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Abstract
This paper uses a new set of country data for 14 countries, members of the OECD, and a non-parametric approach to provide new evidence on the impact of Information and Communication Technology (ICT) on labour productivity growth between 1995 and 2005. For the first time, in the present paper a bootstrap approach for the decomposition of labour productivity change, proposed by Kumar and Russell (2002), is employed. This approach permits to conduct statistical inference on the parameters of interest, and to analyse the effects of ICT technologies on capital accumulation. The results confirm the role of ICT as a general purpose technology that needs organizational and business process changes to fully exploit its growth opportunities. The paper also finds out, by applying a non-parametric test, that ICT technologies positively contribute to the generation of convergence clubs in the evolution of labour productivity. Finally, the empirical evidence offers some basic guidance for future policy intervention in supporting ICT capital investments.

Keywords: ICT; economic growth; labour productivity; bootstrap; convergence.

1. Introduction

Since the mid-1990s, the rapid growth of output and labour productivity across countries has largely been driven by advances in Information and Communication Technology (ICT) (Jorgenson, 2001; Venturini, 2009; Lam & Shiu, 2010; Vu, 2011). In particular, numerous studies have shown that ICT investments boosted the economy of the United States (USA) (Jorgenson & Stiroh, 2000; Jorgenson, 2001; Oliner & Sichel, 2002; Stiroh, 2002; Jorgenson, Ho, & Stiroh, 2005, 2008) and some economies of the European Union (EU) (Colecchia & Schreyer, 2002; Daveri, 2002; van Ark, Inklaar, & McGuckin, 2003; Jalava & Pohjola, 2007). One aspect of ICT investment relates to Solow's well-known paradox (Solow, 1987): "You can see the computer age everywhere but in the productivity statistics". In other words, given the nature of general purpose technology (GPT), returns to ICT are not possible without investments in complementary assets (tangible and intangible). Consequently, these returns will only become fully manifest in the long-term (Basu, Fernald, Oulton, & Srinivasan, 2004;

O'Mahony & Vecchi, 2005; Basu & Fernald, 2007). Previous analyses, both at the industry and macroeconomic levels, have attempted to measure the impact of ICT on growth through standard growth accounting or growth regression techniques (Bosworth & Collins, 2003; Jorgenson, 2005). The former cannot fully incorporate the effect of ICT because the share of growth due to technological progress (Solow residual) is erroneously attributed to the growth of capital (Barro & Sala-i-Martin, 1995). In contrast, the latter techniques do not assume that the returns of capital accumulation have a direct impact on growth. Thus, they are more appropriate to measure the role of ICT on growth and its nature of GPT (David, 1990). However, the growth-accounting approach is heavily model driven, relying on particular assumptions about the technology, market structure, technological change, and other aspects of the growth process. In contrast, Kumar and Russell (2002) employed non-parametric techniques based on Data Envelopment Analysis (DEA) to analyse international macroeconomic convergence. In particular, they decomposed the labour productivity growth components attributable to *(i)* technological change (shifts in the world production frontier), *(ii)* technological catching-up (movements toward or away from the frontier), and *(iii)* capital accumulation (movement along the frontier). These methods offer several potential advantages over regression techniques: they do not specify a functional form for the technology, assume that technological change is neutral, or make assumptions about market structure or the absence of market imperfections. This paper studies, for the first time according to the authors' knowledge, the effects of ICT capital on labour productivity change using DEA techniques. It is well-known that DEA models, which can account for ICT capital as a separate input, can measure the impact of this input on total factor productivity (TFP) change. However, unlike regression models, non-parametric techniques cannot quantify the contribution of ICT capital to TFP shifts. To overcome this drawback, this study followed a strategy like that used by Maffezzoli (2006) to measure the impact of the introduction of an additional variable. Accordingly, two DEA models were employed. In the first model, the aggregate measure of capital stock was used, and in the second model, ICT capital was disembodied from non-ICT capital. To compare the two models, the analysis tried to summarise the effect of ICT capital on growth. Finally, in the spirit of Quah's (1993, 1996, 1997) studies, this paper assessed the effects of ICT capital on the convergence process.

The remainder of this paper is organised as follows. Section 2 discuss the methodology. Section 3 describes the data. Section 4 reports the empirical findings, and Section 5 provides conclusions and policy implications based on those findings.

2. DEA, bootstrap and convergence analysis

2.1. DEA and the decomposition of labour productivity change

This study used an approach based on DEA to analyse the impact of ICT capital on labour productivity change and its components (Charnes, Cooper, & Rhodes, 1978). This non-parametric technique is data driven and allows to draw a piecewise linear production function from a sample of input-output observations. Unlike parametric methods, it relies on identifying best practice reference units without imposing any particular constraint on the form of the production function. This study did not employ the traditional growth account methodologies (Barro & Sala-i-Martin, 1995) because, even if the hypothesis of Hick's neutrality technology should be satisfied, they cannot decompose TFP growth at country level into changes due to technological progress, which should be common to all countries, and catching-up in terms of relative efficiency (Maffezzoli, 2006).

An exhaustive description of DEA can be found in Färe, Grosskopf, and Lovell (1995), and recent applications of this non-parametric technique in the cross-country growth and convergence literature are Färe, Grosskopf, Norris, and Zhang (1994) and Kumar and Russell (2002).

Let $f_t(k_{it};l_{it})$ be the aggregate production function of country i at time t, where k_{it} and l_{it} represent the capital and labour employed, respectively. Then, assuming the existence of a common technology, the dissimilarities in the observed productive levels among countries can be attributed to differences in technical efficiency. Formally:

$$y_{it} = \theta_{it} \cdot f_t(k_{it}, l_{it}) \qquad \text{i = 1,2,…, n; t = 1,.2,….T} \quad (1)$$

ALLORA SE SCRIVO i=1,2,…,n; dovrò scrivere t=1,2,…,T Non locorreggo io su tutte le formule perchè mi cambia i formati. FINO ALLA FORMULA 16 VANNO CORRETTI!!!!!!

where y_{it}, is the output produced, and $\theta_{it} \in [0, 1]$ is the Farrell (output-oriented) efficiency index for country *i* at time *t*. DEA allows to jointly estimate θ_{it} and f_t. The Farrell efficiency index is defined by:

$$\theta_{it} = \min_{\theta} \{\theta \,|[y_{it} / \theta, k_{it}, l_{it}] \in \Omega_t\} \qquad \text{i = 1,2,…, n; t = 1,.2,….T} \qquad (2)$$

where:

$$\Omega_t \equiv \left\{ [y, l, k] \in \Re^3_+ \middle| y \leq \sum_{i=1}^{n} \lambda_i y_{it}, l \geq \sum_{i=1}^{n} \lambda_i l_{it} , k \geq \sum_{i=1}^{n} \lambda_i k_{it} , \lambda_i \geq 0; \forall\, i = 1,...,n \right\} \qquad (3)$$

is the constant return to scale technology set (Farrel cone)[1] for the world at time *t*. Each observation defined in the technology set can be interpreted as a unit operation of a linear process, λ_i. Consequently, every point in the technology set is a linear combination of an observed data point or a point dominated by such a linear combination. The constructed technology is therefore a polyhedral cone, with piecewise linear isoquant (Kumar & Russell, 2002).

