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A Stochastic Production Frontier Finite Mixture Model Approach

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Abstract

A common and longstanding assumption in the economic growth literature has been that total factor productivity growth is lower in the agriculture sector than in the rest of the economy. Using a stochastic production frontier finite mixture model, labor productivity change is decomposed into catch-up, technological change and factor accumulation effects and stochastic shocks. This decomposition is investigated separately in the agriculture sector and the economy as a whole using a balanced panel data set of 45 countries in different development stages during the time period 1967-1992. The impact of labor productivity change components on the evolution of the cross-country counterfactual distribution of labor productivity is also analyzed. For the overall economy, the empirical results indicate that growth and the twin-peak distribution of labor productivity are driven by capital deepening. However, the results for the agriculture sector suggest that labor productivity distribution is brought by total factor productivity changes rather than factor accumulation. Furthermore, the agriculture sector exhibits reductions in capital per worker as well as stronger catch-up and technological change effects. Thus, growth of the rest of the economy appears to owe more to capital deepening and resource reallocation from agriculture than to faster productivity change.

Key words: Agriculture, Labor Productivity Growth, Catch-Up, Total Factor Productivity, Factor Accumulation, Panel data, Stochastic Production Frontier, Finite Mixture Model.

JEL classification numbers: O10, O14, O30, O47, C23, C49, D24

1. Introduction

Recent empirical studies of economic growth (e.g., Quah, 1996a, 1997) have shown that the second half of the 20st century was characterized by a phenomenon of bipolar international divergence of labor productivity. More specifically the distribution of labor productivity across countries, which had a conventional unimodal shape in the early sixties, became clearly bimodal at the end of the century. Having in mind that labor productivity is a rough indicator of a nations' welfare, such evidence suggests that the world has become bipolarized into the rich and the poor, with the middle-income group of countries nearly disappearing.

The empirical research that has been done on the determinants of economic growth has provided important clues for explaining why the inequality among countries has significantly increased in the last few decades. In particular, various studies have investigated which one of the two factors – capital accumulation or total factor productivity growth – is the main responsible for the observed differences in labor productivity growth across countries.

Mankiw, Romer and Weil (1992) are among the first to perform cross-country analysis of economic growth determinants. Using data for 98 countries, these authors conclude that factor accumulation accounts for approximately 80% of the variation in output per worker between 1965 and 1985. Young (1995) applies the approach known as growth rates accounting to the growth miracles of the East Asia between 1965 and 1990 and concludes that total factor productivity (TFP) growth rates for these countries ranged between 0 and 2%, clearly less than previously found by growth accounting studies, which attributed 1/3 of growth to TFP. Thus, both studies of Mankiw, Romer and Weil (1992) and Young (1995) are consistent with the idea that factor accumulation is the crucial determinant of growth.

This view was initially questioned by the works of Hall and Jones (1999) and Klenow and Rodriguez-Clare (1997), suggesting that disparities in TFP are the main explanation for output per worker differences. Hall and Jones (1999) present a new technique of level accountings instead of growth rates accounting in the decomposition of output per worker into capital intensity, human capital and TFP. Assuming a small capital share coefficient in the Cobb-Douglas production functions, these authors conclude that most of the growth gap between any country and the United States of America is due to residual productivity differences, which are primarily related to differences in social infrastructures across countries. Klenow and Rodriguez-Clare (1997) apply a similar method, with the difference of using two production functions: one for consumption goods and physical capital, the other for human capital. These authors report that TFP explain more than 60% of the differences in output per worker.

More recently, Kumar and Russell (2002) have used a nonparametric and deterministic method known as Data Envelopment Analysis (DEA) to estimate a world production frontier for the years of 1965 and 1990 from a large sample of countries. Assuming constant returns to scale (CRS) it is possible to decompose labor-productivity growth into components attributable to capital accumulation (movements along the frontier), technological change (shifts in the world production frontier) and technological catch-up (movements towards the frontier). The two latter effects can be combined into the TFP growth effect. The empirical results suggest that capital deepening, as opposed to technological change or technological catch-up, is the main explaining factor for the international divergence of economies. Furthermore, the authors argue that wealthy countries have benefited more from technological progress than less developed countries and find striking examples of technological regress in low-income countries. Comparing this approach with the one presented by Hall and Jones (1999), it is important to mention that none of the effects is determined residually and that catch-up is not measured relatively to a single country.

An additional perspective for attempting to explain why the gap between rich and poor countries has widened concerns the sectoral composition of output. In particular, the fact that in developing countries agriculture still accounts for a significant share of the overall economy appears to be a major source of disadvantage for the developing world for at least three main reasons. Firstly the demand for agricultural products is rather inelastic. Therefore, a developing country will never be able to base a process of fast growth on the agricultural sector, unless it manages to exploit its comparative advantages by increasingly supplying foreign markets. Unfortunately, the highly protective agricultural policies of the rich countries strongly constrain this possibility.

Secondly, since the days of Adam Smith and David Ricardo, agriculture has often been regarded as a sector of low productivity growth relatively to the rest of the economy, due to a more limited scope for division of labor and also to diminishing returns to land. Thirdly, empirical studies have suggested that agricultural productivity growth is higher in developed countries than in developing countries.

All those theoretical predictions and empirical results appear to indicate that the agricultural sector cannot play the role of the “engine of economic growth” in the developing world. Fast capital accumulation in the other sectors of the economy appears therefore to be one of the recipes for overcoming those countries’ poor performance in terms of welfare and economic growth. Indeed, these ideas seem to have contributed to strong policy biases against agriculture and towards manufacturing in many developing countries (e.g., Krueger, Schiff and Valdés, 1992).

However, some of those findings appear to be challenged by recent empirical research. The study of Krueger, Schiff and Valdés (1992), focusing on 18 developing countries over the time period of 1960-83, indicates that the more countries discriminate against agriculture, the lower is their Gross Domestic Product (GDP) growth. Moreover, recent international studies suggest that TFP growth is higher in agriculture than in other sectors of the economy. Bernard and Jones (1996) have estimated annual TFP growth rates at 2.6 percent for agriculture and 1.2 percent for industry in a sample of 14 OECD countries for the period 1970-87. Martin and Mitra (2001), using data from an extended sample of countries for the period 1967-1992, find evidence that technical progress has been faster in agriculture than in manufacturing for both developing and developed countries. In addition, the study conducted by Martin and Mitra (2001) indicates a tendency for a relatively rapid convergence in agricultural productivity across countries, contradicting the notion that agricultural productivity growth is larger in developed than in developing countries.

There seems therefore to be recent conflicting evidence on agricultural productivity growth both in relation to the other sectors of the economy as well as across countries. In our view, such evidence brings new interest to the issue of measuring agricultural productivity growth and investigating the role of agriculture in economic development. If empirical results such as those of Martin and Mitra (2001) are correct, then the agricultural sector may well have the potential for playing a decisive role in the growth strategies of developing countries and in reversing the trend for global divergence that has been observed in the last few decades.

Although estimates of productivity growth for the economy as a whole abound, there are surprisingly very few studies that provide comparisons between productivity in agriculture and the rest of the economy, particularly in developing countries. This essay attempts to make a contribution in filling that gap. More specifically, our main purposes are the following: firstly we compare the economy as a whole with the agricultural sector in terms of how their distributions of labor productivity have changed through time. Secondly, we measure the determinants of labor productivity growth across countries and again compare agriculture with the overall economy in that respect.

Methodologically, our paper tries to extend the work of Kumar and Russell (2002), in some important directions: our model is estimated from panel data; the production frontier is not assumed to be common to all countries; and we adopt a fully stochastic approach.

The rest of the paper is organized as follows. Section 2 explains the method employed in distribution analysis of output per worker. Sections 3 and 4 describe the empirical model and the labor decomposition growth using a production frontier approach, respectively. Section 5 gives details about data sources and section 6 reports the empirical results. Section 7 proceeds to summary and concluding remarks.

2. Distribution Analysis of Output per Worker

The starting point of our study involves the analysis of the evolution of the distribution function of labor productivity through time. Regarding the estimation of the probability density function of labor productivity, we purpose the use of a nonparametric kernel density estimator. The goal of density estimation is to approximate the probability density function $f(.)$ of a random variable X. Assuming n independent observations $x_1, x_2, \ldots, x_n$ from the random variable X, the kernel density estimator of the density value $f(x)$ at point x, $\hat{f}(x)$, is defined as:

$$\hat{f}(x)=\frac{1}{nh}\sum_{i=1}^{n}k\left(\frac{x_i-x}{h}\right) \quad (1)$$

where *k(.)* denotes a Gaussian kernel function and *h* is the optimal bandwidth (for details, please see Pagan, A. and A. Ullah, 1999).

The choice of the optimal bandwidth for a kernel density estimate is typically calculated on the basis of the minimization of the mean integrated squared error function:

$$MISE(\hat{f})=\int E\left[\hat{f}(x)-f(x)\right]^2 dx \quad (2)$$

Under the asymptotic conditions $h\to 0, nh\to\infty$:

$$MISE(\hat{f}) \underset{asymp.}{\approx} \frac{1}{nh}\|k\|_2^2+\frac{h^4}{4}\left[\mu_2(k)\right]^2\|f''\|_2^2 \quad (3)$$

where:

- $\|k\|_2^2$ and $\left[\mu_2(k)\right]^2$ are constants depending on the kernel function k(.),

- $\|f''\|_2^2$ is a unknown term, denoting the second derivative of the unknown density *f*.

