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Testing for Contribution of TFP, ICT and Non-ICT Capital Deepening onto Economic Growth in Developed Countries

Abstract

In this paper, we try to understand why the distribution of income per worker across a sample of developed countries have changed so dramatically during 1980-1995. Specifically, we adapt a statistical test for equality of densities for investigating significance of contribution of various sources, suggested by growth accounting method, onto the change in the income per worker distribution across the 15 developed countries. Considering three sources of growth in income per worker—(i) *change in ICT-capital per unit of labor,* (ii) *change in Non-ICT-capital per unit of labor,* and (iii) *change* in *TFP*—we find that none of these sources alone, but only if coupled with another source, was significant in changing the income per worker distribution in our sample.

Key words: Growth Accounting, Density estimation, ICT

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1. Introduction

In this paper, we challenge the question of why the income per worker (i.e., average labour productivity) distribution across 15 developed countries have changed so dramatically during 1980-1995. Some economists have argued that the key factor was the technological change and, in particular, the revolution in Information and Communication Technology (ICT) sectors of economies (e.g., see Jorgenson (2000, 2001, 2003), Brynjolfsson and Hitt (2000), Timmer, Ypma and van Ark (2003), Piatkowski and van Ark (2003) and Badunenko and Zelenyuk (2003)).

Indeed, using kernel density estimates of the distribution of income per worker for these 15 countries, we have observed a dramatic change over the 15 years and, remarkably, the change from unimodal to multi-modal distribution. This finding is intriguing but consistent with theoretical justification for a multi-peak convergence offered by Quah (1996), and with empirical evidence observed in Henderson and Russell (2001) and Kumar and Russell (2002), for different samples of countries.

A particular issue of our major concern is how large was the (direct) impact of the changes in ICT-capital onto the change in distribution of income per worker across countries—was it the ICT-capital deepening that dramatically changed the distribution?

Our methodology is very simple. We first use the growth accounting (GA) methodology (Solow, 1957) to decompose the growth in income per worker into three sources: (i) *change in ICT-capital per unit of labor*, (ii) *change in Non-ICT-capital per unit of labor*, and (iii) *change in Total Factor Productivity* (*TFP*). Given estimates of these sources, we then construct the 'virtual' or 'fitted' samples of income per worker for these 15 countries under various assumptions that isolate the impact of one or more of these sources onto the income per worker. We then use the kernel density estimates for these samples to visualize and informally compare the impact of each of the sources alone and jointly with another source. Finally, similarly to Henderson and Russell (2001), Kumar and Russell (2002), we use the Li (1996) test of equality of distributions to formally investigate *significance* of contribution of each source separately and jointly with another source.

Quite unexpectedly, we find that the dramatic change has been caused more likely by the change in TFP, rather than by the ICT or Non-ICT Capital deepening. Moreover, none of the sources alone was significant in changing the distribution of the income per worker, but only significant when coupled with another source.

2. Methodology

Let us first describe the growth accounting technique (Solow, 1957) to decompose the growth in income per worker into several sources. Let q_t^k and $x_t^k = (x_{t,1}^k, ..., x_{t,N}^k)' \in \Re_+^N$ denote the total output (GDP) and vector of endowed resources, respectively, that each country *k* (*k* = 1, …, *n*) is endowed with in period *t*. For simplicity, assume that the production possibilities of a country *k* in any period *t* is charaterized by the aggregate production function with Hicks-neutral-type technological change, i.e.,

$$q_t^k \equiv \psi_t^k(x_t^k) = a_t^k \psi^k(x_t^k), \qquad k = 1, \ldots, n \qquad (1)$$

where ψ^k is the independent of time part of country *k*'s aggregate production function, which is augmented by a_t^k—a function of time often referred to as the total factor productivity (TFP).

The growth accounting method is based on noting that, given appropriate differentiability of (1) w.r.t time, the growth rate of the aggregate output, denoted with $g(q_t^k)$, is given by

$$g(q_t^k) \equiv \frac{dq_t^k / dt}{q_t^k} = \frac{d \ln q_t^k}{dt} = \sum_{i=1}^{N} e_{i,t} \frac{d \ln x_{i,t}^k}{dt} + \frac{d \ln a_t^k}{dt}$$

$$= \sum_{i=1}^{N} e_{i,t} g(x_{i,t}^k) + g(a_t^k), \qquad k = 1, \ldots, n \qquad (2)$$

