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April 2005

Online at <https://mpra.ub.uni-muenchen.de/28029/>

MPRA Paper No. 28029, posted 12 Jan 2011 21:16 UTC

# Testing the Impact of ICT in Developed Countries During 1980-1995: Distributional Analysis in Solow's Growth Accounting Framework

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# Testing the Impact of ICT in Developed Countries During 1980-1995: Distributional Analysis in Solow's Growth Accounting Framework

## Abstract

In this paper we study the impact of ICT capital in developed countries during 1980-1995. We use Solow's growth accounting methodology synthesized with statistical testing about equality of distributions and multimodality of distributions. We test for significance of a contribution from each source of Solow's decomposition, including contribution of ICT capital, as well as test whether any of the contributions are responsible for a multi-club convergence phenomenon and find interesting results.

**Key words:** Growth Accounting, ICT, Density estimation and tests.

**JEL:** O31, O47, O52, P27

## 1. Introduction

Most of the wealth in the world continues to be possessed by a couple of dozens of developed countries. Being accumulated over hundreds of years and invested into various types of capital, this wealth kept generating stable (although not very high, compared to some developing countries) economic growth, ensuring high and rising living standards for these nations. A particular type of capital, often referred to as the ICT-capital (Information and Communication Technologies), is claimed to have had a pronounced impact on the growth of these nations in the last quarter of the previous century. In this paper we try to size the effect of this type of capital relative to other major sources of economic growth in developed nations, by synthesizing existing methodologies.

Many researchers analyzed empirically the patterns of economic growth in the world. A major wave of the literature was inspired by the seminal works of Abramovitz (1986) and Baumol (1986), which was constructively criticised and in many ways complemented by the influential works of Barro (1991, 2001), Mankiw, Romer and Weil (1992), Quah (1993, 1996a, 1996b, 1997), Färe, Grosskopf, Norris and Zhang (1994), Bernard and Jones (1996), Durlauf (1996), Jones (1997), Hall and Jones (1999), Sala-i-Martin (1996, 1997) as well as more recent works by van Ark (2002), Kumar and Russell (2002), Henderson and Russell (2005), Henderson and Zelenyuk (2006), Fagerberg, Srholec and Knell (2007), Badunenko, Henderson and Zelenyuk (2008), Castelacci (2008), Castelacci and Archibugi (2008), Filippetti and Peyrache (2011), to mention just a few.

Our main empirical question is about testing whether it was the ICT-capital deepening that dramatically changed the distribution. The importance of ICT capital on economic growth and productivity was recorded and discussed in Brynjolfsson and Hitt (1998, 2000), Jorgenson (2000, 2001, 2003), Stiroh (2002), Timmer, Ypma and van Ark (2003), Piatkowski and van Ark (2003), to mention just a few.<sup>1</sup> In our study, we use a different technique to statistically address

this question. In particular, our study is fitting to the existing stream of literature by making a synthesis of methodologies from Solow (1957), Quah (1993, 1996a, 1996b, 1997), Kumar and Russell (2002) and by applying it towards tackling the question about the main driving forces for the change in the (average) labor productivity<sup>2</sup> distribution across *developed* countries during 1980-1995. A particular contribution of our study is that we attempt to statistically measure how large was the (direct) impact of the changes in ICT-capital onto the change in *distribution* of labor productivity across countries within the classical Sollow's growth accounting framework.

The methodological task of this paper is to adopt the Solow's growth accounting methodology for statistical testing of significance of contribution from each source of decomposition of country's labor productivity growth. We do such modernization similar to the way Kumar and Russell (2002) worked within the DEA framework for measuring productivity changes and its sources.

Specifically, we first use the growth accounting (GA) methodology (Solow, 1957) to decompose the growth in labor productivity into three sources: (i) *change in ICT-capital per worker*, (ii) *change in Non-ICT-capital per worker*, and (iii) *change in Total Factor Productivity (TFP)*. Given estimates of these sources, we then construct the 'virtual' or 'fitted' samples of labor productivity for these developed countries under various assumptions that isolate the impact of one or more of these sources onto the distribution of labor productivity. We then use the kernel density estimates for these samples to visualize and informally compare the impact of each of the sources alone, as well as jointly with another source. Finally, we use the Li (1996) test of equality of distributions and the Silverman (1981) test for multi-modality to formally investigate *significance* of contribution of each source separately or jointly with another source.

