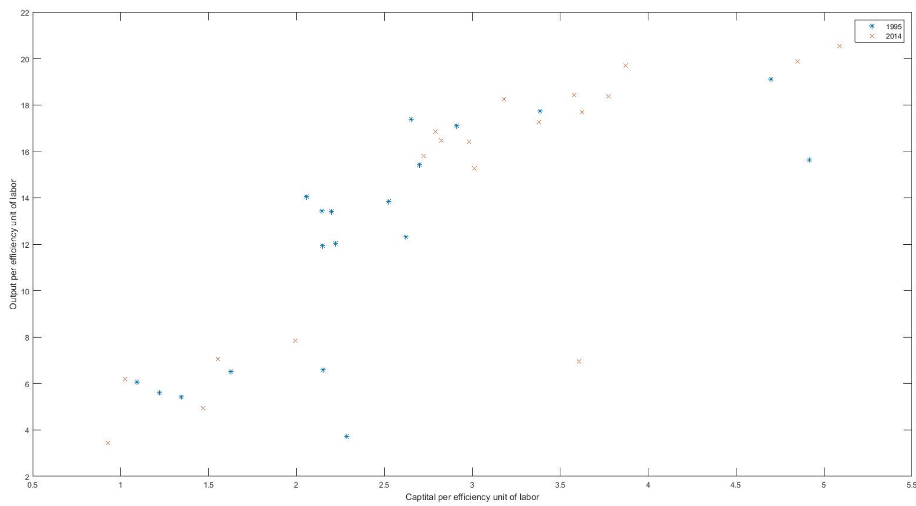
An emergence of two groups. I plot the output and capital per efficiency unit of labor for the selected countries in Figure 2.[12] Clearly, two groups are present in the graph. The first group in the lower left has level of output and capital similar in 1995 and 2014. This group is composed by central and eastern European countries. The second group in the upper right has bigger level of output and capital in 2014 than in 1995. This group is composed by the EU12. The presence of two groups confirms the non-neutrality of the technical change.[13] This results was found for the world by Kumar and Russell (2002), Henderson and Russell (2005) and Badunenko,

[12]Contrary to the standard production-frontier approach, the frontier cannot be seen on this graph since I do not assume monotonicity, convexity, and constant return-to-scales of the country-level technology set but monotonicity, convexity, and constant return-to-scales of the sector-specific technology sets (T_t^i).

[13]Technological change would be Hicks neutral if the production frontier in $\langle \hat{y}, \hat{k} \rangle$ space shifted vertically by the same proportional factor; it would be Harrod neutral if it shifted radially by a constant proportional factor. None of these two definitions of neutrality hold for the frontier drawn in Figure 2.

Henderson and Russell (2013), and by Walheer (2016) for the OECD countries. Allen (2012) explain the non-neutrality of the technical change by two main reasons: (1) almost no technological change occurs at low levels of capitalization and, (2) most innovation, that aims at expanding the frontier, occurs in advanced economies with high levels of capitalization.

Figure 2: Output-capital graph in 1995 and 2014

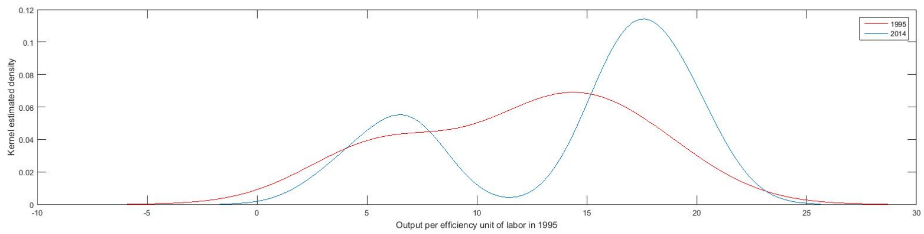


From all previous results, it is now well established that two groups are present within the European countries. In the following, I test the convergence/divergence question of these two groups. I use two complementary tools: the distribution of output per worker and the β-convergence.

I plot the distribution of output per worker in 1990 and 2014 in Figure 3. One important facts can be seen on this graph. The distribution of 1995 seems unimodal while the distribution of 2014 seems bimodal. To confirm this observation, I resort to the test proposed by Silverman (1981). The null hypothesis of the Silverman test is that a kernel distribution has n modes and the alternative hypothesis is that it has more than n modes. Using this test, I find that the 1995 distribution contains one mode (p-value $= 0.008$), but no more than two (p-value $= 0.2312$). Similarly, the 2014 distribution contains two modes (p-value $= 0.0550$), but no more than three (p-value $= 0.2513$). The change from a unimodal distribution to a bimodal distribution speak in favor of a divergence of the two groups.