where $e_{i,t}^k \equiv (\partial \psi_t^k(x_t^k) / \partial x_{i,t}^k) / (x_{i,t}^k / q_t^k)$ is the *partial scale elasticity* w.r.t. input *i* and $g(x_{i,t}^k) \equiv (dx_{i,t}^k / dt) / x_{i,t}^k$ is the *growth rate* of this input *i*, and $g(a_t^k) \equiv (da_t^k / dt) / a_t^k$ is the growth rate of TFP, also known as the 'Solow residual'. In words, the growth rate in GDP is the weighted average of growth rates in each input $x_{i,t}^k$ weighted by the corresponding partial scale elasticity plus the growth rate in TFP. Assuming in addition constant returns to scale allows normalizing each variable by one of the input variables, thus getting

$$g(q_t^k / x_{j,t}^k) \equiv \sum_{\substack{i=1 \\ i \neq j}}^{N} e_{i,t} \frac{d \ln(x_{i,t}^k / x_{j,t}^k)}{dt} + \frac{d \ln a_t^k}{dt}$$

$$= \sum_{i=1, i \neq j}^{N} e_{i,t} g(x_{i,t}^k / x_{j,t}^k) + g(a_t^k), \qquad k = 1, \ldots, n \qquad (3)$$

In our empirical analysis, input vector x_t^k consist of three elements—labor, ICT-capital and Non-ICT-capital and the normalizing variable is labor, so that we obtain decomposition of the growth in income per worker into three sources of growth: (i) due to change in ICT-capital per unit of labor, (ii) due to change in Non-ICT-capital per unit of labor, and the rest is due to (iii) change in other factors, attributed to the change in TFP. In practice, since data is observed discontinuously, we use the discrete version of (3), given by

$$\Delta \ln(q_t^k / x_{j,t}^k) = \sum_{i=1, i\neq j}^{N} e_{i,t} \Delta \ln(x_{i,t}^k / x_{j,t}^k) + \Delta \ln(a_t^k), \qquad k = 1, \ldots, n \qquad (4)$$

where Δ is the first-differences operator.

Upon computing the total growth rate for income per worker and its sources according to decomposition given in (4), for each country *k* (*k=1,…, n*) in a sample, we can then analyze the contribution of each of the three sources onto the change in the distribution of income per worker in the population we are studying. Specifically, note first that from (4), it immediately follows that

$$(q_t^k / x_{j,}^k) = (q_{t-1}^k / x_{j,t-1}^k) \exp\left(\sum_{i=1, j\neq j}^{N} e_{i,t} \Delta \ln(x_{i,t}^k / x_{j,t}^k) + \Delta \ln(a_t^k)\right), \quad k = 1, \ldots, n \qquad (5)$$

Given this expression (5), we can analyse the aggregate (across countries) contribution of change in i^{th} input (per unit of j^{th} input) onto the growth in GDP (per unit of j^{th} input) by comparing the original sample of income per worker estimates in the base period to the sample of 'fitted' values that account only for the change in i^{th} input (per unit of j^{th} input)—obtained by setting all other changes in eq. (5) to zero. Formally, the sample of such fitted values is defined by

$$\left.\frac{q_t^k}{x_{j,t}^k}\right|_{\substack{\text{only change}\\ \text{in input } i\\ \text{per input } j}} = (q_{t-1}^k / x_{j,t-1}^k) \exp(e_{i,t} \Delta \ln(x_{i,t}^k / x_{j,t}^k)), \qquad k = 1, \ldots, n. \qquad (6)$$

Similarly, contribution to change in GDP (per unit of input *j*) due to change in TFP can be done by comparing the original sample to the sample of 'fitted' values that account only for the change in TFP (setting all other changes in (5) to zero), thus obtained from

$$\left.\frac{q_t^k}{x_{j,t}^k}\right|_{\substack{\text{only change}\\ \text{in TFP}}} = (q_{t-1}^k / x_{j,t-1}^k) \exp(\ln(a_t^k)), \qquad k = 1, \ldots, n. \qquad (7)$$

In the same fashion, we can analyze contribution to change in GDP (per input *j*) coming from any number of inputs with or without TFP—using (5) with all the other changes set to zero.

The question that naturally arises is how to compare those samples. Perhaps the most popular way is to investigate the first moments of the distributions using the sample means. Another way is to analyze the dispersion or spread of the samples, using for example variance or coefficient of variation. This would be in the spirit of sigma-convergence of Abramovitz (1986) and Barro and Sala-i-Martin (1992). Another way that incorporates *all* moments of the distribution and allowing for a visual impression of phenomenon is to investigate the whole distributions via estimating densities of the distributions. This method is in the spirit of Quah (1996), Jones (1997), Kumar and Russell (2002), Henderson and Russell (2001) and Badunenko and Zelenyuk (2003), and we will use a version of this method in our study.