Interestingly, using the kernel density estimates of the distribution of labor productivity for the developed countries, we have observed a dramatic change over these 15 years and, remarkably, the change from a *unimodal* into a *multi-modal* distribution. This finding is intriguing but consistent with theoretical justification for a multi-peak convergence hypothesis offered by

Quah (1996) and theoretical model of Basu and Weil (1999). It is also consistent with the empirical evidence observed in Kumar and Russell (2002), who have argued that the driving engine of growth in the world, from 1965 till 1990, was the capital accumulation. This argument was also recently supported by Los and Timmer (2005). We find that the dramatic change has been caused more likely by the change in TFP—i.e., the mysterious Solow-residual—rather than by the ICT or Non-ICT Capital deepening. It is this factor that caused the largest change, comparable to overall capital (ICT and Non-ICT together) change, in particular, causing a shift from a uni-modal distribution of labor productivity in 1980 towards a *multi-modal* distribution in 1995.

The paper is structured in the following way: Section 2 briefly outlines the methodology, Section 3 describes the data used, Section 4 summarizes the estimation results and section 5 concludes.

## 2. Methodology

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

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

where  $\psi^k$  is the independent of time part of  $k$ 's country 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 GDP, denoted with  $g(q_t^k)$ , is given by

$$\begin{aligned} g(q_t^k) &\equiv \frac{dq_t^k / dt}{q_t^k} = \frac{d \ln q_t^k}{dt} = \sum_{i=1}^N e_{i,t} \frac{\partial \ln x_{i,t}^k}{\partial t} + \frac{\partial \ln a_t^k}{\partial t} \\ &= \sum_{i=1}^N e_{i,t} g(x_{i,t}^k) + g(a_t^k), \quad k = 1, \dots, n \end{aligned} \quad (2)$$

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. In addition, assuming *constant returns to scale* would allow normalizing each variable by one of the input variables, thus yielding

$$\begin{aligned} g(q_t^k / x_{j,t}^k) &\equiv \sum_{\substack{i=1 \\ i \neq j}}^N e_{i,t} \frac{\partial \ln(x_{i,t}^k / x_{j,t}^k)}{\partial t} + \frac{\partial \ln a_t^k}{\partial t} \\ &= \sum_{i=1, i \neq j}^N e_{i,t} g(x_{i,t}^k / x_{j,t}^k) + g(a_t^k), \quad k = 1, \dots, n \end{aligned} \quad (3)$$

In our empirical analysis, input vector  $x_t^k$  consist of three elements—*labor*, *ICT-capital* and *Non-ICT-capital*. The normalizing variable is labor, so that we obtain decomposition of the growth in labor productivity into three sources of growth: (i) due to change in ICT-capital per worker, (ii)

due to change in Non-ICT-capital per worker, 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

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

where  $\Delta$  is the first-differences operator.

Upon computing the total growth rate for labor productivity and its sources according to decomposition given in (4), for each country  $k$  ( $k=1, \dots, n$ ) in a sample, we can analyze the contribution of each of the three sources onto the change in the distribution of labor productivity in the entire population. Specifically, note first that from (4), we can obtain

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

Expression (5) is describing the evolution of labor productivity from base to current period, depending on the sources of growth, and we call it the ‘*contribution equation*’. Using (5), we can analyse the contribution of change in  $i^{\text{th}}$  input (per unit of  $j^{\text{th}}$  input) onto the growth in GDP (per unit of  $j^{\text{th}}$  input), for each country  $k$ . This is done by comparing the labor productivity estimates in the base period to the ‘*fitted*’ values that account only for the change in  $i^{\text{th}}$  input (per unit of  $j^{\text{th}}$  input)—obtained by setting all other changes in eq. (5) to zero. Formally, the sample of such ‘*fitted*’ values is defined by

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



Similarly, contribution to change in GDP (per unit of input  $j$ ) due to change in TFP only, 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 equation (5) to zero), thus obtained from

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

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, by using (5) with all the other changes set to zero.

The question that naturally arises now 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 analysis of Abramovitz (1986) and Barro and Sala-i-Martin (1992). Yet another way is to use regression analysis of the growth rates onto the base period GDP per worker, with possibly some conditioning variables hypothetically influencing the evolution of labor productivity. This would be in the spirit of (absolute or conditional) beta-convergence analysis of Barro and Sala-i-Martin (1992).

Finally, another way that incorporates *all* moments of the distribution and allows for a visual impression of changes in the shape of the distribution is to estimate densities of the distributions. This method is in the spirit of Quah (1996), Kumar and Russell (2002) and Badunenko, Henderson and Zelenyuk (2008) and we will use a modified 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  $U$  (labor productivity, in our case) and let

$\{u^k : k = 1, \dots, n\}$  be a random sample from this distribution. The histogram or ‘naïve’ estimator for the density of  $U$  gives a simple way of estimating and visualising the distribution. A generalization of the histogram, and in some sense its “smooth version, is the Rosenblatt (1956) *kernel density estimator*,

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

where  $h = h(n)$  is the bandwidth ( $h \rightarrow 0, nh \rightarrow \infty$ , as  $n \rightarrow \infty$ ) while  $K$  is an appropriate kernel function, and  $u$  is a point at which we aim to estimate the density  $f$ .<sup>3</sup> The estimator (8) is consistent for the true  $f$  and asymptotically normally distributed (for underlying assumptions and resulting theoretical properties, see, for example, Pagan and Ullah, 1999).