Figure 4 plots the output growth against the initial level of output per work.

Figure 3: Distribution of output per worker in 1995 and 2008



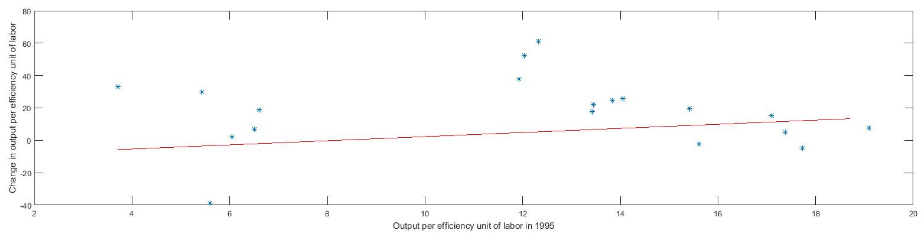
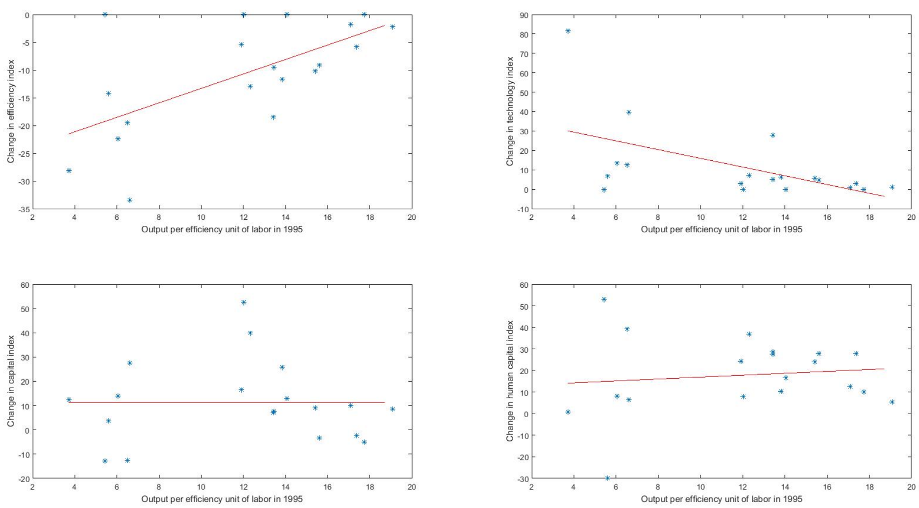


Figure 4: Output growth against initial output level

Clearly, the (significantly different from zero) positive slope speaks against a β-convergence, which confirms the conclusion of Figure 3 (i.e. divergence between the two groups). Indeed, β-convergence, which postulates that initially poorer countries reach a more dynamic growth, is characterized by a negative slope in the regression of output growth against initial level of output per work.

I now investigate which component of the quadripartite decomposition plays a role in the convergence/divergence of the two groups. Figure 5 gives the linear regressions between the output per efficiency unit of labor in 1995 and the four components of the quadripartite decomposition. A negative slope implies that the component contributes to the converge between countries. A positive slope implies the opposite. The slopes (significantly different from zero, except for capital accumulation) show that efficiency change and human capital accumulation have played a role in the divergence between the two groups (the slope of efficiency change is clearly bigger than the slope of human capital), while technological change has played a role in the convergence between the two groups. The slope of capital accumulation is close to zero implying that the two groups have similar capital accumulation. Those results are completely in lines with the results found with the medians (see Table 5).

Figure 5: Role of the quadripartite decomposition in the divergence of the two groups



Sector-level quadripartite decomposition. To contrast the previous results based on the country-specific scores, I give now the decomposition per sector (see the end of Section 2.2 for the computational details). I compute the median per sector over the countries in Table 6; and the median per sector for the two groups identified before (i.e. the central and eastern European countries and the EU12) in Table 7. These Tables allow to better explain the role of the sectors in the convergence/divergence between countries/groups.