To briefly outline the kernel density estimation method, let *f* be the probability density function of a univariate random variable *u* (income per worker, in our case) whose cumulative distribution function is given by *F* and let $\{u^k : \quad k = 1,..., n\}$ be a random sample from this distribution. The histogram or 'naïve' estimator for the density of *u* gives a simple and common way of estimating and visualising the distribution. A generalization of the histogram is the Rosenblatt (1956) *kernel density estimator*,

$$\hat{f}_h(u) \equiv \frac{1}{nh}\sum_{k=1}^{n} K\left(\frac{u-u^k}{h}\right), \tag{8}$$

where $h = h(n)$ is the band- or interval- width (as in the histogram), satisfying $h \to 0, nh \to \infty$, whenever $n \to \infty$, while *K* is an appropriate kernel function (e.g., Gaussian density), and *u* is a point at which we aim to estimate the density *f*. The estimator (8) is consistent for the true *f* and asymptotically normally distributed under quite weak regularity conditions on the data generating process (for theoretical properties, see, for example, Pagan and Ullah, 1999). In our study we estimate *h* using the 'state of the art' bandwidth proposed by Sheather and Jones (1991) method.

Using (8) for samples of original and fitted estimates of income per worker would give us estimates of the corresponding true, but unknown densities at any points of their supports. These estimates will then be plotted against the corresponding points of the support, thus giving visual representation of the changes in the income per worker. Visual representations are very useful, but often are not enough to make accurate statements. To make formal statement, we use the statistical test on equality of densities proposed by Li (1996, 1999) and Fan and Ullah (1999) (see appendix for details).

3. Estimation Results

As a way of illustrating the methods described above, we use the Growth Accounting results of Timmer, Ypma and van Ark (2003), applied to 15 OECD countries, which for convenience are replicated in the table below.

For description of the data used, other estimates and corresponding implications of these results, we refer to Timmer, Ypma and van Ark (2003). Here we will focus only on the visualization and formal testing of the changes in distributions of income per worker across the 15 countries, from 1980 to 1995, that occurred due to the sources suggested from using the GA method, as described above. In particular, we consider impact of three sources: (i) change in ICT-capital per labor, (ii) change in Non-ICT-capital per labor, and the rest is due to (iii) change in other factors, attributed by convention to changes in TFP.

Table 1. Percentage contribution to growth in income per worker, 1980-1995

	%-point contribution			
	ICT per hour	Non-ICT per hour	TFP	GDP per hour
United States	0.5	0.2	0.7	1.4
European Union	0.3	0.9	1.1	2.3
Ireland	0.2	0.7	2.9	3.9
Spain	0.3	0.9	1.6	2.8
Germany	0.4	0.8	1.7	2.8
Finland	0.3	1.0	1.4	2.7
France	0.3	1.2	0.9	2.4
United Kingdom	0.4	0.8	1.3	2.4
Belgium	0.7	0.9	0.8	2.3
Portugal	0.2	0.8	1.2	2.2
Italy	0.3	0.8	0.9	2.0
Denmark	0.5	0.7	0.8	1.9
Netherlands	0.3	0.5	0.9	1.7
Austria	0.2	0.8	0.6	1.7
Sweden	0.4	0.7	0.5	1.6
Greece	0.2	0.4	-0.5	0.1
unweighted average	0.32	0.79	1.06	2.17
variance	0.01	0.04	0.52	0.66

Source: Timmer, Ypma and van Ark (2003) "IT in the European Union: Driving Productivity Divergence?" Research Memorandum GD-67 (Groningen Growth and Development Centre).

Notes: Contributions as defined in equation (4) (countries are ranked in descending order of GDP growth).

Table 2 presents the results of the bootstrapped p-values for the Li (1996) test and Figures 1 through 5 visualize the estimated densities. The solid lines in Figure 1 visualize the distributions of income per worker in 1980 and 1995 by plotting the kernel estimates of the corresponding true densities. We see that a very dramatic change has occurred over 15 years--from Table 2, the Li-test suggests very significant change, with p-value of 0.0032.

Table 2. Bootstrap estimated p-values for the Li-test for various hypotheses.

Null Hypothesis	p-value
Equality of Distributions of Labor Productivity (i.e., income per worker) in 1980 and in 1995.	0.0032
Equality of Distributions of Labor Productivity in 1980 and 1995-assuming only ICT Capital per labor change (with change in TFP and in Non-ICT Capital per labor in (5) set to zero).	0.8554
Equality of Distributions of Labor Productivity in 1980 and 1995-assuming only Non-ICT Capital per labor change (change in TFP and in ICT Capital per labor in (5) set to zero).	0.5090
Equality of Distributions of Labor Productivity in 1980 and 1995-assuming only ICT and Non-ICT Capital per labor change (with change in TFP in (5) set to zero).	0.0988
Equality of Distributions of Labor Productivity in 1980 and 1995-assuming only TFP Capital per labor change (with change in ICT and in Non-ICT Capital per labor in (5) set to zero).	0.2530
Equality of Distributions of Labor Productivity in 1980 and 1995-assuming only TFP and ICT Capital per labor change (with change in Non-ICT Capital per labor in (5) set to zero).	0.0606
Equality of Distributions of Labor Productivity in 1980 and 1995-assuming only TFP and Non-ICT Capital per labor change (with change in ICT Capital per labor in (5) set to zero).	0.0062

Notes: p-values were estimated according to (15) for test statistic (13) and variance estimator (14), with B=5000 bootstrap replications. Results are robust to different bandwidth choices.