The Farrel efficiency index can be calculated by solving the following linear program for each country:

[1] Non increasing returns to scale technology (NIRS) can be obtained by adding the condition $\sum_{i=1}^{n} \lambda_i \leq 1$, and variable returns to scale technology (VRS) are constructed by imposing $\sum_{i=1}^{n} \lambda_i = 1$

$$\max_{\{\theta,\lambda_1,\dots\lambda_n\}} \theta^{-1}$$

$$\begin{aligned} \text{st.} \quad & y_{it}/\theta \leq \sum_{i=1}^{n} \lambda_i y_{it} \\ & k_{it} \geq \sum_{i=1}^{n} \lambda_i k_{it} \qquad \forall \text{i} = 1,2,\dots,\text{n}; \forall \text{t} = 1,.2,\dots.\text{T} \\ & l_{it} \geq \sum_{i=1}^{n} \lambda_i l_{it} \\ & \lambda_i \geq 0, \quad \forall\, i \end{aligned} \tag{4}$$

The potential output, which is the output level on the production frontier, is attainable by employing the inputs k_{it} and l_{it}, given the technology Ω_t, is given by:

$$y_{it}^{\bullet}(k_{it}, l_{it}) = \max_{y^{\bullet}} \left\{ y^{\bullet} \,\middle|\, \left[y^{\bullet}, k_{it}, l_{it} \right] \in \Omega_t \right\} \qquad \text{i} = 1,2,\dots,\text{n}; \text{t} = 1,.2,\dots.\text{T} \quad (5)$$

Taking into consideration relation (5), an observed country's output can be expressed as the product of country's potential output by its efficiency index:

$$y_{it} = \theta_{it} \cdot y_{it}^{\bullet}(k_{it}, l_{it}) \qquad \text{i} = 1,2,\dots,\text{n}; \text{t} = 1,.2,\dots.\text{T} \quad (6)$$

Assuming constant return to scale, it is possible to define the technology set in a two dimensional space $\langle \mathrm{k}_{\mathrm{it}} = k_{it}/l_{it} \,,\, \mathrm{y}_{\mathrm{it}} = y_{it}/l_{it} \rangle$, and, consequently, relation (6) can be written as follows:

$$\mathrm{y}_{\mathrm{it}} = \theta_{it} \cdot \mathrm{y}_{\mathrm{it}}^{\bullet}(\mathrm{k}_{\mathrm{it}}) \qquad \text{i} = 1,2,\dots,\text{n}; \text{t} = 1,.2,\dots\text{T} \quad (7)$$

Relation (7) represents the starting point to analyse the evolution of labour productivity shifts. In fact, following Kumar and Russell (2002), the relative change in labour productivity between time *s* and *t* *(t≠s)* for country *i* can be written as follows:

$$\mathrm{l}_{\mathrm{i,st}} = \frac{\mathrm{y}_{\mathrm{it}}}{\mathrm{y}_{\mathrm{is}}} = \frac{\theta_{it}}{\theta_{is}} \cdot \frac{\mathrm{y}_{\mathrm{it}}^{\bullet}(\mathrm{k}_{\mathrm{it}})}{\mathrm{y}_{\mathrm{is}}^{\bullet}(\mathrm{k}_{\mathrm{is}})} = \frac{\theta_{it}}{\theta_{is}} \cdot \frac{\mathrm{y}_{\mathrm{it}}^{\bullet}(\mathrm{k}_{\mathrm{it}})}{\mathrm{y}_{\mathrm{is}}^{\bullet}(\mathrm{k}_{\mathrm{it}})} \cdot \frac{\mathrm{y}_{\mathrm{it}}^{\bullet}(\mathrm{k}_{\mathrm{it}})}{\mathrm{y}_{\mathrm{is}}^{\bullet}(\mathrm{k}_{\mathrm{is}})} \qquad \text{i} = 1,2,\dots,\text{n}; \text{t} = 1,.2,\dots.\text{T} \quad (8)$$

The three terms in the above relation represent i) efficiency change (change in the distance from the frontier); ii) technological change (shifts in the frontier) and iii) capital accumulation (movement along the frontier), respectively. Relation (8) measures changes using the period *s* capital labour ratio. Symmetrically, it is possible to measure variations using the period *t* capital labour ratio:

$$l_{i,st}=\frac{y_{it}}{y_{is}}=\frac{\theta_{it}}{\theta_{is}}\cdot\frac{y^{\bullet}_{it}(k_{it})}{y^{\bullet}_{is}(k_{is})}=\frac{\theta_{it}}{\theta_{is}}\cdot\frac{y^{\bullet}_{it}(k_{it})}{y^{\bullet}_{is}(k_{is})}\cdot\frac{y^{\bullet}_{is}(k_{is})}{y^{\bullet}_{is}(k_{is})} \qquad i=1,2,\ldots,n;\ t=1,.2,\ldots.T \tag{9}$$

Following Färe et al. (1994) and Kumar and Russell (2002), it is possible to summarise the two alternative measures of the labour productivity variation between time *s* and *t* by adopting the "Fisher ideal" decomposition:

$$l_{i,st}=\frac{y_{it}}{y_{is}}=\frac{\theta_{it}}{\theta_{is}}\cdot\left(\frac{y^{\bullet}_{it}(k_{it})}{y^{\bullet}_{is}(k_{it})}\cdot\frac{y^{\bullet}_{it}(k_{is})}{y^{\bullet}_{is}(k_{is})}\right)^{0.5}\cdot\left(\frac{y^{\bullet}_{is}(k_{it})}{y^{\bullet}_{is}(k_{is})}\cdot\frac{y^{\bullet}_{it}(k_{it})}{y^{\bullet}_{it}(k_{is})}\right)^{0.5}= \tag{10}$$

$$i=1,2,\ldots,n;\ t=1,.2,\ldots.T$$

$$=EFF_{i,st}\cdot TECH_{i,st}\cdot KACC_{i,st}=TFP_{i,st}\cdot KACC_{i,st}$$

Thus, labour productivity change can be expressed as a function of efficiency change (*EFF*), technological change (*TECH*), and capital accumulation change (*KACC*). A value that is greater than one of each component of the above relation denotes an increase in productivity.