The medians in Table 6 contrast the results found previously. Clearly, the sectors present different patterns, which one more time, advocates for a multi-sector analysis to capture the sector heterogeneity. The productivity change is higher for the Electricity, Gas and Water sector (+56.32%) due to high technical, capital and human capital accumulations; the Public Administration (+36.73%) due to technical, capital and human capital accumulations; and the Manufacturing sector (+34.02%) due to technical and human capital accumulations. All the sectors present a negative efficiency change as found previously for the countries in Table 4. Only, the Wholesale, Agriculture and Health sectors have a negative capital accumulation; and only the Transport sector has a (low) negative human capital accumulation.

Table 7 presents the median per sector for the two groups identified before: the central and eastern European countries (top) and the EU12 (bottom). Clearly, the medians per sector allow to contrast the results found previously based on the country-

Table 6: Sector-level quadripartite decomposition: median per group

Sector	Productivity change	EFF	TECH	KACC	HACC
A	3.32	-5.55	2.47	-5.99	33.42
Mi	8.90	-34.34	10.23	-9.88	5.20
Ma	34.02	-39.18	67.36	4.55	25.58
EGW	56.23	-40.98	45.29	36.01	41.83
C	13.15	-16.84	22.05	1.54	18.45
W	14.80	-24.54	39.56	-10.73	19.35
T	2.28	-40.70	48.87	39.98	-1.36
PA	36.73	-14.19	18.86	16.24	24.25
E	16.25	-2.76	0.27	2.01	21.27
H	11.10	-7.85	4.85	-1.95	19.81

specific scores. Indeed, while it is clear that on average the sectors in the Central and eastern European countries have worse performances than the EU12 countries, this is not a rule. The Electricity, Gas and Water and the Health sectors have a bigger productivity change in the central and eastern European countries; explained by a bigger technical, capital and human capital accumulations. I believe that these results are particularly of interest since they allow the countries to understand in which sector they perform better and in which sector an effort (in terms of investment for example) has to be made.

Comparison with previous studies. It is important to compare those results to what have been found previously in the literature. I compare my results to those of Henderson and Russell (2005), Badunenko, Henderson, Zelenyuk (2008), Badunenko, Henderson and Russell (2013) and Walheer (2016).[14] These papers compare countries of different continents but isolates the results for the OECD countries which makes our results comparable. Table 8 gives the median of the quadripartite decomposition of the OECD group for the four papers.

Walheer (2016) found that capital accumulation plays the biggest role in the increase of labor productivity, while technological change and human capital accumulation also play an important role, but it is twice as small as capital accumulation. Badunenko, Henderson and Zelenyuk (2008) found that efficiency change contributes

[14]The study of Cherchye, De Rock, Estache and Walheer (2014) is also close to my analysis. These authors analyze eighteen European countries in three sectors during 2000-2007. The problem is that they only compute output efficiency scores and catching-up effect which implies that the comparison with my results is difficult.

Table 7: Sector-level quadripartite decomposition: median per sector

Sector	Productivity change	EFF	TECH	KACC	HACC
A	4.72	-22.39	5.96	1.97	33.46
Mi	4.90	-23.34	8.93	-4.88	3.99
Ma	29.59	-39.12	58.58	-3.15	29.86
EGW	63.87	-59.82	68.89	77.59	44.68
C	-1.45	-16.03	30.64	-9.33	-3.71
W	0.54	-21.74	52.05	-15.62	4.91
T	-0.62	-62.95	30.97	48.80	-21.79
PA	3.86	-15.53	3.25	0.04	20.38
E	-3.73	-3.30	-5.54	-6.90	13.84
H	23.61	-4.7	24.20	1.30	0.47
A	3.46	-5.44	-1.22	-11.02	33.24
Mi	11.90	-35.34	4.33	-5.93	2.18
Ma	41.25	-38.29	71.95	8.64	18.57
EGW	58.63	-35.57	44.75	32.90	37.58
C	16.54	-17.72	18.29	2.92	21.70
W	21.54	-24.60	33.51	-6.24	21.12
T	14.16	-34.76	39.08	33.45	5.04
PA	37.15	-13.66	14.44	22.24	23.27
E	26.35	-2.52	0.68	11.66	27.19
H	10.15	-8.84	2.68	-2.20	20.98

negatively and that the main role is played by technological change. Henderson and Russell (2005), who consider an earlier sample, found that capital accumulation is the main driver, while technological change and human capital play a smaller role. Finally, Badunenko, Henderson and Russell (2013), who consider a bigger sample, found that technological change contributes more significantly, while technological change and human capital accumulation are equal to approximately two-thirds of capital technological change.