From this figure we see a three-modal distribution of income per worker in 1995—suggesting that three ‘clubs’ of countries have emerged after 1980. This finding is consistent with theoretical justification for a multi-peak convergence offered by Quah (1996), as well as similar to the empirical evidence (for twin-peak world convergence) found in Henderson and Russell (2001) and Kumar and Russell (2002). Our results, however, must be interpreted with a caution—additional modes might have appeared due to small sample size (we only had 15 observations). The multi-modality can be tested using, for example, Silverman (1986) test for multi-modality of a distribution, but we will not focus on it in this paper. In any case, whether there is multi-modality or not, the figure suggest that the changes in the distribution of income per worker were not 'uniform' over countries—some grew faster than others—and we are interested in learning what sources have contributed the most to this 'divergence'.

<Insert Figure 1 here>

The dotted curve in Figure 1 is the estimated density of distribution of income per worker in 1995 under condition that only change in ICT-capital per labor is accounted for (i.e., other changes in (5) are set to zero). We see that a relatively small change has occurred, relatively 'uniformly' over all the countries in the sample—in the sense that the totally different shape of distribution observed in 1995 has not being caused by the change in ICT-capital per labor. Giving the p-value of 0.8554 (see Table 2), the Li-test suggests that this contribution was statistically insignificant. One should be careful interpreting this result, however, since statistical insignificance might have occurred due to low power of our asymptotic test in our *small* sample. More data is needed to check for robustness of this conclusion. Finally, the dashed curve in Figure 1 is the estimated density of distribution of income per worker in 1995 under condition that the change in TFP in (5) is set to zero (i.e., only change in ICT and Non-ICT capitals per labor are accounted for). When both, the changes in ICT-capital per unit of labor and Non-ICT-capital per unit of labor, are accounted together, the distribution does not changes the shape dramatically (as when all changes are accounted for). It only skews the distribution in base (1980) to the right in somewhat 'uniform' fashion. This time, however, the power of the Li-test was enough to identify significance of the contribution with p-value of 0.0988.

<Insert Figure 2 here>

Figure 2 is similar to Figure 1, except that the dotted curve is the estimated density of distribution of income per worker in 1995 when we only account for the change in Non-ICT capital per labor, and other curves are the same as in Figure 1. From both figures we see that Non-ICT capital deepening alone was also not detrimental in dramatically changing the distribution of income per worker (p-value of the test is 0.5090), but slightly larger than the

ICT-Capital deepening. Again, small sample size might be a reason for inability (low power) to identify significance of the contribution.

Figure 3 is similar to Figure 1 and 2, but the dotted curve is the estimated density of distribution of income per worker in 1995 under condition that all changes except TFP (5) are set to zero (i.e., no changes in ICT and Non-ICT capitals per labor are accounted for). The figure clearly suggests that the changes in TFP were responsible for the *dramatic* change in the shape of the distribution of income per worker across countries over 15 years. The Li-test, however, gives the p-value of only 0.2530.

<Insert Figure 3 here>

In Figure 4, the dotted curve is the estimated density of distribution of income per worker in 1995 under condition that the changes in Non-ICT capital per labor in eq. (5) is set to zero (i.e., only changes in TFP and in ICT-capital deepening are accounted for). Li-test suggests that the contribution is significant (at 10%), with p-value of 0.0606. Finally, in Figure 5, the dotted curve is the estimated density of distribution of income per worker in 1995 under condition that the changes in ICT capitals per labor in eq. (5) is set to zero (i.e., only changes in TFP and in Non-ICT capital are accounted for). The Li-test suggests high significance of the contribution, by giving the p-value of 0.0062. These figures and the Li-test suggest that the contribution from the change in Non-ICT-deepening during 1980-95, for our sample was, overall, relatively larger than from the change in ICT-deepening, with accounting for TFP change (as in Figure 4,5) or without it (as in Figure 1,2).

<Insert Figure 4 here>

<Insert Figure 5 here>

4. Concluding Remarks

The main goal of this paper was to investigate significance of contribution of each source (derived within growth accounting approach) onto the change in income per worker distribution across countries. Using the limited data on 15 developed countries (from Timmer, Ypma and van Ark (2003)) we have discovered quite interesting results. First of all, the distribution of income per worker across countries have changed dramatically during 1980-1995: from uni-modal to, apparently, three-modal.