Using (8) for samples of *original* and *fitted* estimates of labor productivity 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 to obtain a visual representation of the changes in the distribution. To make formal statement, we use the statistical test on equality of densities proposed by Li (1996, 1999)<sup>4</sup> as well as a test on multimodality of the distribution proposed by Silverman (1981).<sup>5</sup>

### 3. Data

We use the Growth Accounting results obtained by Timmer, Ypma and van Ark (2003), applied to 15 developed countries, which for convenience are replicated in the Table 1 below. For description of the data used we refer to Timmer, Ypma and van Ark (2003). Here we will only

focus on the visualization and formal testing of the changes in distributions of labor productivity across the countries (from 1980 to 1995).

**< Insert Table 1 here >**

In particular, we will consider impact of three sources: (i) change in ICT-capital per unit of labor, (ii) change in Non-ICT-capital per unit of labor, and the rest is due to (iii) change in other factors, attributed by convention to changes in TFP. Although our sample exhausts most of the population of developed countries in the world, it is still small. (Yet, it is perhaps the best one could currently find for the context of accurate ICT-capital data. For this reason, a bootstrap for the Li (1996) test statistic would be particularly useful (although certainly would not resolve the small sample problem.)

#### **4. Estimation Results**

Figures 1 through 5 visualize the estimated densities, while Table 2 presents the results of the bootstrapped p-values for the Li (1996) test where the null hypothesis is that the distribution of labor productivity in 1980 is equal to another distribution we compare it to.

**<Insert Figure 1 here>**

The solid lines in Figure 1 visualize distributions of labor productivity 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: in Table 2, the Li-test suggests very significant change, with p-value of 0.0062 (i.e., reject the hypothesis of equality of these two distributions at less than 1% significance level).

From this figure we also see a three-modal distribution of labor productivity in 1995—suggesting that three distinct ‘clubs’ of countries have emerged within the set of developed countries, after 1980 up to 1995. The “richest club” consist of Belgium, Denmark, France, Germany, Italy, Netherlands and the US, with Netherlands being the leader (in terms of labor productivity) among these seven. The “middle club” of our sample of developed countries consists of Austria, Finland, Spain, Sweden and the U.K, with Austria being the leader among these five. Finally, the “club of poorest” in our sample of developed countries consist of Greece and Portugal, having similar labor productivity, with Greece being slightly in the lead. Application of the Silverman (1981) *smooth-bootstrap* based test for multi-modality of the distribution of labor productivity in the developed countries in 1995 yields p-value of 0.0414, thus *rejecting* the hypothesis of unimodality at less than 5% level.

This finding shall not be surprising and is consistent with theoretical justification for a multi-peak convergence offered by Quah (1996) and Basu and Weil (1999), and with empirical evidence (for twin-peak *world* convergence) found in Kumar and Russell (2002).

**< Insert Table 2 here >**

Figure 1 suggests that the changes in the distribution of labor productivity were not ‘uniform’ over countries—some grew faster than others—and we are interested in learning what sources have contributed the most to this type of distributional ‘divergence’. Let us focus on the dotted curve in Figure 1, which is the estimated density of distribution of labor productivity in 1995 under condition that only change in ICT-capital per labor is accounted for (i.e., other changes in eq. (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 totally different shape of distribution observed in 1995 was *not* caused by the change in ICT-capital per unit of labor. Giving the p-value of 0.9040 (see Table 2), the Li-test suggests that this contribution was statistically insignificant. However, one should be careful interpreting this result, since statistical insignificance might have occurred because our asymptotic test might not have reached a desired power for our small sample to be able to reject the null hypothesis. More data is needed to check the robustness of this conclusion. Moreover, statistical insignificance of a contribution does not always imply economic insignificance of the same contribution, especially if this insignificance is due to small sample. This evidence is also consistent with earlier studies, e.g., van Ark (2002) summarizing many studies in the field notes that “... In the rest of the advanced world the evidence of acceleration in productivity growth due to ICT is weaker [than in US] though not wholly absent.”

Let us now focus on the dashed curve in Figure 1, which is the estimated density of distribution of labor productivity 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 these two changes are accounted together, the shape of the distribution is not changed dramatically (as when all changes are accounted for). It only skews the distribution in base period (1980) to the right in somewhat ‘uniform’ fashion. This time, the power of the Li-test was enough to identify significance of the contribution only with p-value of 0.2480.