The study of Walheer (2016) is very close to mine except that he includes also the Asian countries and his data ends in 2008. It is then interesting to compare more in details with his analysis. To do so, I reproduce the graphs of the output and capital per efficiency unit of labor (Figure 6) and the distribution of output per worker (Figure 7) including 2008. Those two extra figures confirm the divergence of the two groups over time. Using the intermediate year 2008 show that the divergence clearly increase with time. In Figure 6, the first group in the lower left has level of output and capital similar in 1995, 2008 and 2014. This group is composed by central

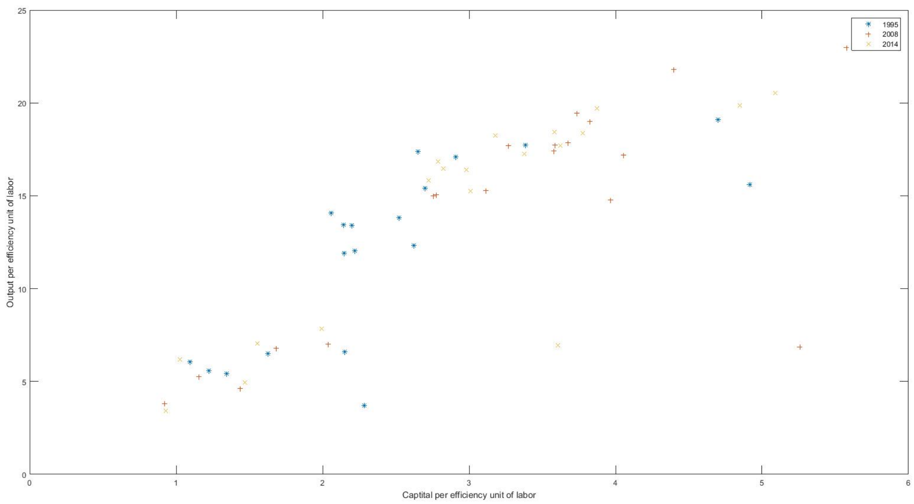
Table 8: Median for the quadripartite decomposition: comparison

	Period	Productivity change	EFF	TECH	KACC	HACC
This paper	1995-2014	18.89	-9.54	5.14	9.14	16.73
W	1995-2008	14.19	-18.86	12.27	20.14	8.91
BHZ	1992-2000	20.25	-4.88	22.33	3.34	/
HR	1965-1990	83.3	0.4	14.3	39.5	14.8
BHR	1965-2007	142.8	9.4	36.2	26.1	25.7

W: Walheer (2016); BHZ: Badunenko, Henderson and Zelenyuk (2008); HR: Henderson and Russell (2005);

BHR: Badunenko, Henderson and Russell (2013).

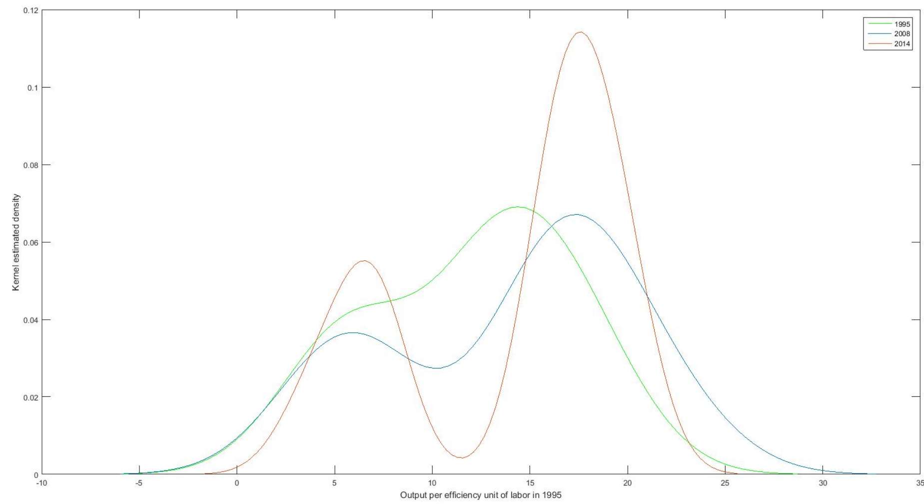
Figure 6: Output-capital graph in 1995, 2008 and 2014



and eastern European countries. The second group in the upper right has bigger level of output and capital in 2014 than in 2008, and in 2008 tthan in 1995. This group is composed by the EU12. In Figure 7, the presence of the two modes clearly increase with time. (this fact is once more confirmed by the Silverman test).