Second, by considered three sources of growth (i) *change in ICT-capital per unit of labor*, (ii) *change in Non-ICT-capital per unit of labor*, and (iii) *change* in *TFP*, we found that none of these sources *alone* have brought contribution that is significantly different from zero with p-value lower than 0.10. As in the seminal study of Solow (1957), the effect of change in TFP was the largest, although for our sample the p-value of our 'significance of contribution test' was only 0.25. The joint effect of changes in both ICT and Non-ICT capitals per unit of labor were significant at about 10% level. Changes in TFP jointly with changes in ICT or Non-ICT capitals (per unit of labor) were also highly significant at about 6% and 1%, respectively.

It must be noted however that the insignificance of each source alone is very likely to have occurred due to very small sample size—due to our asymptotic test not reaching the desired power of detecting alternative hypothesis that are relatively close to the null hypothesis. Thus, a natural extension would be to use larger data set. Another important issue is that we considered only the *direct* effect of ICT-capital onto the change in income per worker. Much of the change in TFP, which was the largest source among the three, might have resulted from *indirect* influence of the ICT on other inputs. Needless to say is that an improvement can be reached by modelling the aggregate production function more accurately by considering other crucial inputs, especially the human capital, or/and relaxing assumptions of Hicks-neutrality and constant returns to scale. The considered methodology can handle all those improvements—their incorporation is just subject to data limitations and we hope our study would provoke further investigations on this.

APPENDIX: Test on Equality of Densities using Li (1996, 1999) test

To outline the essence of the test for equality of distributions of two random variables, $u^A, u^Z \in \Re^1_+$, suppose we have two random samples, $\{u^{A,k}: \ k = 1,...,n_A\}$ and $\{u^{Z,k}: \ k = 1,...,n_Z\}$, potentially representing two sub-groups in a population or two different populations, A and Z, respectively. We would like to test whether the distributions of these random variables, characterised by density functions $f_A(u^A)$ and $f_Z(u^Z)$, respectively, are equal or not. Formally, our null hypothesis is:

H_0: $f_A(u^A) = f_Z(u^Z)$, almost everywhere, against the alternative hypothesis

H_1: $f_A(u^A) \neq f_Z(u^Z)$, on a set of positive measure.

To devise such a test, Mammen (1992), Anderson et al. (1994), Li (1996, 1999) and Fan and Ullah (1999) have considered the integrated square difference criterion,

$$I \equiv \int \left(f_A(u) - f_Z(u)\right)^2 dt = \int \left(f_A{}^2(u) + f_Z{}^2(u) - 2f_A(u)f_Z(u)\right)du$$

$$= \int f_A(u)dF_A(u) + \int f_Z(u)dF_Z(u) - \int f_A(u)dF_Z(u) - \int f_Z(u)dF_A(u) \qquad (9)$$

(which satisfies the property that $I \geq 0$ and $I = 0$ if and only if H_0 is true) and suggested slightly different empirical analogues for it as possible tests statistics. A particularly convenient statistic that we have used has been proposed by Li (1996, 1999), who suggested replacing the unknown densities in (9) with the *kernel density estimators*, $\hat{f}_{A,n_A}(\cdot)$ and $\hat{f}_{Z,n_Z}(\cdot)$, according to (8), and the unknown distribution functions $F_A(\cdot)$ and $F_Z(\cdot)$ in (9) with corresponding *empirical distribution functions*, $F_{A,n_A}(\cdot)$ and $F_{Z,n_Z}(\cdot)$. Making these substitutions the empirical analogue of (9) becomes

$$\hat{I}_{n_A,n_Z,h} = \int \hat{f}_A(u)dF_{A,n_A}(u) + \int \hat{f}_Z(u)dF_{Z,n_Z}(u) - \int \hat{f}_A(u)dF_{Z,n_Z}(u) - \int \hat{f}_Z(u)dF_{A,n_A}(u) \qquad (10)$$

$$= \frac{1}{hn_A(n_A-1)}\sum_{j=1}^{n_A}\sum_{k=1}^{n_A} \mathrm{K}\left(\frac{u^{A,j}-u^{A,k}}{h}\right) + \frac{1}{hn_Z(n_Z-1)}\sum_{j=1}^{n_Z}\sum_{k=1}^{n_Z} \mathrm{K}\left(\frac{u^{Z,j}-u^{Z,k}}{h}\right)$$

$$- \frac{1}{hn_A(n_Z-1)}\sum_{j=1}^{n_Z}\sum_{k=1}^{n_A} \mathrm{K}\left(\frac{u^{Z,j}-u^{A,k}}{h}\right) - \frac{1}{hn_Z(n_A-1)}\sum_{j=1}^{n_A}\sum_{k=1}^{n_Z} \mathrm{K}\left(\frac{u^{A,j}-u^{Z,k}}{h}\right) \qquad (11)$$