2.2. Bootstrapping the components of labour productivity change: Bias correction

One of the main shortcomings of the DEA method is that it does not have any immediate statistical foundation. That is, it is not possible to make an inference, in the classical sense (Kneip, Simar, & Wilson, 2008), about the estimated components of the decomposition of labour productivity growth defined by relation (10). In fact, the components for a given sample of countries are only estimates of the true population values (Simar & Wilson, 1998, 1999) and are affected by uncertainty due to sampling variation. However, the bias for each parameter can be corrected using the bootstrap simulation method. Simar and Wilson (1999) employed this technique to estimate the empirical distributions of Malmquist indices of *TFP* changes. The general principle behind the bootstrap is to simulate the observed sample *B* times *(b=1,2,…,B)* and to calculate in each iteration, *b*, the parameter of interest. Then, the *B* estimates (realisations) of the parameter can be used to obtain its distributional property. Empirically, the bootstrap procedure simulates the observed value of the parameter by re-sampling it with a replacement. In other words, the procedure assumes that the data generation process (DGP) can create the observed sample. When labour productivity change is calculated according to relation

(10), the first step of the Simar-Wilson approach is to calculate DEA efficiency scores $\{(\hat{\theta}_{1t},\hat{\theta}_{1s}),(\hat{\theta}_{2t},\hat{\theta}_{2s}),...,(\hat{\theta}_{nt},\hat{\theta}_{ns})\}$ at time *s* and *t* for *n* countries and to determine for each observation the three components of the right hand side of relation (10):

$$\left\{ \hat{EFF}_{i,st}; \hat{TECH}_{i,st}; \hat{TFP}_{i,st}; \hat{KACC}_{i,st} \right\} \qquad i = 1,2,\dots,n;\ t = 1,.2,\dots.T\cdot \tag{11}$$

The second step of the procedure is to project each country at time *t (s)* onto the frontier at time *t (s)*: $(\tilde{k}_{it}, \tilde{y}_{it}) = (k_{it} \cdot \theta_{it}, y_{it})$. Then, in the third step, the observed sample of DEA scores, $\{(\hat{\theta}_{1t},\hat{\theta}_{1s}),(\hat{\theta}_{2t},\hat{\theta}_{2s}),...,(\hat{\theta}_{nt},\hat{\theta}_{ns})\}$, is used to generate a pseudo sample of DEA efficiency scores $\{(\tilde{\theta}_{1t},\tilde{\theta}_{1s}),(\tilde{\theta}_{2t},\tilde{\theta}_{2s}),...,(\tilde{\theta}_{nt},\tilde{\theta}_{ns})\}$ by drawing them with a replacement and employing a bivariate smoothed representation of the probability density *F* (Simar & Wilson, 1999). The new set of efficiencies allows to compute a sample of pseudo observations $(\tilde{k}^b_{it}, \tilde{y}^b_{it}) = (\tilde{k}_{it} / \tilde{\theta}_{it}, \tilde{y}_{it})$. In another words, each country *i* is moved away from the frontier by an amount equal to $\tilde{\theta}_{it}$ along a ray through the original observation.

In the fourth step, new efficiency measures are calculated based on the sample of pseudo observations, and a new labour productivity growth index is determined:

$$\left\{ \hat{EFF}^b_{i,st}; \hat{TECH}^b_{i,st}; \hat{TFP}^b_{i,st}; \hat{KACC}^b_{i,st} \right\} \qquad i = 1,2,\dots,n;\ t = 1,.2,\dots.T \tag{12}$$

Then, the bootstrap procedure described above is repeated *B* times *(b=1,2,...,B)* to obtain the samples of the components of labour productivity change. Without losing generality, if *KACC* component is considered, then the following relation can express the true estimate of the variable:

$$KACC^*_{i,st} = \hat{KACC}_{i,st} - bias\left(\hat{KACC}_{i,st} \right) \qquad i = 1,2,\dots,n;\ t = 1,.2,\dots.T \tag{13}$$

where $bias\left(\hat{KACC}_{i,st} \right) = \frac{1}{B} \cdot \sum_{b=1}^{B} \hat{KACC}^b_{i,st} - \hat{KACC}_{i,st}$ is the bias estimated in the bootstrap procedure. However, the bias corrected estimator should be not employed if the variance, σ^2_b, of the bootstrap values $\left\{ \hat{KACC}_{i,st}^{b} \right\}_{b=1,2,\ldots B}$ is greater than (1/3) of the squared bias correction

(Simar & Wilson, 1999): $\sigma_b^2 > \frac{1}{3} \cdot \left[bias\left(\hat{KACC}_{i,st} \right) \right]^2$. A similar procedure is applied to each

components defined in (10).

2.3. Convergence analysis

The measurement of convergence in income levels, or other macroeconomic indicators, is usually carried out differently according to the various meanings attributed to the term convergence by the literature (Baumol, Nelson, & Wolff, 1994). Homogenization and catching-up are concepts of considerable importance. However, in reality, there are cases in which relationships are more complex than pure homogenization or catching-up. For instance, when a leader pulls ahead of the pack, the followers may catch up only after a considerable delay or most followers may pull closer to one another, not to the leader. Thus, an analysis of the distribution dynamics of macroeconomic indicators is of considerable interest (Quah, 1993, 1996, 1997; López-Pueyo & Mancebón Torrubia, 2009). Thus, it is possible to rewrite the tripartite decomposition of labour productivity changes in equation (10) as follows:

$$\mathrm{y}_{\mathrm{it}} = EFF_{i,st} \cdot TECH_{i,st} \cdot KACC_{i,st} \cdot \mathrm{y}_{\mathrm{is}} \qquad \mathrm{i} = 1,2,\ldots,\mathrm{n};\ \mathrm{t} = 1,.2,\ldots.\mathrm{T} \qquad (14)$$

According to relation (14), the labour productivity distribution in period *t* can be constructed by successively multiplying labour productivity in period s by each of the three factors. This step, in turn, allows us to construct counterfactual distributions by the sequential introduction of each of these factors. Thus, the counterfactual labour productivity distribution of the variable

$$\mathrm{y}_{\mathrm{i,t}}^{\mathrm{EFF}} = EFF_{i,st} \cdot \mathrm{y}_{\mathrm{is}} \qquad \mathrm{i} = 1,2,\ldots,\mathrm{n};\ \mathrm{t} = 1,.2,\ldots.\mathrm{T} \qquad (15)$$

measures the effect on the distribution of changes in efficiency for country *i* and assumes no technical change or capital accumulation. The contribution of *TECH* can be obtained by the following relation:

$$y_{i,t}^{TECH} = EFF_{i,st} \cdot TECH_{i,st} \cdot y_{is} = y_{i,t}^{EFF} \cdot TECH_{i,st} \qquad i = 1,2,\ldots,n;\ t = 1,.2,\ldots.T \qquad (16)$$

Thus, by comparing relations (14) and (16), it is possible to study the effects of the *KACC* on the distribution dynamics of labour productivity.

2.4. Assessing the impact of ICT: A distributional analysis

The two main questions of the present paper concern the evaluation, at the country level, of the impact of ICT capital on the production process and on labour productivity convergence. To address these questions, the analysis used two DEA specifications, which only differ in the capital inputs considered. In the first, *m1*, the aggregate measure of capital is considered, and in the second, *m2*, the stock of ICT capital is disembodied from the aggregate capital stock, implying two capital inputs. The resulting differences in the efficiency measures related to the two models produce two different decompositions of the labour productivity change (relation (10)). By comparing the two labour productivity growth decompositions, it is possible to understand the impact of ICT capital on the production process. Such impacts are not identifiable when an aggregate measure of the capital stock is employed. At the country level, the contribution of ICT capital stock to the countries considered in the analysis is marginal (i.e., no more than 0.13; see Table 1 in the next section).