**<Insert Figure 2 here>**

Figure 2 is similar to Figure 1, except that the dotted curve is the estimated density of distribution of labor productivity in 1995 when we only account for the change in Non-ICT capital per labor, and the 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 labor productivity (p-value of the test is 0.6606), but slightly larger than the ICT-Capital deepening. Again, small sample size might be a reason for inability to identify statistical significance of the contribution.

Figure 3 is similar to Figure 1 and 2, but the dotted curve here is the estimated density of distribution of labor productivity 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 labor productivity across countries over 15 years. The Li-test, for comparing it with the base period distribution, gives the p-value of only 0.2938. However, the application of the Silverman (1981) test for multi-modality of this distribution (when only changes in TFP are accounted for) gives p-value of 0.0422, thus strongly suggesting us to reject the hypothesis of unimodality (with more than 95% confidence) in favour of the multimodality.

**<Insert Figure 3 here>**

In Figure 4, the dotted curve is the estimated density of distribution of labor productivity in 1995 under condition that the changes in Non-ICT capital per labor in eq. (5) are set to zero (i.e., only changes in TFP and in ICT-capital deepening are accounted for). The Li-test suggests that the contribution is far from significant, with p-value of 0.5776. Finally, in Figure 5, the dotted curve is the estimated density of distribution of labor productivity in 1995 under condition that the changes in ICT-capital per labor in eq. (5) are set to zero (i.e., only changes in TFP and in Non-ICT capital are accounted for). The Li-test here suggests high significance of the contribution, by giving the p-value of 0.0330. These figures and the Li-test suggest that the contribution from the change in Non-ICT-deepening 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>**

This completes our empirical illustration. Overall, even for a small sample like the one we used, we could extract some interesting information about the distribution of labor productivity, its most detrimental factors in changing distributions in general and towards multi-modality phenomenon in particular.

**<Insert Figure 5 here>**

## 5. Concluding Remarks

In this paper we adopted the Solow's growth accounting methodology towards statistical testing of significance of contribution from each source of decomposition of productivity growth on distributional level. We apply this methodology for investigation of significance of contribution from 3 sources: TFP change, changes in ICT-capital and non-ICT-capital. Using almost all population of developed countries we have discovered quite interesting results.

First, a somewhat disappointing result was that we found *no* evidence that from 1980 to 1995, the ICT-capital deepening was a (statistically) significant force of change in the distribution of labor productivity of the developed countries. This is, however, not a surprising result. One should just recall the famous debate about the Productivity Paradox (e.g., see Griliches (1994, 1997), Brynjolfsson and Hitt (1998, 2000) and Triplett (1999), van Ark (2002), etc.), which has been succinctly described by one of the founders of the growth literature:

“You can see the computer age everywhere but in the productivity statistics.”

(Robert Solow, New York Review of Books, July 12, 1987).

Another explanation can be that we had relatively small sample size—however we had almost all the population (of developed countries). We also had a relatively short time-span (e.g., Kumar and Russell (2002) had 25 year-span for about 60 countries to make their conclusion), while the long-run effect could be very important here. So, we fully consent with van Ark (2002) that

“... there is still good reason to believe that ICT will have a longer lasting impact on the potential for economic growth ... [because] ICT may be characterized as a typical general purpose technology.” (van Ark (2002, p.1))



And, our conjecture is that the evidence can and will be found with this methodology for larger data sets and more likely for longer time horizons.

Another important issue is that we considered only the *direct* effect of ICT-capital onto the change in labor productivity. However, much of the change in TFP, which was the largest source among the three, might have resulted from *indirect* influence of the ICT: due to enormous technological change experienced by ICT industry itself and due to innovations that became possible in other industries because of ICT use (e.g., see discussion of van Ark (2002) on different channels of ICT impact).

Perhaps the most interesting finding in our empirical illustration is that the distribution of labor productivity across countries has changed dramatically during 1980-1995: from uni-modal to a multi-modal, confidently suggested by statistical tests. Moreover, the estimated density plots suggest that TFP was the only driving force (among the three in our decomposition) that caused such multi-modality, and this again was supported by the statistical tests, with fairly high confidence. One might recall that in his seminal study, Solow (1957) also found that the effect of changes in TFP was the largest. On the other hand, for a broader sample of countries (that also included developing countries) and using different methodology, Kumar and Russell (2002) found that it was the capital deepening that have caused the shift toward the multimodality of distribution from 1965 to 1990. Henderson and Russell (2005) also find that efficiency change, not considered in our study, was important for such shift. Note, however that the time span for these studies stop in 1990—before the boom in Hi-Tech industries. Similar methodology applied to the period of 1992-2000 by Badunenko, Henderson and Zelenyuk (2008) gave strong evidence that the technological change (an analog of TFP in our study) was the major source of growth and further (distributional or twin-peak) divergence.