Li (1996) notes that the statistic (11) without the 'diagonal terms' (i.e., where *k* = *j*), given by

$$\hat{I}^{nd}_{n_A,n_Z,h} = \left\{ \frac{1}{hn_A(n_A-1)} \sum_{j=1}^{n_A} \sum_{k\neq j,k=1}^{n_A} \mathrm{K}\left(\frac{u^{A,j}-u^{A,k}}{h}\right) + \frac{1}{hn_Z(n_Z-1)} \sum_{j=1}^{n_Z} \sum_{k\neq j,k=1}^{n_Z} \mathrm{K}\left(\frac{u^{Z,j}-u^{Z,k}}{h}\right) \right.$$
$$\left. - \frac{1}{hn_A(n_Z-1)} \sum_{j=1}^{n_Z} \sum_{k\neq j,k=1}^{n_A} \mathrm{K}\left(\frac{u^{Z,j}-u^{A,k}}{h}\right) - \frac{1}{hn_Z(n_A-1)} \sum_{j=1}^{n_A} \sum_{k\neq j,k=1}^{n_Z} \mathrm{K}\left(\frac{u^{A,j}-u^{Z,k}}{h}\right) \right\} \quad (12)$$

performed (slightly) better in most of Monte Carlo experiments than the centred statistic based on (11). Using the Hall (1984) CLT, Li (1996) have shown that after appropriate 'standardization' the limiting distribution of (12) is standard normal. Specifically,

$$\hat{J}^{nd}_{n_A,n_Z,h} \equiv \frac{n_A h^{S/2} \hat{I}^{nd}_{n_A,n_Z,h}}{\hat{\sigma}_\lambda} \xrightarrow{d} N(0,1) \quad (13)$$

where $\hat{\sigma}_{\lambda,h}$ is a consistent estimator of $\sigma_\lambda^{\ 2} = 2\left(\int \left(f_A(u) - \lambda f_Z(u)\right)^2 du\right)\left(\int \mathrm{K}^2(u)du\right)$, obtained as

$$\hat{\sigma}^2_{\lambda,h} = 2\left\{ \frac{1}{hn_A^2} \sum_{j=1}^{n_A} \sum_{k=1}^{n_A} \mathrm{K}\left(\frac{u^{A,j}-u^{A,k}}{h}\right) + \frac{\lambda_n^2}{hn_Z^2} \sum_{j=1}^{n_Z} \sum_{k=1}^{n_Z} \mathrm{K}\left(\frac{u^{Z,j}-u^{Z,k}}{h}\right) \right.$$
$$\left. - \frac{\lambda_n}{hn_A n_Z} \sum_{j=1}^{n_Z} \sum_{k=1}^{n_A} \mathrm{K}\left(\frac{u^{Z,j}-u^{A,k}}{h}\right) - \frac{\lambda_n}{hn_A n_Z} \sum_{j=1}^{n_A} \sum_{k=1}^{n_Z} \mathrm{K}\left(\frac{u^{A,j}-u^{Z,k}}{h}\right) \right\} \left[\int \mathrm{K}^2(u)du\right] \quad (14)$$

with $\lambda_n = n_A / n_Z$, assumed to satisfy $\lambda_n \to \lambda, \, as \; n_A \to \infty$, with $0 < \lambda < \infty$ being a constant. (Also see Li (1999) for alternative estimators for σ_λ.)

Due to the fact that the statistic (12) is asymptotocally pivotal, more accurate inference might be obtained via consistent bootstrap estimation. Standard bootstrap from one sub-sample for this statistic has shown very good performance in various Monte Carlo experiments of Li (1996, 1999). To convince ourselves that the test works for 15 observations (as our sample is) we have also done limited Monte Carlo experiments and found that performance is slightly 'worse' than that of Li (1996) for sample sizes of 100 observations, but the difference is statistically insignificant for most cases.