Minimizing (23) with respect to *h*, we obtain the following optimal bandwidth:

$$h_{opt}=\left\{\frac{\|k\|_2^2}{\|f''\|_2^2\left[\mu_2(k)\right]^2 n}\right\}^{1/5} \quad (4)$$

Using the method of Silverman (1986) and assuming a normal distribution $N\left(\mu,\sigma^2\right)$ for *f*, the optimal bandwidth for a Gaussian kernel:

$$\widehat{h_{opt}}=1.06\hat{\sigma}n^{1/5} \quad (5)$$

The nonparametric kernel approach is used to test Quah's findings (Quah, 1996a, 1997) that the distribution of labor productivity has been transformed from a unimodal into a bimodal distribution over the last decades.

3. A Stochastic Frontier Finite Mixture Model

Kumar and Russell (2002) use a nonparametric framework to estimate a common production frontier function encompassing a sample of 57 countries for the period 1965-90. However, one can challenge the underlying belief that the production technology is common to all these countries in so different development stages. If this assumption is not valid, technological differences may be labeled as inefficiency and the decomposition of output per worker is imprecisely determined.

One method to solve this problem is a two-stage approach: first, countries are classified into several classes, according, for instance, to a cluster analysis applied to the dependent variable; and second, a production frontier is estimated separately for each class (e.g., Kolari and Zardkoohi, 1995; Mester, 1997). This procedure has the disadvantage of estimating the production frontier of a particular class without using information regarding the other classes. This problem may be overcome using the Stochastic Frontier Finite Mixture Model that allows simultaneous estimation of the probability of class membership and the parameters of mixed frontier functions. The stochastic frontier finite mixture model is based on the approach proposed by Heckman and Singer (1984) and on recent developments suggested by Greene (2001).

The parametric and panel data version of the model presented in Kumar and Russell (2002) can be expressed by the equation of the Cobb-Douglas stochastic frontier:

$$y_{it} = \beta' x_{it} + v_{it} - u_{it} \qquad i = 1,...,N\,;\ t = 1,...,T \tag{6}$$

where:

- *'i'* indexes countries and *'t'* indexes time periods,

- y_{it} is the log of the production level in year t for the i-th country,

- x_{it} is a 1 × K vector of the log of inputs in year t for the i-th country,

- β is a 1 × K vector of coefficients,

- v_{it} is the measurement error, and u_{it} refers to the inefficiency component.

In this framework, heterogeneity in the distribution of y_{it} is assumed to impact the density function in the simple form of a random effect. We prefer that unobserved heterogeneity might be accommodated with a model where the density function is specific to each country class that is endogenously determined:

$$y_{it}|j = \beta_j^{'} x_{it} + v_{it}|j - u_{it}|j \quad ; \quad i = 1,...,N \; ; \; t = 1,...,T \; ; \; j = 1,..., M \tag{7}$$

where j indicates class number.

The observations of the sample arise from M unobserved classes in unknown proportions, $p_1, p_2, \ldots, p_M$, such that:

$$\left(0 \leq p_j \leq 1\right) \text{ and } \sum_{j=1}^{M} p_j = 1 \tag{8}$$

To ensure conditions in (8), a logit parameterization is used as follows:

$$p_j = \frac{\exp\left(c_j\right)}{\sum_{\gamma=1}^{M} \exp\left(c_\gamma\right)} \qquad j = 1,...,M \; ; \; c_M = 0. \tag{9}$$

where c_j refers to lower level parameters.

Within each class, the basic form of half normal specification in (6) applies:

$$v_{it}\,|\,j = N[0, \sigma_{vj}^2] \quad ; \quad u_{it}\,|\,j = |\,N[0, \sigma_{uj}^2]\,| \tag{10}$$

After some algebra work, the distribution of the dependent variable conditional on the j class has the form:

$$f(y_{it}\,|\,\mathbf{x}_{it}, j) = \frac{\Phi(\lambda_j \varepsilon_{it|j} / \sigma_j)}{\Phi(0)} \frac{1}{\sigma_j} \phi\left(\frac{\varepsilon_{it|j}}{\sigma_j}\right) \tag{11}$$

where:

- $\varepsilon_{it|j} = y_{it} \left| j - \beta'_j x_{it} \right.$,

- $\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$,

- $\lambda_j = \sigma_{uj} / \sigma_{vj}$,

- $\Phi(.)$ refers to the standard normal cumulative distribution function,

- $\phi(.)$ designates the standard normal probability density function.

It is unknown a priori from which class a particular observation arises. Assuming that the T events are independent within each class, the contribution of country i to the likelihood function is:

$$\sum_{j=1}^{M} p_j \left[\prod_{t=1}^{T} f\left(y_{it} \left| x_{it}, j \right. \right) \right] \tag{12}$$

Thus, the log likelihood function for the sample is given by:

$$\ln L(\alpha) = \sum_{i=1}^{N} \ln \left\{ \sum_{j=1}^{M} p_j \left[\prod_{t=1}^{T} f\left(y_{it} \left| x_{it}, j \right. \right) \right] \right\} \tag{13}$$

where

$$\alpha = \left[(\beta_{11},...,\beta_{1M}),...,(\beta_{K1},...,\beta_{KM}),(p_1,...,p_M),(\sigma_{u1},...,\sigma_{uM}),(\sigma_{v1},...,\sigma_{vM}) \right]$$

The log likelihood can be maximized with respect to α using conventional gradient methods. Once estimates of α are calculated, we can also obtain the posterior estimate of the probability of a particular class membership using these parameters estimates and Bayes theorem:

$$\mathrm{P}(j\,|i) = \frac{p_j \times \prod_{t=1}^{T} f\left(y_{it} \left| x_{it}, j \right. \right)}{\sum_{j=1}^{M} p_j \left[\prod_{t=1}^{T} f\left(y_{it} \left| x_{it}, j \right. \right) \right]} . \tag{14}$$

Using (14), we can identify the index of the group with the highest posterior probability and therefore determine which class generates each observation. Furthermore, the posterior probability can be used in the computation of the efficiency estimates. Following Greene (2001), the individual efficiencies are computed as:

$$\ln EF_{it} = \sum_{j=1}^{M} P\left(j \mid i\right) \ln EF_{it} \left| j \right. \tag{15}$$

where $EF_{it}|j$ is the estimator of the efficiency of the i-th country, calculated applying the Jondrow *et al.* (1982) approach to the production frontier of class j.[1]

There remains an unsolved question: how to determine the number of classes, M? In fact, M is not an estimable parameter and, therefore, it cannot be obtained by maximization of the likelihood function. A model with (M-1) classes is nested within a model with M classes by imposing restrictions on the parameters. Testing 'up' from (M-1) to M is not a valid procedure because if there are M classes, then estimates based only on (M-1) are inconsistent. Nevertheless, as suggested by Greene (2002), testing 'down' is a correct method. Therefore, we only need to pick a large M^* and test down to the true M based on likelihood ratio tests. Unfortunately, the latent class model is a little volatile and the estimation of models with larger number of classes or/and restrictions may not be possible with poor panel data samples, because the estimated variance matrix of estimates can be singular. Furthermore, according to McLachlan (1987) and Feng and McCulloch (1996), Pearson fit, Kolmogorov-Smirnov and likelihood ratio tests do not have a nice distribution for this sort of problems. Thus, some authors (see, for example, Fraley and Raftery,1998 and Roeder *et al.*, 1999) propose the use of information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Bayesian Information Criterion (SBIC). Both AIC and SBIC take the following form:

$$MSC(k) = -2 \ln \max L(k) + a(n)m(k) \tag{16}$$

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[1] In models with a unique frontier, it is a standard procedure the application of the Jondrow *et al.* (1982) estimator of individual inefficiencies $E[u_{it}|v_{it}-u_{it}]$ to calculate efficiency $E[exp(-u_{it})|v_{it}-u_{it}]$.

where:

- $MSC(h)$ is the value of the criterion for the h-th model - the lower the score the better,

- $L(h)$ is the likelihood for the h-th model,

- $m(h)$ is the number of parameters used in the h-th model,

- $a(n) = 2$ for AIC but $a(n) = \ln n$ for SBIC, and

- $h = 1, 2, \ldots, H$ indexes the alternative models.

Most statisticians who are involved with the theory and application of model selection criteria prefer SBIC since it penalizes models with more components heavier than AIC. Moreover, Leroux (1992) concludes that SBIC does not underestimate the number of classes; and Roeder and Wasserman (1997) argue that this method is consistent. On the other hand, Berger and Pericchi (1998) suggest that SBIC approximation is valid only for nice problems: large sample sizes models with regular asymptotics and models for which the likelihood is not concentrated in the boundary of the parameter space. We must proceed cautiously, taking into account the advices of Zhang (1997) who prefers to select a simpler model that approximates sufficiently the true one. Thus, we will conjugate the use of SBIC with an evaluation of the estimation results.

4. Decomposition of Labor Productivity Growth

We define a CRS reference technology with one aggregate output, Y, and a K-dimensional vector of inputs, X. The CRS hypothesis allows us to transform the dependent variable in labor productivity, y, and the vector X into the $(K\text{-}1)$-dimensional vector of inputs per worker, x. For the economy as a whole, K=2 and X=(labor, capital); and for agriculture, K=3 and X=(labor, land, capital).