Next, to measure if ICT capital produces significant differences in the counterfactual distributions, relations from (14) to (16), the Maasoumi and Racine (2002) test was performed. The test is based on non-parametric metric entropy, which is defined by:

$$S_\rho = \frac{1}{2} \int_{-\infty}^{+\infty} \left(f_1^{1/2} - f_2^{1/2} \right)^2 dx \qquad (17)$$

where f_1 and f_2 are the two density functions of interest. The null hypothesis states that the two densities can be considered equal: $S_\rho = 0$. The significance level associated with the S_ρ statistic is obtained with the bootstrap re-sampling technique.

3. Data and variables

The data source is the EU KLEMS database (2009)[2], and the variables employed are the total hours worked by the employee (H_EMP), the gross capital stock (K_GFCF), the ICT gross capital stock (K_ICT), the non-ICT gross capital stock (K_NonICT), the value added (VA) and the purchasing power parity (PPP).

VA are deflated by the consumer and K_NonICT by the gross fixed capital formation price index respectively. ICT assets are deflated by a quality-adjusted index obtained by employing the so called hedonic technique, except for those countries which lack of data, where the harmonisation procedure suggested by Schreyer (2002) is used. However, Timmer and van Ark (2005) noticed that the harmonised deflation procedure applied is not the perfect method to deflate ICT investment. In fact, the methodology is based on the assumption that there is a global (US) hedonic model on the basis of which the predicted price of a model can be estimated across the OECD countries. Moreover, for those countries where most of ICT goods are imported it is not possible to know if the associated price index is computed in the same way of that one developed for the ICT produced.

The introduction of ICT capital restricted the sample to 14 countries. The number of countries in the sample is clearly not high, but it is comparable with those of other similar studies (e.g., Fare, Grosskopf, & Margaritis, 2006; Margaritis, Fare, & Grosskopf, 2007). Table 1 provides sample statistics for the variables considered in the analysis.

Insert Table 1 approximately here.

Looking at the average values it can be noticed that all variables increase from 1995 to 2005. However, K_ICT shows an increase, which is significantly higher than that one registered by K_NonICT. Moreover, the ratio K_ICT /K_GFCF suggests that the weight of ICT assets on gross capital is substantially increased over ten years. Finally, the analysis of coefficients of variation indicates that differences among the 14 OECD countries are slightly increased.

[2] Retrieved from http://www.euklems.net/

4. Empirical results

4.1. Labour productivity evolution: A bias corrected analysis

In the first step of the analysis, the bias corrected estimates are employed to draw a preliminary picture of the labour productivity evolution between 1995 and 2005 (Fig. 1).

Insert Fig. 1 approximately here.

The average labour productivity growth (+21%) shows that, as a whole, the sample of countries experienced an important rise in productivity from 1995 to 2005. On the other hand, the performances of the individual countries reveal wide differences. The countries that sign the highest increase in the labour productivity are Korea (+44%), Czech Republic (+30%), Japan (+27%) and Sweden (+27%); Italy, with its low growth (+2%), is in the least productive. A value of correlation coefficient between labour productivity rate and the variation of unit labour cost equals to 0.815 reveals that differences in the labour productivity growth might also be related to difference in unit labour costs growth. However, further analysis, in line with the study by Naastepad and Storm (2007) among others, should be conducted to test in a more robust setting the relation among these two variables. Now, before drawing conclusions about the results of the Kumar and Russell (2002) decomposition, the comparability of the two DEA models, which differ in the number of inputs, is investigated. In fact, DEA results are sensitive to the number of variables introduced: the increase in the number of variables tend to rise the average efficiency score (Nunamaker, 1985). So, in order to deal with such a shortcoming, the procedure proposed by Kirjavainen and Loikkanen (1998) was followed by depicting the efficiency distributions for *EFF*, *TECH*, *TFP* and *KACC* as shown in Fig. 2. There, the countries are ranked according to their efficiency score from lowest (number 1) to highest (number 14).

Insert Fig. 2 approximately here.

From Fig. 2, it can be noticed that the introduction of the ICT capital shifts downward *TECH* and TFP distributions, while it move upward the *KACC* distribution. Besides the changes in the component distributions the countries may also change their rankings. These changes were analysed by calculating the Spearman's rank correlation coefficients between each components of the two models.

Insert Table 2 approximately here.

Looking at Table 2 it can be noticed that the Spearman's rank correlation coefficients, for the components of the labour productivity decomposition are above 0.5[3]. In other terms, the introduction of the ICT capital, model *m2*, significantly modifies the countries rankings obtained through the *m1* model. So, the above evidence supports the hypothesis that ICT-capital contribution to labour productivity is effective and non merely related to a variation of the average efficiency scores. Taking into account the previous evidences, in what it follow the Kumar and Russell decomposition is analysed for the model *m1* and *m2* respectively (see Fig. 3).

Insert Fig. 3 approximately here.

Model *m1* shows that *KACC* is the driving force of labour productivity growth for most countries. In particular, there is evidence of a significant contribution to productivity in Portugal (+70%), Korea (+49%), Czech Republic (+38%) and Japan (+33%). It is interesting to observe that in three European countries (Germany, Denmark and Netherlands), employment growth outstripped capital growth, resulting in a negative *KACC*. The analysis of *TFP* shifts revealed a generalised stagnation, with some important exceptions. Finland showed the highest *TFP* growth (+20%), which confirms the economic benefits of the Nokia phenomenon (Jalava & Pohjola, 2007). The other countries that had positive growth are Australia, Austria, Denmark, Germany, Netherlands, Sweden and USA. The negative evolution of *TFP* change in the Czech

[3] The analysis of the countries distribution by quartiles confirms the results of the Sperman's correlations analysis.

Republic, Italy, Portugal and UK confirm the existence of opposite growth trends in the EU. Moreover the analysis confirms the slowdown of Portugal's total factor productivity (-31%) due to the increase of employment shares in sectors with low productivity or low productivity growth (Lains, 2008). The positive values of *TECH* indicate that all countries, with the exclusion of Portugal and Korea, experienced technological progress.

In contrast, the negative values obtained for almost all *EFF* scores support the presence of a divergent process among the countries. However, this finding is tested in Section 4 in a more robust statistical setting.

In model *m2* the first noticeable result is an inversion in the components dynamic, with the sole exclusion of the variable *KACC*, which positively contributes to labour productivity growth. The higher values of the *KACC* component in model *m2* indicate that ICT capital, on average, exerts a higher growth rate than non-ICT capital does[4].