Finally, we certainly admit that our approach is far from perfect. Besides extending the data set or its time-span, one improvement can be made towards modelling the aggregate production function more accurately by considering other crucial inputs, especially the human

capital and/or relaxing assumptions of constant returns to scale. The developed methodology can handle all those improvements—their incorporation is just subject to data limitations and some additional mathematical tricks—and we hope that our study, together with others, would provoke further works and data collection on these and other related questions.

## References

- Abramovitz, M. (1986). "Catching up, forging ahead and falling behind," *Journal of Economic History* 46, pp. 386-406.
- Badunenko, O, D.J. Henderson and V. Zelenyuk (2008) "Technological Change and Transition: Relative Contributions to Worldwide Growth During the 1990's," *Oxford Bulletin of Economics and Statistics* 70:4, pp. 461-492.
- Barro, R. and X. Sala-I-Martin (1992), "Convergence," *Journal of Political Economy* 100:2, pp. 223-51.
- Basu, Susanto and David N. Weil (1998), "Appropriate Technology and Growth," *Quarterly Journal of Economics* 113, pp. 1025-1054.
- Baumol, J. W. (1986), "Productivity Growth, Convergence, and Welfare: What the Long-Run Data Show," *The American Economic Review* 76:5, pp. 1072-1085.
- Brynjolfsson, E. and L. M. Hitt (2000), "Beyond Computation: Information Technology, Organizational Transformation and Business Performance," *Journal of Economic Perspectives* 14:4, pp. 23-48.
- Brynjolfsson and L. Hitt (1998) "Beyond the Productivity Paradox: Computers are the catalyst for bigger changes," *Communications of the ACM*, Vol. 41, No. 8.
- Färe, R., S. Grosskopf, M. Norris and Z. Zhang (1994), "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries," *American Economic Review* 84:1, pp. 63-83.
- Griliches, Z. (1994) "Productivity, R&D, and the data constraint," *American Economic Review* 84:1 (March), pp. 1-23

- Griliches, Z. (1997) 'Plenary Session: perspectives on the productivity paradox,' Centre for the Study of Living Standards, Conference on Service Sector Productivity and the Productivity Paradox, Ottawa, Transcription (April 11-12).
- Henderson, D. J. and R. R. Russell (2005). "Human Capital and Convergence: A Production-Frontier Approach." *International Economic Review* 46:4, pp. 1167-1205.
- Henderson, D.J. and Zelenyuk, V. (2006). "Testing for (Efficiency) Catching-up." *Southern Economic Journal* 73:4, pp. 1003–1019.
- Jones, C. (1997) "On the evolution of world income distribution," *The Journal of Economic Prospective* 11:3, pp. 19-36.
- Jorgenson, D. W. (2001), 'Information Technology and the US Economy', *American Economic Review*, 91:1, pp. 1-32.
- Jorgenson, D. W. (2003), "Information Technology and the G7 Economies," *World Economics* 4:4, pp.139-169.
- Jorgenson, D. W. (2000), *Econometrics. Volume 3: Economic Growth In the Information Age*, The MIT Press, Cambridge, Massachusetts, London, England.
- Kumar S. and R.R. Russell (2002), "Technological Change, Technological Catch-up, and Capital Deepening: Relative contributions to Growth and Convergence," *American Economic Review* 92:3, pp. 527-548.
- Li, Q. (1996), "Nonparametric Testing of Closeness between Two Unknown Distribution Functions," *Econometric Reviews*, 15, pp. 261-274.
- Li, Q. (1999), "Nonparametric Testing the Similarity of Two Unknown Density Functions: Local Power and Bootstrap Analysis," *Nonparametric Statistics*, 11, pp. 189-213.