Figure 1 illustrates the decomposition of output per worker growth, assuming an aggregate input per labor x. Let b and c stand for the base period and the current period, respectively. For simplicity in the analysis, we suppress the subscript i, and consider only one country.

In period b, x_b units of input per worker are used to produce y_b units of output per worker. However, the country faces a positive shock v_b in this period and, in reality, it could produce $\overline{y_b}(x_b)$. Therefore, efficiency in period b is measured as:

$$Eff_b = \frac{y_b}{\overline{y_b(x_b)}} = \frac{y_b}{\exp(\beta' x_b + v_b)} = \frac{y_b}{\exp(\beta' x_b) \cdot \exp(v_b)} = \frac{y_b}{y_b(x_b) \cdot \exp(v_b)} \tag{17}$$

Thus, labor productivity in period b can be expressed as:

$$y_b = Eff_b \cdot \exp(v_b) \cdot y_b(x_b) \tag{18}$$

Mutatis mutandis, labor productivity in period c is given by:

$$y_c = Eff_c \cdot \exp(v_c) \cdot y_c(x_c) \tag{19}$$

Dividing (19) by (18), we obtain labor productivity growth:

$$\frac{y_c}{y_b} = \frac{Eff_c}{Eff_b} \cdot \frac{\exp(v_c)}{\exp(v_b)} \cdot \frac{y_c(x_c)}{y_b(x_b)} \tag{20}$$

Multiplying the numerator and the denominator of equation (20) by $y_c(x_b)$, labor productivity growth can be rewritten as:

$$\frac{y_c}{y_b} = \frac{Eff_c}{Eff_b} \cdot \frac{\exp(v_c)}{\exp(v_b)} \cdot \frac{y_c(x_b)}{y_b(x_b)} \cdot \frac{y_c(x_c)}{y_c(x_b)} \tag{21}$$

The ratio Eff_c to Eff_b is the efficiency change or technological catch-up between the current period and the base period. The second component on the right hand side of (21), $\frac{\exp(v_c)}{\exp(v_b)}$, represents the stochastic shocks effect. The ratio of $y_c(x_b)$ to $y_b(x_b)$ captures the shift in the "deterministic" frontier caused by technological change, since input quantity per worker does not change. The last term on the right hand side captures the effect of factor accumulation, since it measures the output per worker change along the "deterministic" frontier in period c. If we consider the combined effect of efficiency variation with technological change, we obtain total factor productivity growth.

Alternatively, equation (20) could be multiplied and divided by $y_b\left(x_c\right)$ and a different, but valid, decomposition would be obtained:

$$\frac{y_c}{y_b}=\frac{Eff_c}{Eff_b}\cdot\frac{\exp(v_c)}{\exp(v_b)}\cdot\frac{y_c\left(x_c\right)}{y_b\left(x_c\right)}\cdot\frac{y_b\left(x_c\right)}{y_b\left(x_b\right)} \tag{22}$$

This means that labor productivity decomposition is path dependent, forcing the use of the geometric average of equations (21) and (22):

$$\frac{y_c}{y_b}=\frac{Eff_c}{Eff_b}\cdot\frac{\exp(v_c)}{\exp(v_b)}\cdot\left[\frac{y_c\left(x_b\right)}{y_b\left(x_b\right)}\cdot\frac{y_c\left(x_c\right)}{y_b\left(x_c\right)}\right]^{1/2}\cdot\left[\frac{y_c\left(x_c\right)}{y_c\left(x_b\right)}\cdot\frac{y_b\left(x_c\right)}{y_b\left(x_b\right)}\right]^{1/2} \tag{23}$$

In the stochastic finite mixture model, there is not a unique frontier for the entire sample, but one frontier for each class. Furthermore, one observation does not belong to only one class; it has a probability of class membership. Thus, the decomposition of labor productivity in equation (23) must be adjusted to this framework. Following a similar procedure used in the computation of individual inefficiencies, the potential output per worker of each country in each year is determined by:

$$y_{it}\left(x_{it}\right)=\sum_{j=1}^{M}P\left(j\ |i\right)y_{it}\left(x_{it}\right)\big|j \tag{24}$$

Using (23) and (24), labor productivity is decomposed as:

$$\frac{y_c}{y_b}=\frac{Eff_c}{Eff_b}\cdot\frac{\exp(v_c)}{\exp(v_b)}\cdot\left[\frac{\sum_{j=1}^{M}P\left(j\ |i\right)y_c\left(x_b\right)\big|j}{\sum_{j=1}^{M}P\left(j\ |i\right)y_b\left(x_b\right)\big|j}\cdot\frac{\sum_{j=1}^{M}P\left(j\ |i\right)y_c\left(x_c\right)\big|j}{\sum_{j=1}^{M}P\left(j\ |i\right)y_b\left(x_c\right)\big|j}\right]^{1/2}\cdot$$

$$\cdot\left[\frac{\sum_{j=1}^{M}P\left(j\ |i\right)y_c\left(x_c\right)\big|j}{\sum_{j=1}^{M}P\left(j\ |i\right)y_c\left(x_b\right)\big|j}\cdot\frac{\sum_{j=1}^{M}P\left(j\ |i\right)y_b\left(x_c\right)\big|j}{\sum_{j=1}^{M}P\left(j\ |i\right)y_b\left(x_b\right)\big|j}\right]^{1/2} \tag{25}$$

where the third component on the right hand side of equation (25) represents technological change, the last term indicates factor accumulation and all the other terms are defined as before.

Using the components of the labor productivity change decomposition, given in equation (25), it is possible to obtain the counterfactual distributions, described by Quah (1993, 1996a, 1996b, 1997) as more informative than summary measures like the mean or the variance. We derive the nonparametric kernel mean-preserving distribution, as already described in section 2, and test the closeness of each of the counterfactual distributions and the labor productivity distribution in the period *c*, using the T-test of Li (Li, 1996).

The T-statistic of Li (Li, 1996) tests the closeness of two distributions f(x) and g(x) on the integrated-square-error metric space, $I\left(f,g\right)=\int\left[f(x)-g(x)\right]^2 dx$:

$$T=\frac{I\cdot n\cdot\sqrt{h}}{\hat{\sigma}} \tag{26}$$

where:

$$I=\frac{1}{n^2 h}\sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n}\left[k\left(\frac{x_i-x_j}{h}\right)+k\left(\frac{y_i-y_j}{h}\right)-k\left(\frac{y_i-x_j}{h}\right)-k\left(\frac{x_i-y_j}{h}\right)\right], \text{ and} \tag{27}$$

$$\hat{\sigma}^2=\frac{1}{n^2 h\sqrt{\pi}}\sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n}\left[k\left(\frac{x_i-x_j}{h}\right)+k\left(\frac{y_i-y_j}{h}\right)+2k\left(\frac{x_i-y_j}{h}\right)\right]. \tag{28}$$

Li (1996) demonstrates that this statistic test is valid for dependent and independent variables. Fan and Ullah (1999) show that the T-statistic goes asymptotically to the standard normal.

5. Data

Two samples are used in this study. One sample incorporates information on the economy as a whole and the other contains information on the agricultural sector during the time period 1967-1992. Both samples involve information on 45 countries in different development stages, as indicated in Table 1. Although, each individual sample could have more than 45 countries, the lack of information on the economy as a whole and the agricultural sector restricts the number of countries. Nevertheless, for the overall economy, as it is common in the convergence literature, we drop the two major oil-producing countries and outliers in these kind of empirical studies, Iran and Venezuela (e.g., Kumar and Russell, 2002).

For the Economy as a Whole, we use the following data sources:

(i) Gross Domestic Product at 1990 constant USD is built from Heston, Summers and Aten (2002).

(ii) Economy-Wide Fixed Capital series at 1990 constant USD is drawn from Crego, Larson, Butzer and Mundlak (1998). Its construction is based on aggregate national accounts investment data.

(iii) Total Labor Force is obtained from World Development Indicators (WDI), for 1998. It comprises people who meet the International Labor Organization (ILO) definition of the economically active population: all employed or unemployed people who supply labor for the production of goods and services during a specified period.

For Agriculture, we also recur to several sources:

(i) For the year 1990, the level of total output from the agricultural sector (net of feed and seed) together with its decomposition in crops and livestock are drawn from table 5.4 in Rao (1993, p. 74). FAO production index number series for crops and livestock are obtained from FAOSTAT (2001). These series are used to extend 1990 series to cover the period of analysis, obtaining the value of agricultural output at 1990 constant USD for all years and countries of the database.

(ii) Capital series - defined as the sum of the fixed capital stock, livestock and orchards in 1990 USD - is drawn from Martin and Mitra (2001).

(iii) The agricultural labor data series is obtained from the Mundlak, Larson and Butzer (1997) data set. These authors define labor as the economically active population in the same way as the WDI for the overall economy.

(iv) Land data is taken from FAO Fertilizer data set, defined as arable and permanent cropland and permanent pastures in hectares.

6. Empirical Results

This empirical study involves basically a three-step analysis for both the economy as a whole and agriculture. First, kernel density functions of labor productivity are generated for the years of 1967 and 1992 as well as for the time periods of 1967-1979 and 1980-1992. Second, the number of country classes is determined and production frontiers are estimated accordingly. Third, labor productivity change is decomposed and counterfactual distributions of labor productivity change are estimated. The empirical results of the second and third steps provide possible explanations for the changes in the distribution functions generated in step 1.