This finding supports the common wisdom that investment in ICT is needed to create opportunities for labour productivity growth (Los & Timmer, 2005). In particular, for the EU countries in the analysis, the empirical findings seem to confirm that ICT capital, according to Lisbon strategy, plays a key role in widening the productive gap both among EU countries and between the EU and the USA (Seo, Lee, & Oh, 2009) for the period 1992-1999. The negative values for *TFP* growth obtained in model *m2* confirm the existence of problems in incorporating ICT capital in the productive system, and that this process may need more than a decade. The decline of *TFP* relies both on *EFF* and on *TECH*. Leibenstein (1978) noted that six factors can explain the decrease of efficiency due the introduction of new technologies. The common characteristic of the above factors is that when workers encounter a new technology, there is a technical and/or cultural gap. In turn, this gap causes X-inefficiency. Only two countries in the sample did not present this effect: Italy and Korea. The negative values for *TECH* variable appear to be counterintuitive, even if they are perfectly consistent in a DEA setting. Based on

[4] By employing the capital-labour ratio, it was observed that the growth of ICT capital on labour is more than ten times that one of the Non-ICT capital-labour ratio for almost all countries. This implies an increase in the KACC component as soon as ICT capital are disembodied from the whole capital.

the empirical evidence from model *m1*, it was expected that ICT capital would boost *TECH*. However, on the contrary, a technological decline was found. Technically, the separation of ICT capital stock from all capital stock caused an implosion of the productive frontier between 1995 and 2005. The economic interpretation can be related to two alternative factors. The first may be an over investment in ICT capital, which occurred between 1985 and 2000 due to the dot-com bubble (OECD, 2009). The second factor is the difficulty to measure, over a ten years period span, the impacts of ICT technologies on the production process. Both factors indicate the presence of declining levels of capacity utilization related to ICT technologies. From this perspective, the findings indicate that on average, the countries in the sample experienced a declining level of capacity utilization of ICT technologies rather than a technological regress (Angeriz, McCombie, & Roberts, 2006). Thus, the analysis confirms the GPT nature of ICT technologies, which require complementary investments to attain productivity benefits (Basu & Fernald, 2007; Colombo & Grilli, 2007; Vicente & Lopez, 2011). The USA is the only national economy that marginally suffered from the negative effect of *TECH*.

4.2. Counterfactual distributions and convergence analysis

Here, the paper turns to an analysis of the distribution dynamics of labour productivity. This approach is likely to be more informative than summary measures, such as the conditional mean or variance, which is implicit in regression analysis (Quah, 1996, 1997; Kumar & Russell, 2002). The objective was to evaluate, for the models *m1* and *m2*, the degree to which each of the three components of productivity change account for the change in the distribution of labour productivity between 1995 and 2005. Fig. 4 shows the counterfactual distributions of the labour productivity components.

Insert Fig. 4 approximately here.

The distribution in Fig. 4 (a) indicates that the period of study was characterised by a labour productivity improvement, marked by rightward shifts in the mean of the respective distributions over time. The shape of the distributions highlights that the probability mass spread and that the dispersion remained substantially unchanged. Moreover, in line with Margaritis et al. (2007) and López-Pueyo and Mancebón Torrubia's (2009) results, the distribution of labour productivity tends toward a bimodal shape. Thus, despite the globalisation of the information age, the development paths of countries do not converge in a single direction, but actively spread in various directions (Seo et al., 2009).

To understand the factors that changed the distribution, the differences in the countries' ranks of labour productivity for 1995 and 2005 were studied. This investigation showed that the country ranks did not change in the two periods. However, while Japan reduced its gap, the Czech Republic, Korea and Portugal increased their distance from the other countries. In particular, the movement of the lowest-output per worker countries (the Czech Republic, Korea and Portugal) was the main source of the change from a unimodal to bimodal labour productivity distribution in 2005. Looking at the counterfactual distributions of the components, it can be noticed that a similar pattern appears in *EFF*. In panel (c), the probability mass of the distribution raised the spread, and the range of the density function increased. This pattern implies the presence of a divergence in labour productivity driven by *TECH*.

The distribution in Fig. 4(d) reflects all three adjustments of the labour productivity distribution and concides with the distribution in 2005. This distribution isolates the effect of *KACC*. A comparison of the distributions of panels (c) and (d) provides strong evidence that *KACC* was the primary driving force in increasing labour productivity and that differences in capital accumulation histories across countries were primarily responsible for the tendency toward a bimodal distribution of labour productivity.

Fig. 5 shows the labour productivity distribution and its counterfactual distributions for model *m2*, which is more sensitive to ICT capital stock.

Insert Fig. 5 approximately here.

The first difference in model *m1* is related to the *EFF* component, panel (b), where the distribution shifted from unimodal in 1995 to bimodal in 2005. The effect was mainly caused by four countries: the Czech Republic, Korea, Japan and Portugal. The two European countries benefited poorly from the Lisbon strategy. In particular, for Portugal, the slowdown in labour productivity reflects the reallocation of labour between sectors because labour went into less productive activities (OECD, 2008). The positions of Korea and Japan seem counterintuitive but are connected to the productive characteristics of the countries. These two countries have strong ICT-producing sectors but relatively weaker ICT-usage effects. Lower productivity in service industries due to excessive regulations and lack of competition in public service sectors seems to have worked against the benefits of ICT-usage effects and the effort to find renewed sustainable growth paths (Fukao, Miyagawa, Pyo, & Rhee, 2009).

Panel (c) is characterised by a reduction in mode and an increase in dispersion, which indicate that ICT-capital was one of the possible factors contributing to the creation of convergence clubs.

4.3. Distributional differences

The evidence from Figs. 4 and 5 suggests that the frequency densities of the labour productivity growth decomposition changed between models *m1* and *m2*. In such situations, bootstrap techniques often provide a practical way to obtain inferences. Accordingly, a non-parametric test was performed (Maasoumi & Racine, 2002) by running 500 bootstrap iterations. A key concept in the bootstrap test is that of critical bandwidth, h. The degree of smoothness depends on h; therefore, it is evident that as h decreases, the number of modes increases. The critical value was obtained by applying the least-squares cross-validation criterion (Rudemo, 1982; Bowman, 1984).

Insert Table 3 approximately here.

As shown in Table 3, the separation of ICT capital does not produce a significant difference in the *EFF* component. This finding implies that the distance of countries from the frontier is largely determined by non-ICT capital. While it seems evident that income distribution is significantly altered by *TECH* and *KACC*, some components suggest that economies respond differently to the amount of ICT capital invested. In other words, it is possible to consider ICT capital a conditioning variable that can lead to the existence of convergence group.

5. Conclusion and implications

This study used a non-parametric technique to examine the relationship between labour productivity growth and ICT capital development of a sample of 14 OECD countries between 1995 and 2005. In particular, data envelopment analysis was used to decompose labour productivity shifts into TFP change and capital accumulation growth. Unlike most of the previous studies, this paper developed a non-parametric technique to consider the advantages to be obtained from bootstrap methodologies.

The overall results indicate that capital accumulation was the main driving force of labour productivity growth. However, this study also found that ICT capital seems to produce an opposite effect on labour productivity growth: an increase through capital accumulation and a decrease through technological change. The first positive effect confirms the empirical evidence of related studies for the period between 1995 and 2005 (Jalava & Pohjola, 2007; Lam & Shiu, 2010; Vu, 2011). The second negative effect indicates the presence of a technological regress caused by ICT capital. This counterintuitive result supports the hypothesis that ICT technologies are GPTs, which require complementary investments and significant temporal lags to achieve a productivity benefit. In particular, while the USA suffered the least from the impact of this component, most European countries experienced a significant impact. This finding indicates one of the future milestones of the Lisbon agenda in Europe. In fact, without complementary investments, it will not be possible to fully benefit from the advantages of ICT capital for productivity growth .