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INSERT for FIGURE 1

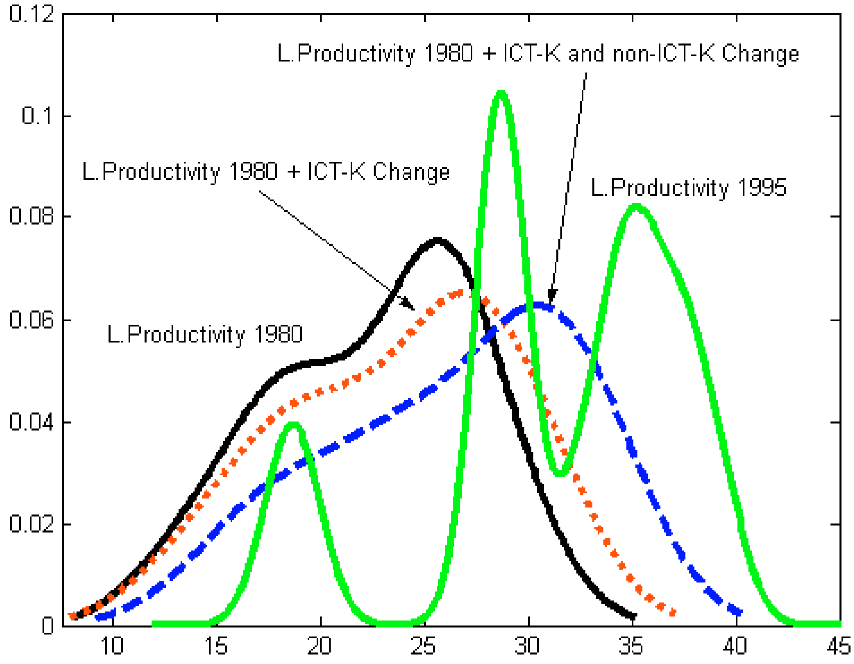

Figure 1. Estimated densities of distributions of Income per Worker in 1980, 1995 and that with accounting only impact of ICT-Capital deepening *alone* (dotted curve) and together with Non-ICT Capital deepening (dashed curve).

INSERT for FIGURE 2

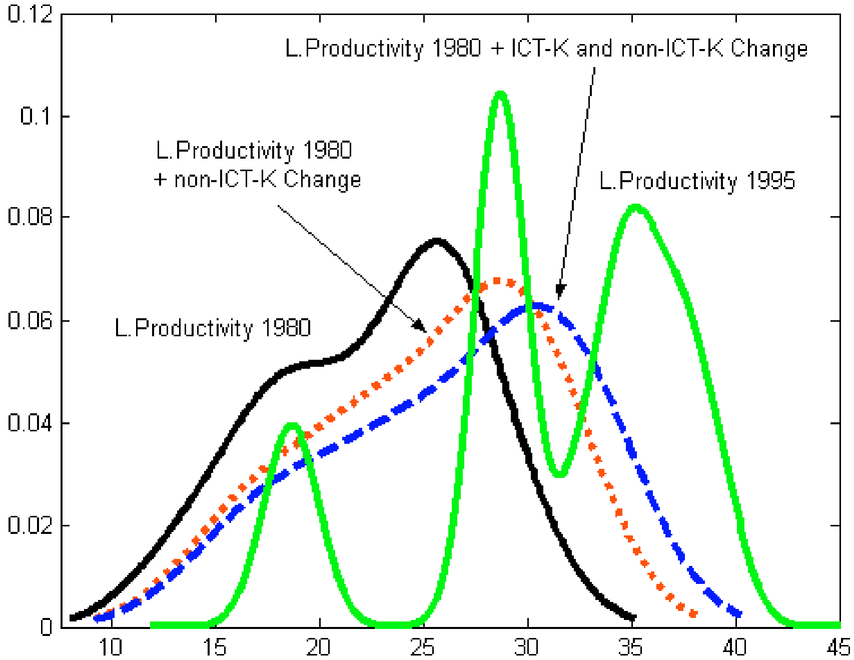

Figure 2. Estimated densities of distributions of Income per Worker in 1980, 1995 and that with accounting only impact of Non-ICT-Capital deepening *alone* (dotted curve) and together with ICT Capital deepening (dashed curve).