6.1 Economy as a Whole

The kernel distributions of labor productivity are presented in figure 2. Figure 2.a describes the first and last year kernels and figure 2.b represents the kernels in the first and last 13-years periods.[2] We focus on mean-preserving distributions, i.e., departures from the productivity mean. For the economy as a whole, the empirical results are similar to the findings in Kumar and Russell (2002) and Quah (1996a, 1997). Labor productivity distribution evolves from a unimodal to a bimodal distribution with a higher mean. Before investigating the factors that cause those changes in the labor productivity distribution, it is necessary to estimate the production frontiers and to decompose the output per labor change.

A translog specification of the production frontier is used (Christensen, Jorgenson and Lau (1971)). This flexible functional form allows the elasticity of substitution to vary with the type of inputs and the returns to scale and output elasticity to vary with the size

[2] Partition of the time period 1967-1992 into two periods of 13 years is explained later.

of the inputs. The production frontier model (ignoring the *j*-class subscript, for notational ease) can be written as:

$$\ln y_{it} = \beta_0 + \beta_1 \ln k_{it} + \beta_2 \left(\ln k_{it}\right)^2 + v_{it} - u_{it} \qquad (29)$$

where:

- y_{it} refers to output per worker in year *t* for the *i*-th country.

- k_{it} designates capital per worker in year *t* for the *i*-th country.

- β*'s* label coefficients.

- v_{it} is the measurement error and u_{it} refers to the inefficiency component.

The production frontier in (29) is estimated separately for the time periods 1967-1979 and 1980-1992. This procedure overcomes the estimation problems when a time trend is included in the specification to capture the technological change. The utilization of these large periods is explained by the need of using richer panels with these models.

We start to estimate our model with a large number of classes. The 4-class model for the economy is over-specified since convergence is not attained. As discussed in section 2, SBIC is the indicator desirable to help choosing class number in these kinds of models. In table 2, we can observe the SBIC scores obtained for the economy. The score values suggest the use of a 3-class model for the economy. However, as suggested by Greene (2002) and following the advices of Zhang (1997), a judgment about estimation results of each model is also advisable. The estimation results for the 3-class model in both periods are presented in table 3. At least one of the lambdas is not statistically significant and some of the estimation results are poor for this class.

Following a testing down procedure, empirical results are generated for the 2-class model (table 4). The estimation results are very satisfactory indicating the assumption of a common production frontier for all countries does not seem appropriate. The grouping of countries between the two classes generated by the stochastic frontier finite mixture model is reported in table 7. This classification is influenced by several factors such as different factor elasticities, efficiency patterns and/or shock effects.

After estimating production frontiers, it is possible to perform the decomposition of labor productivity growth. We use two approaches. In one way, the decomposition is made considering the evolution of all components between the first and the last year of the sample. In the other one, the mean values of all components in the time periods 1967-1979 and 1980-1992 are used to evaluate their contribution to the relative change in output per worker. The decomposition results are reported in Table 8.

Regarding counterfactual distributions, we put side by side only the first and the last year output per worker distribution in order to compare our results with the findings in Kumar and Russell (2002). Counterfactual distributions are not generated for the periods 1967-1979 and 1980-1992. The analysis becomes clearer since distributions are not so close from each other. The analysis of the counterfactual distributions of labor productivity presented in figures 4-6 and the tests of Li (1996) reported in table 10 allow us to enrich the analysis of table 8. Thus, we conclude that:

- The catch-up effect is, in general, small and it does not seem to contribute to convergence, since rich as well as poor countries have, on average, move toward the frontier as we can see in table 8. Panel b of figure 4 reveals that the efficiency change has an almost imperceptible effect on the first year labor productivity distribution. There is a very small shift of the density function from the lower and upper tails to the middle, without significant changes in labor productivity mean.

- As we can observe in panel b of figure 5, technological change is responsible for a small shift of density function from the lower tail to the low-middle and from the high-middle to the upper tail of the distribution, with a small rise of the labor productivity mean. The conjugated effect of the technological change and the efficiency change reveals the same tendency, reinforcing the transfer of mass from the low to the low-middle income countries (Panel c of figures 4 and 5). Kumar and Russell (2002) indicate that technological change has contributed more to the welfare of richer countries than poorer ones. These authors neglect the barely visible effect of the mass increase for the low-middle countries. In this study, this outcome is more evident suggesting that total factor productivity change also help very poor countries. As we can observe in table 8, there are some low and low-middle income countries such as India, Pakistan, Madagascar, Malawi, Chile, Zimbabwe and Dominican Republican in which total factor productivity change is the main contributor to growth.

- Capital deepening is, in general, the most important determinant of labor productivity growth for the majority of countries as we can see in table 8. Comparing panel b in figures 4-6, which reports the effect of a single component, we can infer that capital deepening causes the emergence of a bimodal distribution and leads to significant increase in the mean of labor productivity. Statistic tests of Li support this conclusion (table 10). We can observe that factor accumulation is the only factor that, per se, alters the 1967-labor productivity distribution in a way that we cannot reject the hypothesis of being the same as the 1992-distribution. Additionally, when factor accumulation is combined with each of the other components, the null hypothesis cannot be rejected either.

6.2 Agricultural Sector

The kernel density function of labor productivity is presented in figure 3. Figure 3.a represents the kernel distributions in 1967 and 1992 and figure 3.b represents the kernel distributions in the time periods 1967-1979 and 1980-1992. For agriculture, there is a probability shift from the lower tail toward the rest of the distribution. This is more evident in figure 3.a since distributions are closer when we compare two adjacent periods. The increase of density for the middle-income countries contradicts the idea of the world becoming polarized into rich and poor countries, implying Quah's evidence (Quah, 1996a, 1997) is rejected for the agricultural sector. Investigation of the factors that cause those distributions changes requires first to estimate the production frontier and then to decompose output per labor changes.

As before, a translog specification of the production frontier is used (Christensen, Jorgenson and Lau (1971)). The production frontier model (ignoring the *j*-class subscript, for notational ease) can be written as:

$$\ln y_{it} = \beta_0 + \beta_1 \ln k_{it} + \beta_2 \ln la_{it} + \beta_3 \left(\ln k_{it}\right)^2 + \beta_4 \left(\ln la_{it}\right)^2 + \beta_5 \ln k_{it} \ln la_{it} + v_{it} - u_{it} \qquad (30)$$

where la_{it} designates land per worker in year t for the i-th country and all the other variables are defined as before.

The model is estimated first with a large number of classes. The 3- and 4-class models are over-specified for agriculture since convergence is not attained. By imposing restrictions on parameters to perform likelihood ratio tests, the estimation of such models is impossible because the estimated variance matrix of estimates is singular. Table 2 reports the score values of SBIC for the agricultural sector. The score values suggest a 2-class model for agriculture. Following Greene (2002) and Zhang (1997), the next step consists in evaluating the estimation results of the 2-class model and deciding whether this model should be used or not. The estimation results of the 2-class model are presented in table 5. Inspection of the results indicates that one of the lambdas and some of the coefficients are not statistically significant in both time periods. Hence, a 1-class model is considered and table 6 reports the estimation results. Based on the results for both time periods, there is evidence supporting the use of a single production frontier for all countries.

As mentioned before, the next step of the analysis is to decompose the labor productivity change and to generate the counterfactual distributions. As in the case of the economy as a whole, the decomposition of labor productivity growth is performed considering the years of 1967 and 1992 and the time periods 1967-1979 and 1980-1992 in table 9. The analysis of the counterfactual distributions (figures 7-9) and the T-test of Li (table 11) are performed using only the first and the last years. We can conclude that:

- The catch-up effect is stronger for agriculture than for the economy, as described in table 9. Panel *b* of figure 7 indicates that efficiency change is responsible for an important shift of density from the lower tail to the low-middle and an almost imperceptible mass change from the high-middle to the upper tail of the distribution, with a small increase of the labor productivity mean.

- The analysis of table 9 reveals that technological change is the most important component for the majority of countries. Panel *b* of figure 8 suggests that technological change has a similar effect on the labor productivity distribution as the efficiency change, although the counterfactual distribution is closer to the last year distribution.

Also, the technological change effect leads to a higher increase in the mean of the income per labor. The combined effect of the catch-up and technological change components on the distribution of labor productivity is presented in panel *c* of figures 7 and 8. The analysis of panel c shows that the combined effect of the two components results in a higher mean of output per worker and in a 1967-distribution closer to the 1992-distribution than the individual effect of each component. This conclusion is supported by the statistic tests of Li (1996) presented in table 11. For both significance levels, total factor productivity effect changes the 1967-labor productivity distribution in a way that we cannot reject the null hypothesis of being the same as the 1992-distribution.

- It is notable that many countries experience reductions in factor endowments, as we can observe in table 9. Nevertheless, factor accumulation is a very important determinant of growth for some countries. It is the case of two Southeast Asian growth miracles presented in the sample (Japan, Korea) and some European countries (Austria, Finland, France, Netherlands, Norway, Sweden, Portugal). Panel *b* of figure 9 indicates that factor accumulation effect leads to a shift from the lower tail to the rest of distribution. However, this is a very reduced effect, with very small changes on labor productivity distribution and its mean.

7. Conclusion

This study does not intend to explain economic growth. Using a growth-accounting exercise, our focus is the comparison of each contribution to labor productivity growth between agriculture and the overall economy. One important conclusion of our analysis is that in the overall economy labor productivity was transformed from an unimodal into a bimodal distribution, with the middle-income countries nearly disappearing. This contrast with the changes occurred in agriculture, with an important increase of mass in the middle of the distribution. Furthermore, our results suggest that changes in labor productivity distribution are brought by capital deepening in the overall economy and by total factor productivity changes in agriculture.