Finally, the analysis of the counterfactual distributions reveals that ICT-capital may be one of the factors contributing to the generation of convergence clubs.

References

Angeriz, A., McCombie, J., & Roberts, M. (2006). Productivity, efficiency and technological change in European Union regional manufacturing: A data envelopment analysis approach. *The Manchester School*, *74*(4), 500–525.

Barro, R., & Sala-i-Martin X. (1995). *Economic Growth.* New York, NY: McGraw-Hill.

Basu, S., & Fernald, J. G. (2007). Information and communications technology as a general-purpose technology: Evidence from U.S. industry data. *German Economic Review*, *8*(2), 146–173.

Basu, S., Fernald, J. G., Oulton, N., & Srinivasan S. (2004). The case of the missing productivity growth, or does information technology. Explain why productivity accelerated in the United States but not in the United Kingdom? *NBER Macroeconomics Annual*, *4*, 9-63.

Baumol, W. J., Nelson, R. R., & Wolff, E. N. (1994). *Convergence of productivity: Cross-national studies and historical evidence.* Oxford (UK): Oxford University Press.

Bosworth, B., & Collins S. M. (2003). The empirics of growth: An update. *Brookings Papers on Economic Activity*, *2*, 113-206.

Bowman, A. W. (1984). An alternative method of cross-validation for the smoothing of density estimates. *Biometrika*, *71*(2), 353-360.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444.

Colecchia, A., & Schreyer, P. (2002). ICT investment and economic growth in the 1990s: Is the United States a unique case? A comparative study of nine OECD countries. *Review of Economic Dynamics*, *5*(2), 408-442.

Colombo, M. G., & Grilli, L. (2007). Technology policy for the knowledge economy: Public support to young ICT service firms. *Telecommunications Policy*, *31*(10–11), 573–591.

Daveri, F. (2002). The new economy in Europe: 1992-2001. *Oxford Review of Economic Policy*, *18*(3), 345-362.

David, P. A. (1990). The dynamo and the computer and dynamo: A historical perspective on the modern productivity paradox. *American Economic Review*, *80*(2), 355-361.

Färe, R., Grosskopf, S., & Lovell, K. (1995). *Production frontiers*. Cambridge, UK: Cambridge University Press.

Fare, R., Grosskopf, S., & Margaritis, D. (2006). Productivity Growth and Convergence in the European Union. *Journal of Productivity Analysis*, *25*(1-2), 111-141.

Fare, 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.

Fukao, K., Miyagawa, T., Pyo, H. K., & Rhee, K. H. (2009). *Estimates of multifactor productivity, ICT contributions and resource reallocation effects in Japan and Korea*. RIETI discussion paper, RIETI Discussion Paper Series 09-E-021. Retrieved from http://www.rieti.go.jp/jp/publications/dp/09e021.pdf.

Jalava, J., & Pohjola, M. (2007). ICT as a source of output and productivity growth in Finland. *Telecommunications Policy*, *31*(8-9), 463–472.

Jorgenson, D. W. (2001). Information technology and the U.S. economy. *American Economic Review*, *91*(1), 1–32.

Jorgenson, D. W. (2005). Accounting for growth in the information age. In P. Aghion, & S. Durlauf (Eds), *Handbook of Economic Growth* (pp. 743-815). Amsterdam: North-Holland.

Jorgenson, D. W., Ho, M., & Stiroh, K. J. (2005). *Information Technology and the American Growth Resurgence:* Cambridge (UK): MIT Press.

Jorgenson, D. W., Ho, M. S., & Stiroh, K. J. (2008). A Retrospective Look at the U.S. Productivity Growth Resurgence. *The Journal of Economic Perspectives*, *22*(1), 3-24.

Jorgenson, D. W., & Stiroh, K. J. (2000). Raising the speed limit: US economic growth in the information age. *Brookings Papers on Economic Activity*, *1*, 115–235

Kneip, A., Simar, L., & Wilson, P. W. (2008). Asymptotics and consistent bootstraps for DEA estimators in non-parametric frontier models. *Econometric Theory*, *24*(6), 1663–1697.

Kumar, S., & Russell, R. R. (2002). Technological change, technological catch-up, and capital deepening: Relative contributions to growth and convergence. *American Economic Review*, *92*(3), 527–548.

Lains, P. (2008). The Portuguese economy in the Irish mirror, 1960–2004. *Open Economies Review*, *19*(5), 667–683.

Lam, P. L., & Shiu, A. (2010). Economic growth, telecommunications development and productivity growth of the telecommunications sector: Evidence around the world. *Telecommunications Policy*, *34*(4), 185–199.

Leibenstein, H. (1978). *General X-efficiency theory and economic development.* New York, NY: Oxford University Press.

López-Pueyo, C., & Mancebón Torrubia, M. J. (2009). *Sources of productivity growth and convergence in ICT industries: An intertemporal non parametric frontier approach.* Documento de Trabajo 2009-04, Facultad de Ciencias Económicas y Empresariales, Universidad de Zaragoza. Retrieved from http://www.dteconz.unizar.es/DT2009-04.pdf.

Los, B., & Timmer, M. P. (2005). The “appropriate technology” explanation of productivity growth differentials: An empirical approach. *Journal of Development Economics, 77*(2), 517-531.

Maasoumi, E., & Racine, J. (2002). Entropy and predictability of stock market returns. *Journal of Econometrics*, *107*(1-2), 291-312.

Maffezzoli, M. (2006). Convergence across Italian regions and the role of technological catch-up. *Journal of Macroeconomics*, *6*(1), 1-43.

Margaritis, D., Fare, R., & Grosskopf, S. (2007). Productivity, convergence and policy: A study of OECD countries and industries. *Journal of Productivity Analysis*, *28*(1), 87–105.

Naastepad, C. W. M., & Storm, S. (2007). OECD demand regimes (1960–2000). *Journal of Post Keynesian Economics*, *29*(2), 211–246.

Nunamaker, T. R. (1985). Using data envelopment analysis to measure the efficiency of non-profit organizations: A critical evaluation. *Managerial and Decision Economics*, *6*(1), 50–58.

OECD (2008). *Economic Surveys: Portugal 2008*. Paris: OECD. Retrieved from http://www.datafileportugal.com/OECD062008PortugalSurvey.pdf

OECD (2009). *Science, Technology and Industry Scoreboard 2009*. Paris: France. OECD Publishing.

O'Mahony, M., & Vecchi, M. (2005). Quantifying the impact of ICT capital on output growth: a heterogeneous dynamic panel approach. *Economica*, *72* (288), 615–633.

Oliner, S. D., & Sichel, D. E. (2002). Information technology and productivity: Where are we now and where are we going? *Federal Reserve Bank of Atlanta Economic Review, 87(3rd Quarter)*, 15-44.

Quah, D. T. (1993). Galton's fallacy and tests of the convergence hypothesis. *Scandinavian Journal of Economics, 95*(4), 427-443.

Quah, D. T. (1996). Twin peaks: Growth and convergence in models of distribution dynamics. *The Economic Journal, 106*(437), 1045–1055.