INSERT for FIGURE 3

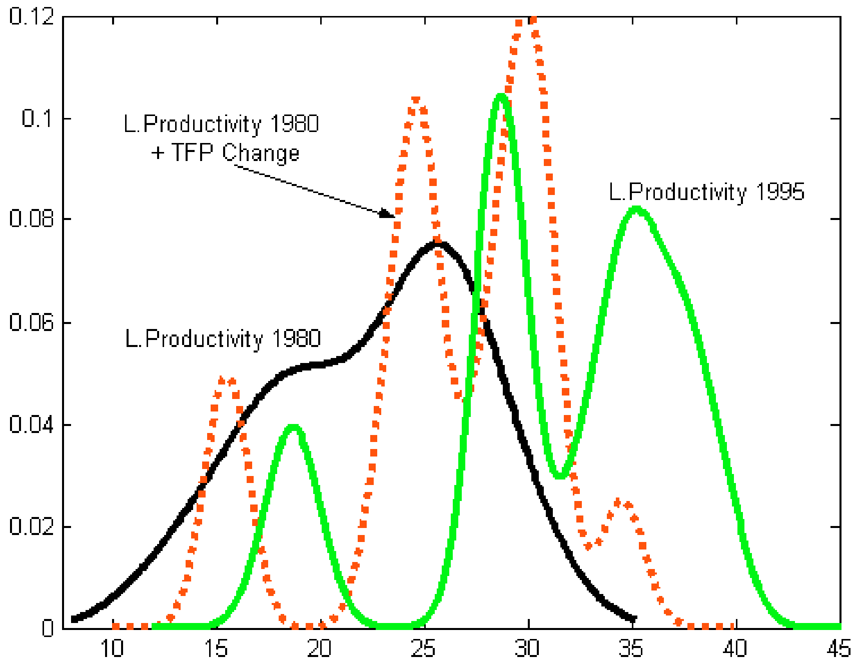

Figure 3. Estimated densities of distributions of Income per Worker in 1980, 1995 and that with accounting only impact of TFP *alone* (dotted line).

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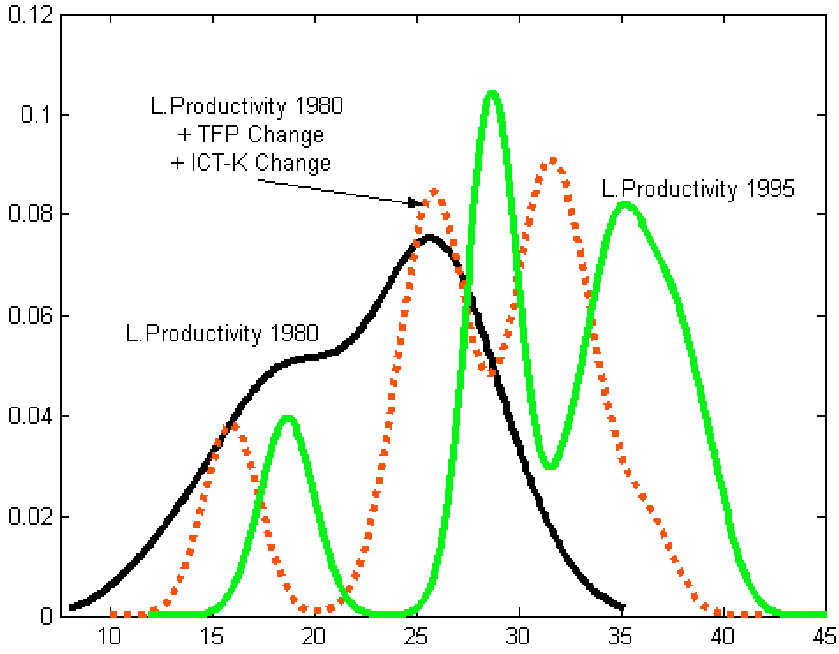

Figure 4. Estimated densities of distributions of Income per Worker in 1980, 1995 and that with accounting TFP jointly with ICT-Capital deepening (dotted line).

INSERT for FIGURE 5

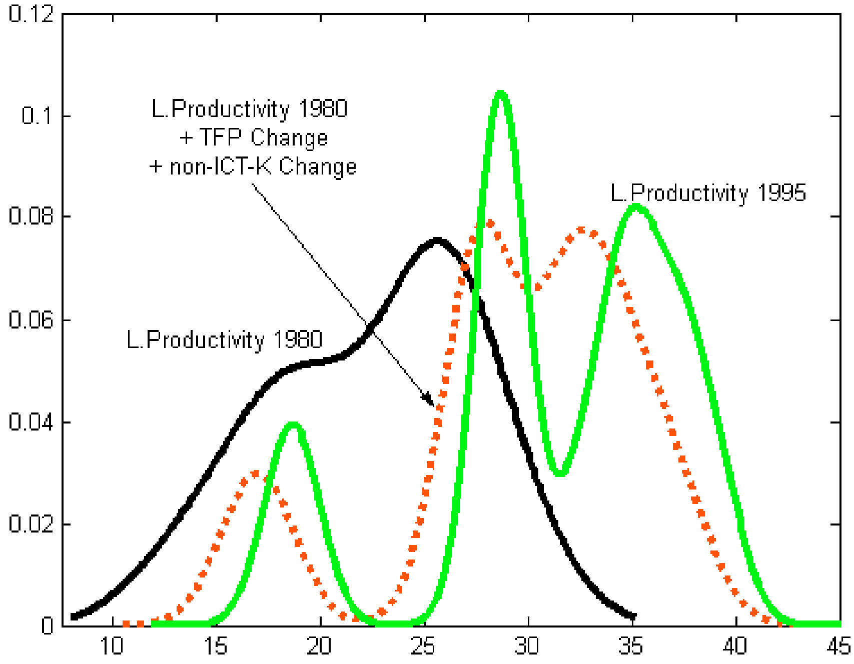

Figure 5. Estimated densities of distributions of Income per Worker in 1980, 1995 and that with accounting TFP jointly with Non-ICT-Capital deepening (dotted line).