Catch-up effect is much reduced for the economy and it does not contribute to convergence since poor and rich experience efficiency increases. In agriculture, it has some expression and it seems to help convergence. Factor accumulation also affects differently labor productivity distribution. For the economy, there is a mass transfer to the upper tail, contributing to the welfare of the rich more than the poor and to the formation of the twin-peak. For agriculture, there is a transfer from the lower tail to the rest of the function and an unimodal counterfactual distribution. Despite having different magnitudes in each decomposition, technologic change acts in the same way for both cases, causing a density transfer from the lower tail and high-middle to the low-middle and upper tail of labor productivity distribution.

Thus, our study seems to confirm the main conclusions of Kumar and Russell (2002) for the overall economy, namely the reduced importance of total factor productivity to growth and the bipolar international divergence of labor productivity. Furthermore, it also supports the results of Bernard and Jones (1996) and Martin and Mitra (2001) by concluding that total factor productivity growth rates are higher in agriculture and by finding important indications of convergence in this sector. These conclusions could lead policy makers to rethink the role of agriculture in economic growth, particularly in developing countries.

References

Ball, V. Eldon, Jean-Christophe Bureau, Jean-Pierre Butault, and Heinz Peter Witzke, (1993), "The Stock of Capital in European Community Agriculture", European Review of Agricultural Economics, 20, pp. 437-450

Berger, J.O. and Pericchi, L.R. (1998), "On Criticisms and Comparisons of Default Bayes Factors for Model Selection and Hypothesis Testing," in Proceedings of the Workshop on Model Selection, ed. W. Racugno, Bologna: Pitagora, pp. 1-50.

Bernard, A. and C. I. Jones (1996), "Productivity across industries and countries: time series theory and evidence", Review of Economics and Statistics, LXXVIII(1), pp. 135-146.

Bureau, C., R. Fare and S. Grosskopf (1995), "A Comparison of Three Nonparametric Measures of Productivity Growth in European and United States Agriculture", Journal of Agricultural Economics, 46, pp. 309-326.

Capalbo, Susan M., and J.M. Antle (eds.) (1988), Agricultural Productivity: Measurement and Explanation, Washington D.C., Resources for the Future.

Christensen, L.R., D.W. Jorgenson and L.J. Lau (1971), "Conjugate Duality and the Transcendental Logarithmic Production Function", Econometrica, 39, pp. 255-256.

Crego, Al, Donald Larson, Rita Butzer, and Yair Mundlak (1998), “A New Database on Investment and Capital for Agriculture and Manufacturing”, World Bank Working Paper No. 2013, Washington D.C., The World Bank.

Fan, Y., and A. Ullah (1999), “On Goodness-of-fit Tests for Weekly Dependent Processes Using Kernel Method," Journal of Nonparametric Statistics, 11, pp. 337-360

FAOSTAT (2001), FAOSTAT Statistical Databases, Rome, Food and Agriculture Organization

Feng, Z. D. and McCulloch, C.E. (1996), “Using bootstrap likelihood ratio in finite mixture models”, Journal of the Royal Statistical Society (Series B), 58, pp. 609-617

Fraley, C. and A.E. Raftery (1998), “How Many Cluster? Which Clustering Method? Answers Via Model-Based Cluster Analysis”, Technical Report No. 329, Department of Statistics, University of Washington.

Fulginiti, L. and R. Perrin (1993), “Prices and Productivity in Agriculture”, Review of Economics and Statistics, 75, pp. 471-482.

Fulginiti, L. and R. Perrin (1997), “Declining Productivity in LDC Agriculture”, mimeographed, Department of Agricultural Economics, University of Nebraska, Lincoln, USA.

Greene, W. (2001), “New Developments in the Estimation of Stochastic Frontier Models with Panel Data”, Efficiency Series Paper 6/2001, Departmento de Economia, Universidad de Oviedo, http://www.uniovi.es/eficiencia/

Greene, W. (2002), “Alternative Panel Data Estimators for Stochastic Frontier Models”, Working Paper, Department of Economics, Stern School of Business, NYU.

Hall and Jones (1999), "Why do Some Countries Produce so Much More Output per Worker than Others?", Quarterly Journal of Economics, pp. 83-116.

Hall, R. E., and C. I. Jones (1999), "Why Do Some Countries Produce So Much More Output Per Worker Than Others?", Quarterly Journal of Economics, 114, pp. 83-116.

Hayami, Y., and V. Ruttan (1970), "Agricultural Productivity Differences Among Countries", American Economic Review, 40, pp. 895-911

Hayami, Y., and V. Ruttan (1971), Agricultural Development: An International Perspective, Johns Hopkins Press, Baltimore

Heckman, J. and B. Singer (1984), "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," Econometrica, 52, pp. 271-320.

Heston, Alan, Robert Summers and Bettina Aten (2002), Penn World Table Version 6.1, Center for International Comparisons at the University of Pennsylvania (CICUP).

Jondrow, J., I. Materov, K. Lovell and P. Schmidt (1982), "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model," Journal of Econometrics, 19, 2/3, 1982, pp. 233-238.

Kawagoe, T. and Y. Hayami (1983), "The Production Structure of World Agriculture: An Intercountry Cross-Section Analysis", Developing Economies, 21, pp. 189-206

Kawagoe, T. and Y. Hayami (1985), "An Intercountry Comparison of Agricultural Production Efficiency", American Journal of Agricultural Economics, 67, pp. 87-92.

Kawagoe, T., Y. Hayami and V. Ruttan (1985), "The Intercountry Agricultural Production Function and Productivity Differences Among Countries", Journal of Development Economics, 19, pp. 113-132.

Klenow and Rodriguez-Clare (1997), "The Neoclassical Revival in Growth Economics: Has it Gone Too Far?", NBER macro annual, pp. 73-114.

Kolari, J. and A. Zardkoohi (1995), "Economies of Scale and Scope in Commercial

Banks with different output Mixes", Texas A&M Working Paper.

Krueger, A., M. Schiff and A. Valdés, (1992), The Political Economy of Agricultural Pricing Policy: A Synthesis of the Economics of Developing Countries, Johns Hopkins University Press, Baltimore.

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, pp. 527-548.

Lau, L. and P. Yotopoulos (1989), "The Meta-Production Function Approach to Technological Change in Worid Agriculture", Journal of Development Economics, 31, pp. 241-269.

Leroux, B.G. (1992), "Consistent estimation of a mixing distribution", Annals of Statistics, 20, pp.1350-1360

Lewis, W. A. (1954), "Economic development with unlimited supplies of labor", Manchester School of Economic and Social Studies, 22, pp. 239-91.

Li, Q. (1996), "Nonparametric Testing of Closeness between Two Unknown Distribution Functions", Econometric Reviews, 15, pp. 261-274.

Lusigi, Angela, Jenifer Piesse, Colin Thirtle (1998), "Convergence of Per Capita Incomes and Agricultural Productivity in Africa", Journal of International Development, 10(1), pp. 105-115

Mankiw, Romer, and Weil (1992), "A Contribution to the Empirics of Economic Growth," Quarterly Journal of Economics, 107, 2, pp. 407-437.

Martin, W. and D. Mitra (2001), "Productivity Growth and Convergence in Agriculture versus Manufacturing", Economic Development and Cultural Change, 49(2), pp. 403-422.

McLachlan, GJ (1987), "On bootstrapping the likelihood ratio test statistic for the number of components in a normal mixture", Applied Statistics 36, pp. 318-324.

Mester, L. (1997), “Measuring Efficiency at US banks: Accounting for Heterogeneity is Important.” European Journal of Operational Research 98, pp. 230-424.

Mundlak, Yair, Donald F. Larson, and Rita Butzer (1997), “The Determinants of Agricultural Production: A Cross-Country Analysis”, World Bank Working Paper No. 1827, Washington D.C., The World Bank.

Pagan, A. and A. Ullah (1999), Nonparametric Econometrics, Cambridge, Cambridge University Press.

Prebisch, R. (1984), “Five stages in my thinking about economic development” in Meier, G. and Seers, D. eds., Pioneers in Development, Oxford University Press for the World Bank.

Quah, D. (1993), “Galton's Fallacy and Tests of the Convergence Hypothesis”, Scandinavian Journal of Economics, 95, pp. 427-443.

Quah, D. (1996a), “Convergence Empirics Across Economies with (Some) Capital Mobility”, Journal of Economic Growth, 1, pp. 95-124.

Quah, D. (1996a), “Twin Peaks: Growth and Convergence in Models of Distribution Dynamics”, Economic Journal, 106 (6), pp. 1045-55.

Quah, D. (1996b), “Convergence Empirics Across Economies with (Some) Capital Mobility”, Journal of Economic Growth, 1, pp. 95-124.

Quah, D. (1997), “Empirics for Growth and Distribution: Stratification, Polarization and Convergence Clubs”, Journal of Economic Growth, 2, pp. 27-59.

Rao D. (1993), Intercountry Comparisons of Agricultural Output and Productivity, FAO Economic and Social Development Paper, No. 112, Rome.

Roeder, K., K. Lynch and D. Nagin (1999), “Modeling Uncertainty in Latent Class Membership: A Case Study in Criminology”, Journal of the American Statistical Association, 94, pp. 766-776.