- Los, B., and Timmer, M.B. (2005). "The "Appropriate Technology" Explanation of Productivity Growth Differentials: An Empirical Approach." *Journal of Development Economics* 77, pp. 517-531.
- Pagan, A. and A. Ullah (1999), *Nonparametric Econometrics*, Cambridge University Press.
- Piatkowski M., and B. van Ark (2004) "Productivity, Innovation and ICT in Old and New Europe," Research Memorandum GD-69.
- Quah, D. (1996) "Twin Peaks: Growth and Convergence in Models of Distribution Dynamics," *Economic Journal* 106:437, pp. 1045-1055.
- Rosenblatt, M. (1956), "Remarks on Some Nonparametric Estimates of a Density Function," *Annals of Mathematical Statistics* 27, pp. 642-669.
- Sheather, S. and M. Jones (1991). "A Reliable Data-Based Bandwidth Selection Method for Kernel Density Estimation," *Journal of the Royal Statistical Society, Series B*, 53, pp.683-90.
- Silverman,B.W. (1981), "Using Kernel Density Estimates to Investigate Multimodality," *Journal of the Royal Statistical Society, Series B*, 43:1, pp. 97-99.
- Simar, L., Zelenyuk, V., (2006), "On testing equality of two distribution functions of efficiency scores estimated from DEA," *Econometric Reviews* 25, pp. 497-522.
- Solow, R. W. (1957). "Technical Change and the Aggregate Production Function," *The Review of Economics and Statistics* 39, pp. 312-20.
- Stiroh, K. (2002), "Are ICT Spillovers Driving the New Economy?" *Review of Income and Wealth*, 48:1, pp.33-57.

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

Triplett, J. (1999) "The Solow productivity paradox: what do computers do to productivity?" *Canadian Journal of Economics*, Vol. 32, No. 2

Van Ark, B. (2002), 'Measuring the New Economy: An International Perspective', *Review of Income and Wealth*, 48 (1), pp.1-14.

INSERT for TABLE 1

**Table 1.** Percentage contribution to growth in labor productivity, 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).

## INSERT for TABLE 2

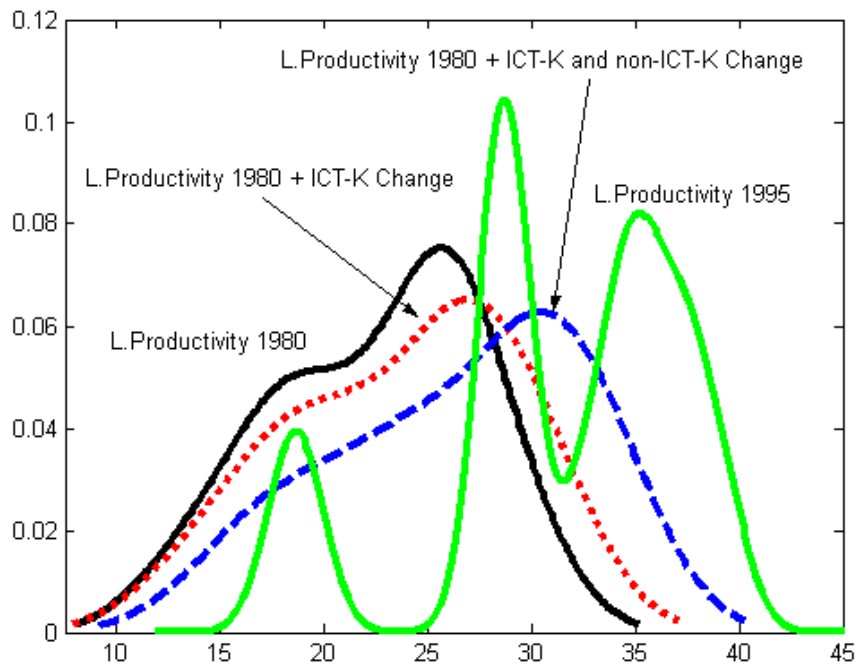
**Table 2.** Bootstrap estimated p-values for the Li-test for various hypotheses.

<b>Null Hypothesis:</b> Distributions of Labor Productivity in 1980 is equal to F, where	<b>p-value</b>
F is distributions of Labor Productivity in 1995.	0.0062
F is distributions of Labor Productivity in 1995 accounting only ICT-Capital per labor change (change in TFP and in Non-ICT Capital per labor in (5) set to zero).	0.9040
F is distributions of Labor Productivity in 1995 accounting only Non-ICT Capital per labor change (change in TFP and in ICT Capital per labor in (5) set to zero).	0.6606
F is distributions of Labor Productivity in 1995 accounting only ICT and Non-ICT Capital per labor change (with change in TFP in (5) set to zero).	0.2480
F is distributions of Labor Productivity in 1995 accounting only TFP change (with change in ICT and in Non-ICT Capital per labor in (5) set to zero).	0.2938
F is distributions of Labor Productivity in 1995 accounting TFP and ICT-Capital per labor change (with change in Non-ICT Capital per labor in (5) set to zero).	0.5776
F is distributions of Labor Productivity in 1995 accounting TFP and Non-ICT Capital per labor change (with change in ICT Capital per labor in (5) set to zero).	0.0330

*Notes:* p-values were estimated 5000 bootstrap replications for the original Li-statistic. Results were robust to different bandwidth choices.