Robustness Checks. Procedures have been suggested to correct the reconstructed frontier for two mains problem: the downward bias (see Simar and Wilson (1998, 2000) amongst others) and the presence of outliers (see Simar (2003) and Daraio and Simar (2007) amongst others). These two problems could have a huge impact on the reconstructed frontier T_t^i and thus on the efficiency measures TE and $MSTE$. These procedures have also been used by, for example, Enflo and Hjertstrand (2008) and Badunenko, Henderson and Russell (2013) in a similar context. I applied these two

Figure 7: Distribution of output per worker in 1995, 2008 and 2014



procedures to my sample. Clearly, the efficiency scores have changed after the two procedures but these small changes do not impact the conclusions. For the sake of compactness, I only produce the main results in Tables 9 and 10 in the Appendix (that should be compared to Table 5). The productivity changes are the same since they are not computed by the model but instead they are given by the data. The other results are available upon request.

The technology set T_t^i is constructed using the data for all the countries. As a consequence, the efficiency measures TE and $MSTE$ based on those sets are very sensitive to outliers. The impact on the resulting efficiency analysis could be huge since outliers disproportionately, and perhaps misleadingly influence the evaluation of the performance of the countries. To solve that issue, two robust efficiency measurements have been suggested: the order-m efficiency measurement (where m can be viewed as a trimming parameter); and the order-α efficiency measurement (analogous to traditional quantile functions). These measures compare the countries using a sub-sample of the data set. As such, they are less sensitive to outliers. I apply these two procedures to my data (using different values of m and α as suggested by Simar (2003)). The efficiency scores obtained are very similar to those in Tables 2 and 3, which suggests that no country is really an outlier (in every sectors) in my sample and thus the conclusions found previously remain valid.

Also, the technology set T_t^i is a lower bound of the true but unknown technology set. This comes from the methodology itself. Indeed, the set T_t^i is the smallest construction that is consistent with the chosen technology Axioms (here: monotonicity, convexity and constant returns-to-scale).[15] As such, the set T_t^i provides a useful inner bound approximation, i.e. T_t^i is a subset of the true but unknown technology set; and is therefore biased by definition. The bootstrap procedures proposed by Simar and Wilson (1998, 2000) and others correct for this bias. Their procedure is based on the idea that the known distribution of the difference between estimated and bootstrapped efficiency measures mimics the unknown distribution of the difference between the true and the estimated efficiency measures. Again, the bias correction procedure modify the efficiency scores but the conclusions remain valid.

4 Conclusion

Using the recent nonparametric production-frontier methodology of Walheer (2016) tailored to analyze the growth and convergence issue taking the sector heterogeneity and interdependence into account, I studied the case of the European countries between 1995 and 2014. I rewrote the methodology of Walheer (2016) to give more results on the sector level, which was not possible with the initial version of his methodology.

The results confirmed the non-neutrality of technological change and highlighted that human capital accumulation plays the biggest role in the increase of output-labor productivity. Technological change and capital accumulation also play an important, if smaller, role in the increase of output-labor productivity. The results also confirmed the presence of two groups within the European counties: eastern and central European countries and the EU12. These two groups diverge over time. The results are not affected by robustness checks.

My sector-specific results confirmed the need for a multi-sector analysis since the presence of heterogeneity between sectors in Europe is clearly observed. Next, the sector-specific results offer several advantages. On the one hand, the sector-specific results allow to better explain the role of each sector in the convergence/divergence between countries/groups. On the other hand, they allow also to understand in which sector each country/group perform better and in which sector an effort (in terms of

[15]This principle is called the minimum extrapolation principle. See Cherchye et al (2016) for a discussion of this principle in a similar context.

investment for example) has to be made. I found that the Electricity, Gas and Water and the Health sectors have a bigger productivity change in the eastern and central European countries while it is the opposite for the other sectors.

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Appendix

Table 9: Quadripartite decomposition: median per group (without outliers)

Group	Productivity change	EFF	TECH	KACC	HACC
Central and eastern Europe	12.81	-20.22	12.67	7.98	8.01
EU12	20.76	-5.18	2.96	9.15	20.75
EU19	18.89	-9.85	4.96	8.79	16.15

Table 10: Quadripartite decomposition: median per group (bias corrected)

Group	Productivity change	EFF	TECH	KACC	HACC
Central and eastern Europe	12.81	-20.41	13.21	8.45	7.12
EU12	20.76	-5.14	2.74	9.43	20.58
EU19	18.89	-9.77	5.46	9.19	16.98