Quah, D. T. (1997). Empirics for growth and distribution: stratification, polarization, and convergence clubs. *Journal of Economic Growth*, *2*(1), 27–59.

Rudemo, M. (1982). Empirical choice of histograms and kernel density estimators. *Scandinavian Journal of Statistics*, 9(2), 65-78.

Schreyer, P. (2002). Computer price indices and international growth and productivity comparisons. *Review of Income and Wealth*, *48*(1), 15–31.

Seo, H. J., Lee, Y. S., & Oh, J. H. (2009). Does ICT investment widen the growth gap? *Telecommunications Policy*, *33*(8), 422–431.

Simar L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in non-parametric frontier models. *Management Science*, *44*(11), 49–61.

Simar L., & Wilson, P. W. (1999). Estimating and bootstrapping Malmquist indices. *European Journal of Operational Research, 115*(3), 459–471.

Solow, R. M. (1987). *We'd better watch out*. New York, NY: New York Times Book Review.

Stiroh, K. J. (2002). Information technology and the U.S. productivity revival: What do the industry data say? *American Economic Review*, *92*(5), 1559–1576.

Timmer, M., & van Ark, B. (2005). Does information and communication technology drive EU-US productivity growth differentials?. *Oxford Economic Papers, 57*(4), 693-716.

van Ark, B., Inklaar, R., & McGuckin, R. H. (2003). 'Changing Gear' Productivity, ICT and Service Industries: Europe and the United States. In J. F. Christensen, P. Maskell (Eds.), *The Industrial Dynamics of the New Digital Economy* (pp. 56-100). Cheltenham (UK): Edward Elgar.

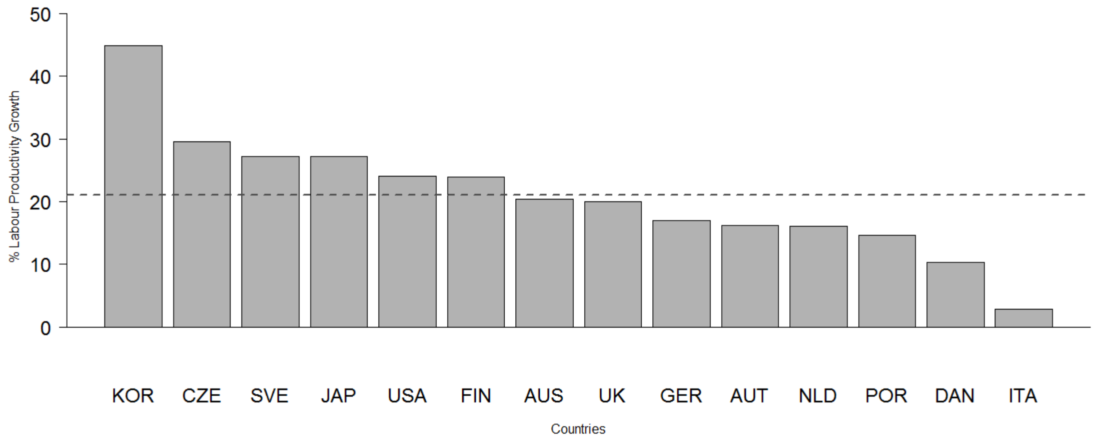
Venturini, F. (2009). The long-run impact of ICT. *Empirical Economics, 37*(3), 497-515.

Vicente, M. R., & Lopez, A. J. (2011). Assessing the regional digital divide across the European Union-27. *Telecommunications Policy*, *35*(3), 220–237.

Vu, K. M. (2011). ICT as a source of economic growth in the information age: Empirical evidence from the 1996–2005 period. *Telecommunications Policy*, *35*(4), 357–372.

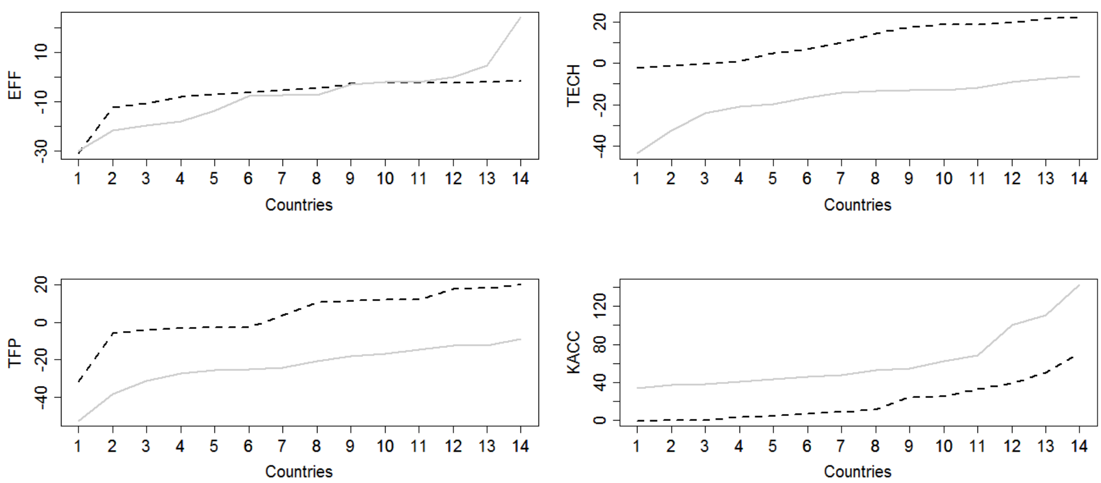
Figures

Fig. 1. Labour productivity growth from 1995 to 2005.



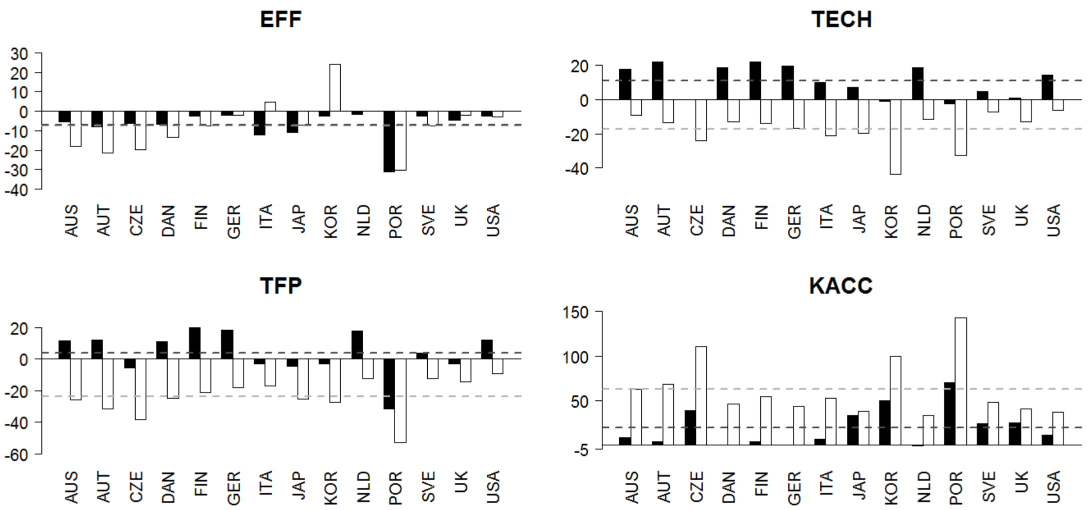
The dashed line indicates the mean

Fig. 2. Distributions of labour productivity change components.