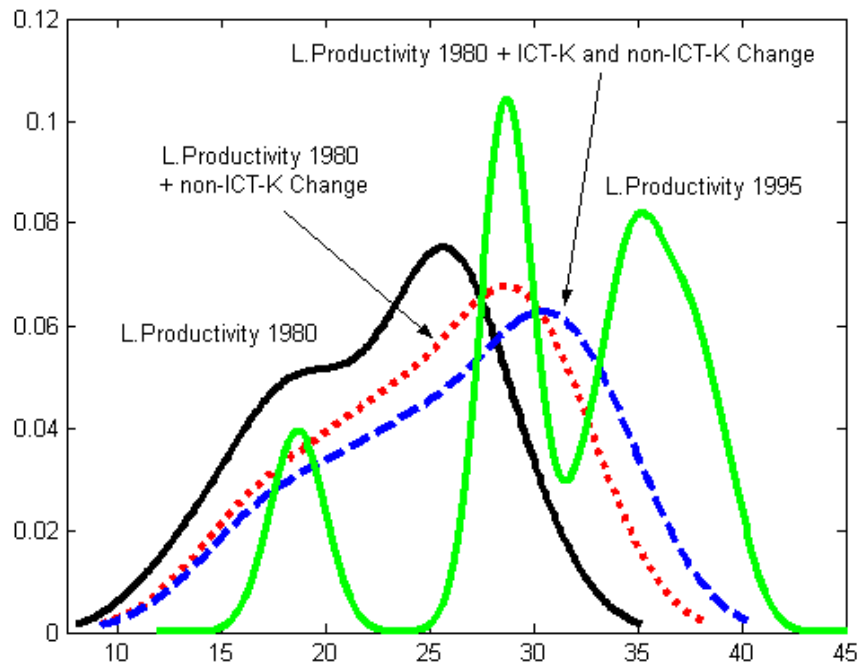


INSERT for FIGURE 1



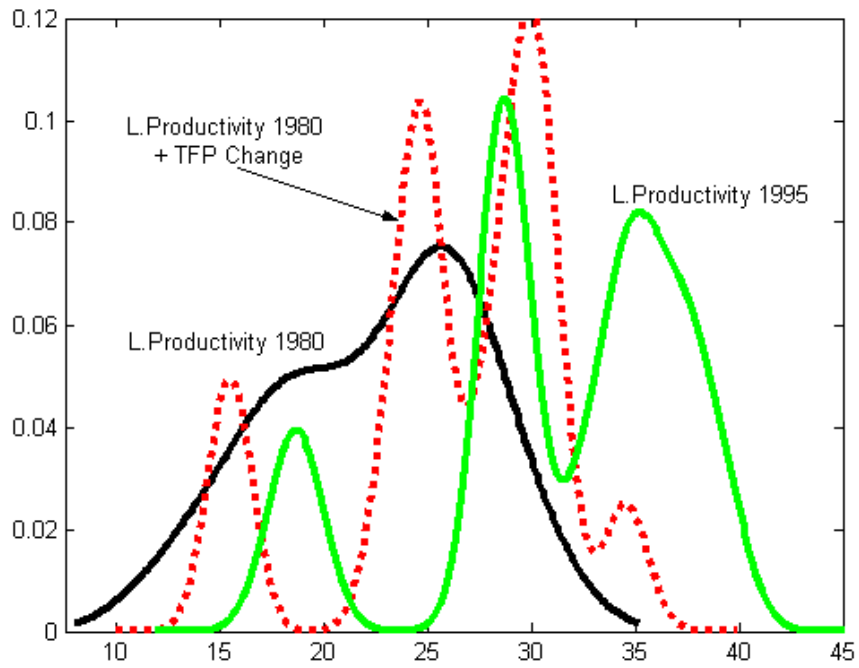
**Figure 1.** Estimated densities of distributions of labor productivity in 1980, 1995 and that with accounting only impact of ICT-Capital deepening *alone* (dotted curve) and together with Non-ICT Capital deepening (dashed curve).