Silverman, B. W. (1986). Density Estimation for Statistics and Data Analysis. Chapman and Hall, London.

World Development Indicators (1998), World Bank Database, Washington D.C., The World Bank.

Young (1995), “The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience,” Quarterly Journal of Economics, 110, 3, pp. 641-680.

Zhang, P. (1997), Comment on "An Asymptotic Theory for Linear Model Selection", Statistica Sinica, 7, pp. 254-258.

APPENDIX

Figure 1 – Illustration of Labor Decomposition

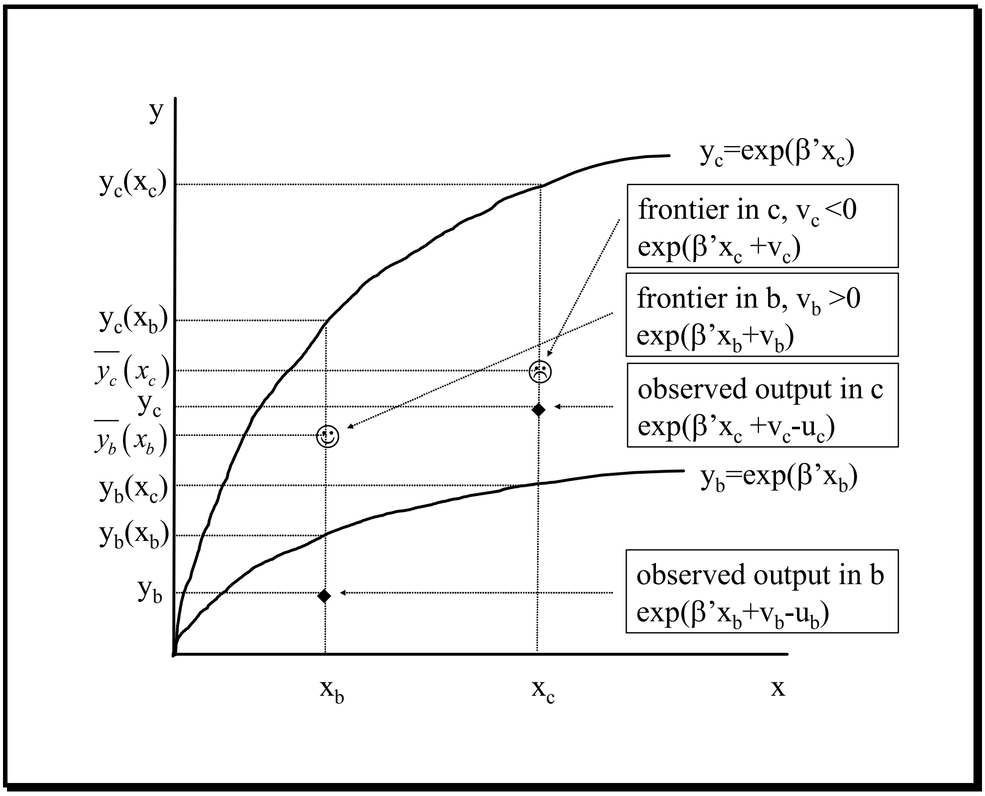
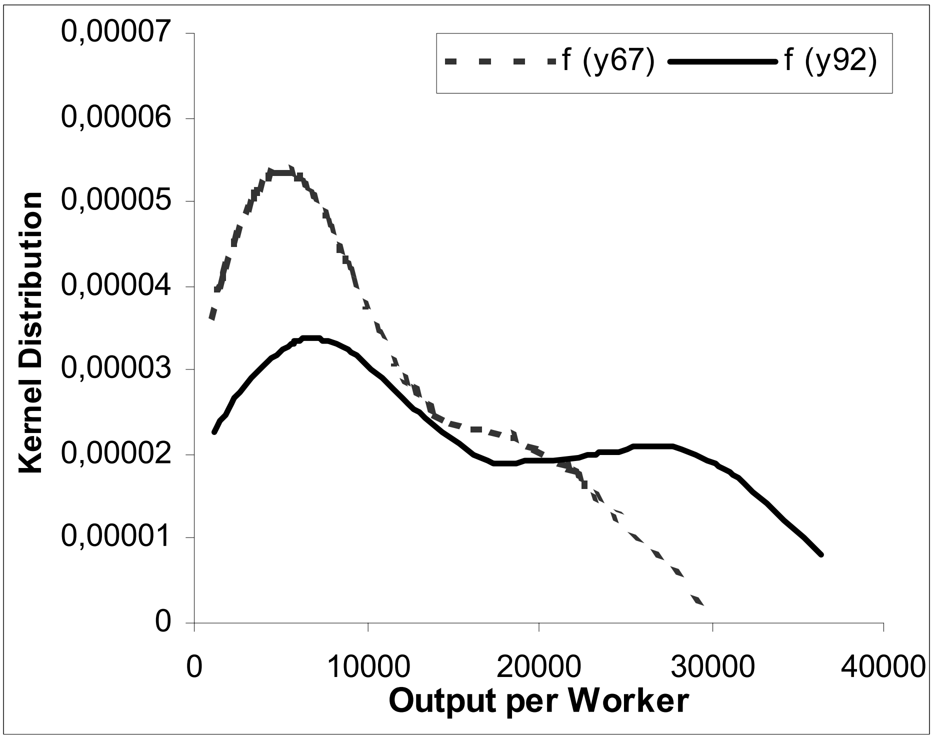


Table 1. Countries List

Code	Country	Code	Country
1	Argentina	24	Korea, Republic of
2	Australia	25	Sri Lanka
3	Austria	26	Morocco
4	Canada	27	Madagascar
5	Chile	28	Malawi
6	Colombia	29	Netherlands
7	Costa Rica	30	Norway
8	Denmark	31	New Zealand
9	Dominican Republic	32	Pakistan
10	Egypt	33	Peru
11	Finland	34	Philippines
12	France	35	El Salvador
13	Great Britain	36	Sweden
14	Greece	37	Syrian Arab Republic
15	Guatemala	38	Tunisia
16	Honduras	39	Turkey
17	Indonesia	40	Uruguay
18	India	41	United States of America
19	Iran	42	Venezuela
20	Israel	43	South Africa
21	Italy	44	Zimbabwe
22	Japan	45	Portugal
23	Kenya		

Figure 2 – Gaussian Kernel of Labor Productivity for the Economy

a) First *vs* Last Year



b) First *vs* Last Period

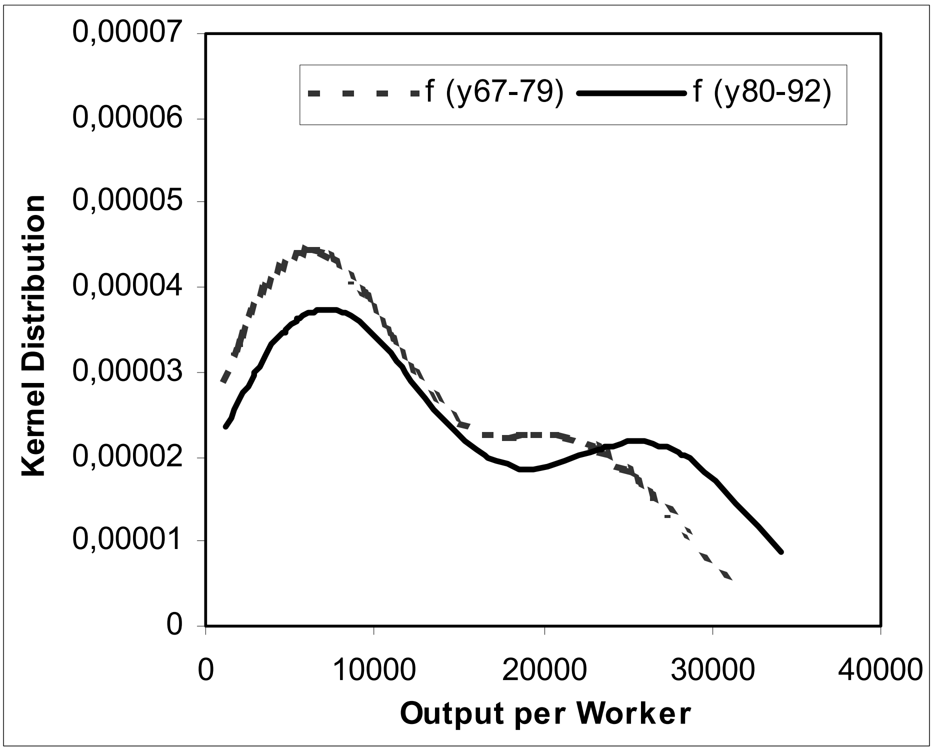
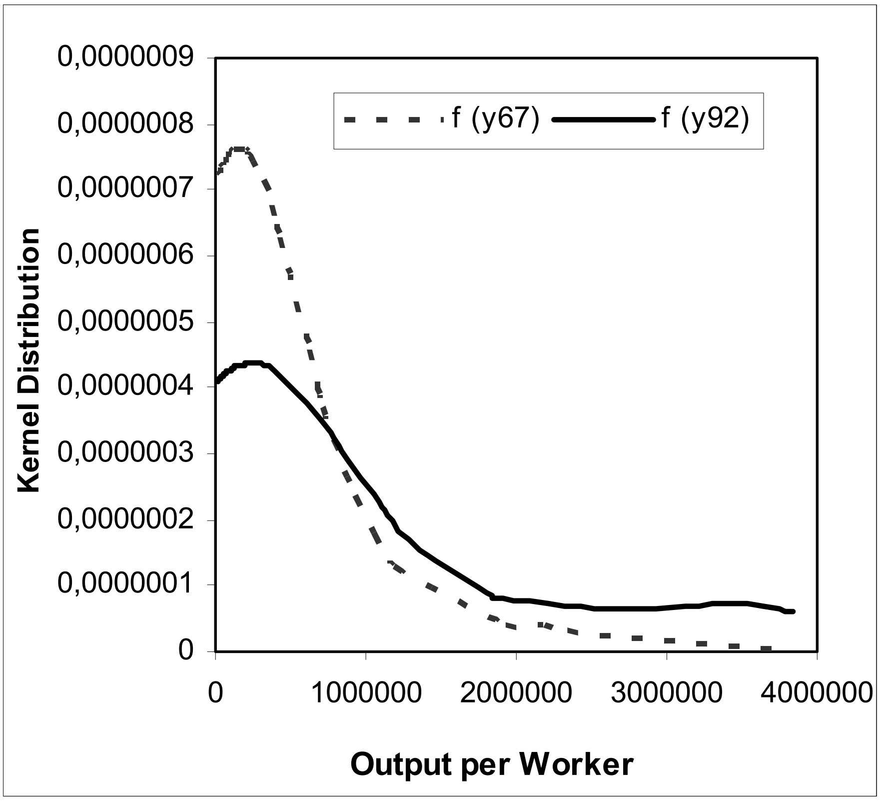