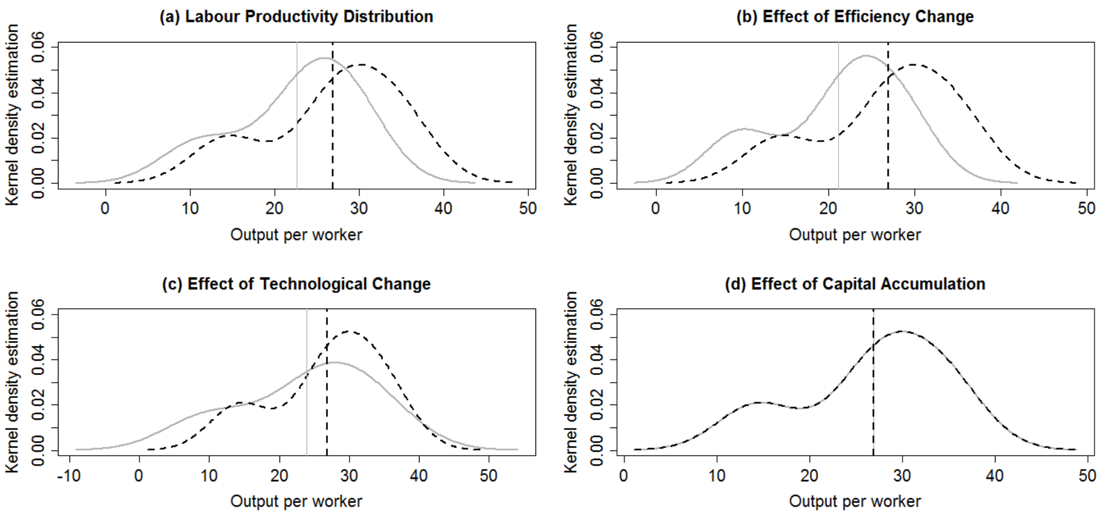
In each panel the dashed curve refers to m1 model and the solid curve to m2 model.

Fig. 3. Labour productivity change decomposition for models *m1* and *m2*.



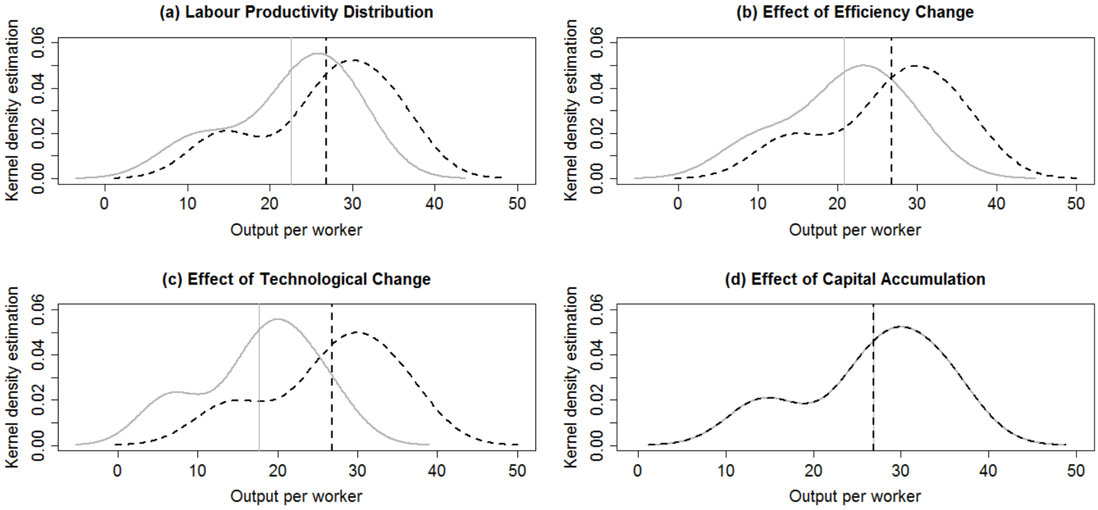
The dark bars refer to the results of model *m1*; the light bars refer to the results of model *m2*. The dark dashed line represents the mean of model *m1;* the light dashed line represents the mean of model *m2.*

Fig. 4. Counterfactual distributions of labour productivity for the model *m1*.



The dashed line refers to 2005, and the solid line to 1995. Vertical lines represent means. In panel (a), the labour productivity distributions are described. In panels (b) and (c). the counterfactual distributions isolating, sequentially, the effects of *EFF* and *TECH* on the 1995 distribution, are shown. Finally, panel (d) reflects all three adjustments of the labour productivity distribution and measures the contribution of the *KACC* component.

Fig. 5. Counterfactual distributions of labour productivity for the model *m2*.



The dashed line refers to 2005, and the solid line refers to 1995. Vertical lines represent means. In panel (a), the labour productivity distributions are described. In panels (b) and (c), the counterfactual distributions isolating, sequentially, the effects of *EFF* and *TECH* on the 1995 distribution, are shown. Finally, panel (d) reflects all three adjustments of the labour productivity distribution and measures the contribution of the *KACC* component.

Tables

Table 1. Descriptive statistics

Variable	Year	Obs	Min.	Max.	Mean	Median	Coeff. of variation
VA	1995	14	86030	7204000	1085000	341600	1.37
	2005	14	121200	9909000	1400000	464700	1.43
H_EMP	1995	14	3646	245600	44970	12840	1.48
	2005	14	4119	270500	46700	14740	1.52
K_GFCF	1995	14	305600	18850000	3238000	1252000	1.55
	2005	14	417000	27220000	4436000	1758000	1.61
K_ICT	1995	14	6141	769600	106300	32590	1.89
	2005	14	26110	3299000	401900	108700	2.11
K_NonICT	1995	14	299500	18080000	3132000	1219000	1.53
	2005	14	390900	23920000	4035000	1579000	1.56
K_ICT /K_GFCF	1995	14	0.019	0.041	0.027	0.024	0.17
	2005	14	0.033	0.13	0.079	0.07	0.36

Table 2. Spearman's rank correlation coefficients between models m1 and m2.

	EFF	***TECH***	***TFP***	***KACC***
Spearman's rank correlation coefficients	0.49	0.43	0.47	0.47

Table 3. Maasoumi and Racine (2002) test results. Number of bootstrap iterations=500.

Counterfactual distribution	H_0: no difference in the distributions between model *m1* and *m2*	P value
y_{1995}**EFF*	H_0 not rejected	0.962
y_{1995}**TECH*	H_0 rejected at 5% significance level	0.024
y_{1995}**EFF*TECH*	H_0 rejected at 5% significance level	0.012
y_{1995}**KACC*	H_0 rejected at 1% significance level	< 2.22e-16