INSERT for FIGURE 2



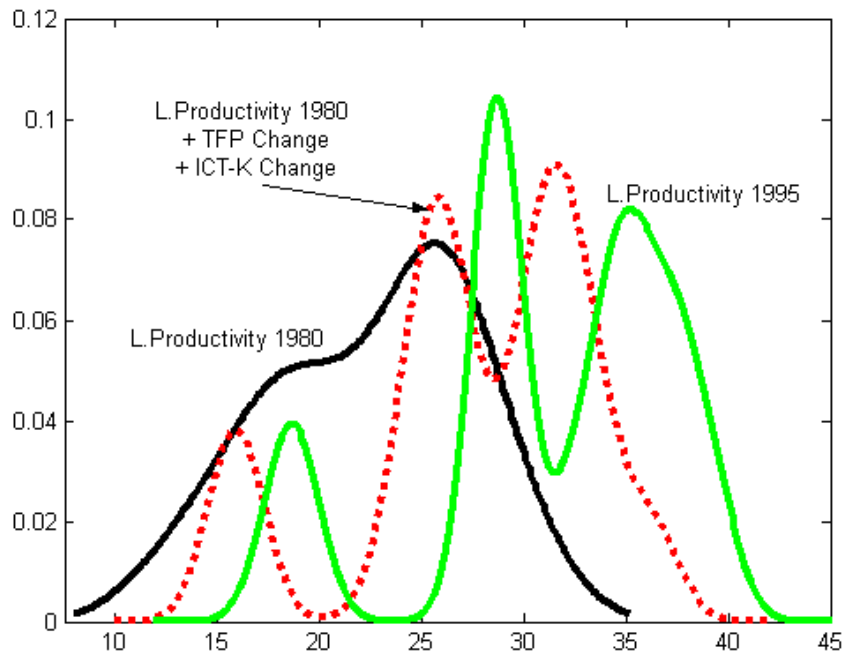
**Figure 2.** Estimated densities of distributions of labor productivity in 1980, 1995 and that with accounting only impact of Non-ICT-Capital deepening *alone* (dotted curve) and together with ICT Capital deepening (dashed curve).

INSERT for FIGURE 3



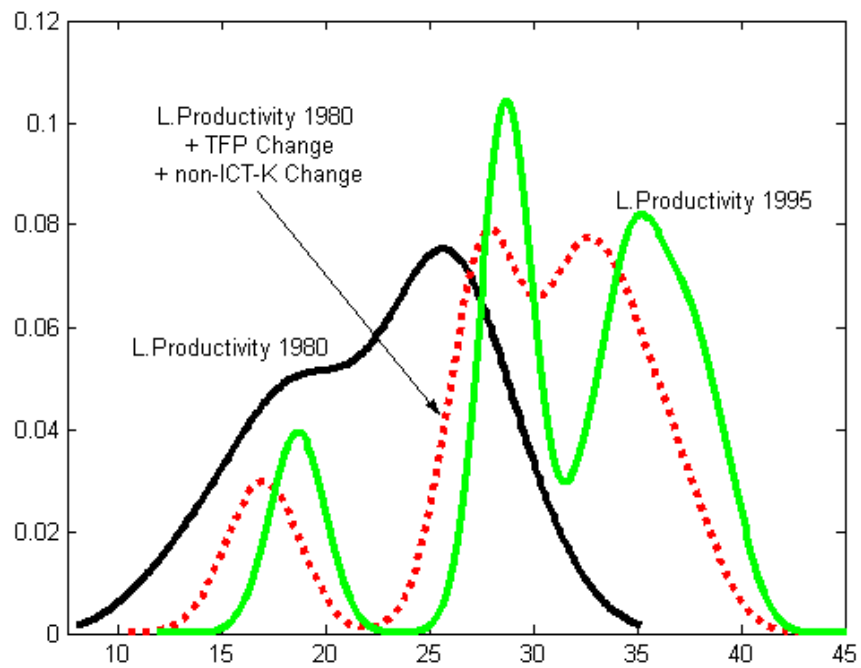
**Figure 3.** Estimated densities of distributions of labor productivity in 1980, 1995 and that with accounting only impact of TFP *alone* (dotted line).

INSERT for FIGURE 4



**Figure 4.** Estimated densities of distributions of labor productivity 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 labor productivity in 1980, 1995 and that with accounting TFP jointly with Non-ICT-Capital deepening (dotted line).

## Endnotes

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<sup>1</sup> Also see van Ark (2002) for a thorough discussion on impact of ICT on productivity and related references.

<sup>2</sup> Labor productivity of a country is defined here as the total income or GDP per unit of labor input.

<sup>3</sup> We estimate the densities at the grid of points on observed range ( $\pm 1/2$  of st. deviation), using Gaussian kernel and choosing  $h$  via method proposed by Sheather and Jones (1991).

<sup>4</sup> Also see Simar and Zelenyuk (2006) for recent application and discussion of power of this test.

<sup>5</sup> The p-values for the Li-test are bootstrapped (via 1-sample re-sampling), with 5000 replications. For the sake of time, we choose Silverman normal adaptive (robust) rule of thumb (with Gaussian kernel) for selecting the bandwidth. For the Silverman test, we also use 5000 bootstrap replications, with Gaussian kernel and the starting value for the bandwidth is obtained via the Sheather and Jones (1991) method.