Figure 3 – Gaussian Kernel of Labor Productivity for Agriculture

a) First *vs* Last Year



b) First *vs* Last Period

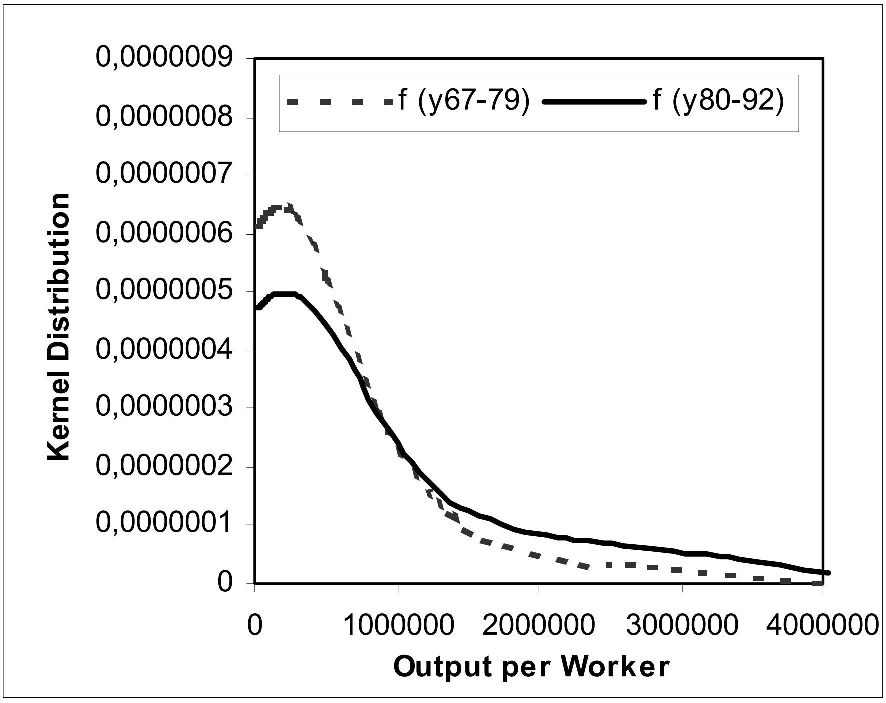


Table 2 – Score for Schwarz Bayesian Information Criterion (SBIC)

		Number of classes			
		1	**2**	**3**	**4**
Economy as a Whole	1967-1979	-18,749	-349,442	-541,640	-
	1980-1992	-21,104	-400,116	-567,284	-
Agriculture	1967-1979	1040,398	491,191	-	-
	1980-1992	736,106	363,016	-	-

Table 3 – Three Class Model Estimation Results for the Economy as a Whole

a) First period: 1967-1979

	Model parameters for latent class 1			**Model parameters for latent class 2**			**Model parameters for latent class 3**		
Variable	***Coeff.***	***St.Err.***	***P[|Z|>z]***	***Coeff.***	***St.Err.***	***P[|Z|>z]***	***Coeff.***	***St.Err.***	***P[|Z|>z]***
Constant	-0,0213	271298	1,0000	1,4252	0,1289	0,0000	2,3218	0,4848	0,0000
$\ln k_{it}$	1,5186	0,0421	0,0000	1,1556	0,0282	0,0000	0,7225	0,1171	0,0000
$(\ln k_{it})^2$	-0,0547	0,0022	0,0000	-0,0350	0,0016	0,0000	0,0002	0,0069	0,9721
$\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$	0,1146	0,0025	0,0000	0,1736	0,0094	0,0000	0,2204	0,0097	0,0000
$\lambda_j = \sigma_{uj} / \sigma_{vj}$	0,0000	2965820	1,0000	1,2826	0,2439	0,0000	46,7975	173,865	0,7878
Prior Probabilities for Class Membership	0,3010	0,0758	0,0001	0,5051	0,0913	0,0000	0,1939	0,0975	0,0466

b) Last period: 1980-1992

	Model parameters for latent class 1			**Model parameters for latent class 2**			**Model parameters for latent class 3**		
Variable	***Coeff.***	***St.Err.***	***P[|Z|>z]***	***Coeff.***	***St.Err.***	***P[|Z|>z]***	***Coeff.***	***St.Err.***	***P[|Z|>z]***
Constant	6,5086	0,2879	0,0000	2,7048	0,2778	0,0000	-0,9588	0,3120	0,0021
$\ln k_{it}$	0,0205	0,0671	0,7605	0,7847	0,0650	0,0000	1,7624	0,0655	0,0000
$(\ln k_{it})^2$	0,0290	0,0037	0,0000	-0,0137	0,0039	0,0004	-0,0680	0,0033	0,0000
$\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$	0,1842	0,0164	0,0000	0,1579	0,0705	0,0251	0,1577	0,0126	0,0000
$\lambda_j = \sigma_{uj} / \sigma_{vj}$	1,3392	0,4973	0,0071	0,7111	1,7676	0,6875	3,1117	0,9559	0,0011
Prior Probabilities for Class Membership	0,4189	0,0756	0,0000	0,1628	0,0563	0,0038	0,4183	0,0756	0,0000

Table 4 – Two Class Model Estimation Results for the Economy as a Whole

a) First period: 1967-1979

	Model parameters for latent class 1			Model parameters for latent class 2		
Variable	***Coeff.***	***St.Err.***	***P[|Z|>z]***	***Coeff.***	***St.Err.***	***P[|Z|>z]***
Constant	0,8585	0,2222	0,0001	-1,3149	0,1741	0,0000
$\ln k_{it}$	1,3241	0,0483	0,0000	1,7275	0,0392	0,0000
$(\ln k_{it})^2$	-0,0431	0,0025	0,0000	-0,0640	0,0022	0,0000
$\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$	0,2089	0,0087	0,0000	0,2768	0,0050	0,0000
$\lambda_j = \sigma_{uj} / \sigma_{vj}$	1,4707	0,2060	0,0000	5,4008	0,7528	0,0000
Prior Probabilities for Class Membership	0,4652	0,0763	0,0000	0,5348	0,0763	0,0000

b) Last period: 1980-1992

	Model parameters for latent class 1			Model parameters for latent class 2		
Variable	***Coeff.***	***St.Err.***	***P[|Z|>z]***	***Coeff.***	***St.Err.***	***P[|Z|>z]***
Constant	4,7043	0,0903	0,0000	1,1935	0,1693	0,0000
$\ln k_{it}$	0,5064	0,0197	0,0000	1,1765	0,0372	0,0000
$(\ln k_{it})^2$	-0,0005	0,0011	0,6766	-0,0338	0,0020	0,0000
$\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$	0,1898	0,0151	0,0000	0,2936	0,0089	0,0000
$\lambda_j = \sigma_{uj} / \sigma_{vj}$	1,4959	0,3978	0,0002	7,8311	2,0985	0,0002
Prior Probabilities for Class Membership	0,5375	0,0765	0,0000	0,4625	0,0765	0,0000

Table 5 – Two Class Model Estimation Results for Agriculture

a) First period: 1967-1979

	Model parameters for latent class 1			Model parameters for latent class 2		
Variable	*Coeff.*	*St.Err.*	*P[|Z|>z]*	*Coeff.*	*St.Err.*	*P[|Z|>z]*
Constant	2,3565	1,2931	0,0684	9,0558	0,2264	0,0000
$\ln k_{it}$	0,7012	0,2254	0,0019	0,4485	0,0479	0,0000
$\ln la_{it}$	1,5487	0,2835	0,0000	-0,3563	0,0655	0,0000
$(\ln k_{it})^2$	0,0127	0,0065	0,0521	-0,0825	0,0041	0,0000
$(\ln la_{it})^2$	-0,0899	0,0419	0,0320	-0,1014	0,0100	0,0000
$\ln k_{it} \cdot \ln la_{it}$	-0,0285	0,0366	0,4371	0,2378	0,0113	0,0000
$\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$	0,1864	0,3559	0,6006	0,6742	0,0078	0,0000
$\lambda_j = \sigma_{uj} / \sigma_{vj}$	0,3477	9,7291	0,9715	6,2148	0,7656	0,0000
Prior Probabilities for Class Membership	0,2221	0,0621	0,0004	0,7779	0,0621	0,0000

b) Last period: 1980-1992

	Model parameters for latent class 1			Model parameters for latent class 2		
Variable	*Coeff.*	*St.Err.*	*P[|Z|>z]*	*Coeff.*	*St.Err.*	*P[|Z|>z]*
Constant	6,5715	0,4885	0,0000	7,9509	0,1258	0,0000
$\ln k_{it}$	0,4140	0,1657	0,0125	0,5748	0,0735	0,0000
$\ln la_{it}$	0,7919	0,0995	0,0000	-0,0543	0,0793	0,4940
$(\ln k_{it})^2$	-0,0173	0,0143	0,2263	-0,1196	0,0065	0,0000
$(\ln la_{it})^2$	-0,0413	0,0110	0,0002	-0,1037	0,0166	0,0000
$\ln k_{it} \cdot \ln la_{it}$	0,0322	0,0174	0,0640	0,2493	0,0219	0,0000
$\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$	0,4413	0,0682	0,0000	0,3561	0,0114	0,0000
$\lambda_j = \sigma_{uj} / \sigma_{vj}$	0,6658	0,4957	0,1792	4,0321	0,9388	0,0000
Prior Probabilities for Class Membership	0,4693	0,0995	0,0000	0,5307	0,0995	0,0000

Table 6 – One Class Model Estimation Results for Agriculture

a) First period: 1967-1979

	Model parameters for latent class 1		
Variable	***Coeff.***	***St.Err.***	***P[|Z|>z]***
Constant	7,8479	0,3347	0,0000
$\ln k_{it}$	0,1632	0,0737	0,0268
$\ln la_{it}$	0,4114	0,0793	0,0000
$(\ln k_{it})^2$	-0,0305	0,0046	0,0000
$(\ln la_{it})^2$	-0,1150	0,0110	0,0000
$\ln k_{it} \cdot \ln la_{it}$	0,1584	0,0150	0,0000
$\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$	0,7570	0,0132	0,0000
$\lambda_j = \sigma_{uj} / \sigma_{vj}$	1,5599	0,1306	0,0000

b) Last period: 1980-1992

	Model parameters for latent class 1		
Variable	***Coeff.***	***St.Err.***	***P[|Z|>z]***
Constant	8,1360	0,2091	0,0000
$\ln k_{it}$	0,4601	0,0715	0,0000
$\ln la_{it}$	0,0151	0,0647	0,8159
$(\ln k_{it})^2$	-0,0600	0,0068	0,0000
$(\ln la_{it})^2$	-0,0884	0,0096	0,0000
$\ln k_{it} \cdot \ln la_{it}$	0,1773	0,0133	0,0000
$\sigma_j = [\sigma_{vj}^2 + \sigma_{uj}^2]^{1/2}$	0,5380	0,0130	0,0000
$\lambda_j = \sigma_{uj} / \sigma_{vj}$	1,1033	0,1177	0,0000

Table 7 – Countries Classification according to the Stochastic Frontier Finite Mixture Model for the Economy as a Whole

1967- 1979				1980-1992			
	Class		**Class**		**Class**		**Class**
Argentina	1	Austria	2	Australia	1	Argentina	2
Australia	1	Chile	2	Canada	1	Austria	2
Canada	1	Costa Rica	2	Chile	1	Costa Rica	2
Colombia	1	Dominican Republic	2	Colombia	1	Denmark	2
Denmark	1	Egypt	2	Dominican Republic	1	Finland	2
France	1	Finland	2	Egypt	1	Greece	2
United Kingdom	1	Greece	2	France	1	Honduras	2
Guatemala	1	Honduras	2	United Kingdom	1	Indonesia	2
Indonesia	1	India	2	Guatemala	1	Japan	2
Israel	1	Japan	2	Índia	1	Kenya	2
Italy	1	Kenya	2	Israel	1	Korea, Republic of	2
Sri Lanka	1	Korea, Republic of	2	Italy	1	Morocco	2
Madagascar	1	Morocco	2	Sri Lanka	1	Malawi	2
Netherlands	1	Malawi	2	Madagascar	1	Norway	2
New Zealand	1	Norway	2	Netherlands	1	Peru	2
Philippines	1	Pakistan	2	New Zealand	1	El Salvador	2
Sweden	1	Peru	2	Pakistan	1	Tunisia	2
Syria	1	El Salvador	2	Philippines	1	Turkey	2
Uruguay	1	Tunisia	2	Sweden	1	South Africa	2
USA	1	Turkey	2	Syria	1	Zimbabwe	2
		South Africa	2	Uruguay	1		
		Zimbabwe	2	USA	1		
		Portugal	2	Portugal	1		

Table 8 – Decomposition of Labor Productivity Growth for the Economy

a) From First to Last Year

Country	Percentage Change in Output per Worker	Contribution to Percentage Change in Output per Worker of			
		Change in Efficiency	Change in Technology	Capital Deepening	Stochastic Shocks
Argentina	19,13%	-11,56%	-17,97%	58,71%	3,47%
Australia	35,76%	1,31%	3,08%	25,41%	3,66%
Austria	84,33%	-4,35%	13,63%	69,73%	-0,07%
Canada	39,33%	1,71%	3,15%	24,47%	6,70%
Chile	24,22%	9,34%	16,61%	-8,74%	6,75%
Colombia	31,98%	8,63%	-3,65%	1,56%	24,17%
Costa Rica	15,18%	1,43%	-0,12%	12,54%	1,04%
Denmark	36,22%	-4,19%	-13,84%	52,90%	7,93%
Dominican Republic	40,71%	1,93%	24,44%	23,85%	-10,43%
Egypt	92,30%	19,45%	32,44%	8,54%	12,00%
Finland	71,42%	0,75%	14,38%	44,59%	2,88%
France	63,81%	1,54%	5,65%	47,81%	3,30%
United Kingdom	51,35%	0,47%	-0,66%	50,97%	0,45%
Greece	108,70%	13,35%	4,73%	67,81%	4,76%
Guatemala	23,56%	5,62%	0,12%	-8,23%	27,33%
Honduras	15,56%	21,23%	2,01%	-14,70%	9,55%
Indonesia	248,48%	2,36%	-20,79%	328,30%	0,35%
India	95,07%	2,90%	79,44%	12,45%	-6,05%
Israel	108,47%	13,08%	-0,90%	43,10%	29,99%
Italy	95,40%	-0,49%	2,14%	97,50%	-2,66%
Japan	167,57%	1,61%	14,67%	118,67%	5,01%
Kenya	15,74%	-14,93%	13,18%	22,65%	-1,99%
Korea, Republic of	422,65%	-0,76%	6,21%	419,20%	-4,50%
Sri Lanka	78,95%	10,90%	4,53%	18,77%	29,98%
Morocco	53,10%	5,10%	0,70%	39,36%	3,80%
Madagascar	-33,85%	8,17%	70,30%	-73,94%	37,81%
Malawi	22,55%	30,81%	25,81%	-33,93%	12,70%
Netherlands	38,77%	-2,36%	3,98%	49,99%	-8,87%
Norway	67,40%	1,23%	18,38%	37,97%	1,25%
New Zealand	4,80%	1,41%	-0,32%	-0,57%	4,26%
Pakistan	66,21%	32,46%	42,82%	-27,04%	20,42%
Peru	-33,56%	-28,76%	-0,07%	0,54%	-7,17%
Philippines	24,41%	10,28%	7,01%	-14,22%	22,90%
El Salvador	3,22%	2,81%	0,25%	-2,83%	3,06%
Sweden	26,29%	-3,97%	6,44%	34,24%	-7,97%
Syrian Arab Republic	126,30%	4,37%	-5,04%	83,33%	24,56%
Tunisia	103,62%	29,59%	-0,09%	39,49%	12,74%
Turkey	107,44%	3,04%	0,91%	94,07%	2,80%
Uruguay	30,30%	6,99%	-6,41%	5,47%	23,37%
USA	23,76%	0,85%	4,21%	12,50%	4,67%
South Africa	17,02%	-12,17%	1,41%	31,10%	0,21%
Zimbabwe	-6,22%	9,36%	3,33%	-25,13%	10,83%
Portugal	160,32%	3,48%	22,25%	130,16%	-10,59%
Mean	**64,83%**	**4,28%**	**8,80%**	**44,15%**	**7,08%**

b) From First to Last 13-years Period

Country	Percentage Change in Output per Worker	Contribution to Percentage Change in Output per Worker of			
		Change in Efficiency	Change in Technology	Capital Deepening	Stochastic Shocks
Argentina	1,39%	-4,04%	-18,01%	23,22%	4,58%
Australia	13,88%	0,10%	5,61%	7,87%	-0,14%
Austria	27,12%	-5,86%	13,21%	22,11%	-2,31%
Canada	18,55%	0,90%	2,69%	10,59%	3,47%
Chile	1,75%	8,26%	16,81%	-18,29%	-1,54%
Colombia	21,31%	3,19%	-4,35%	8,76%	13,00%
Costa Rica	-3,43%	-1,99%	0,01%	-0,52%	-0,96%
Denmark	14,59%	1,03%	-13,30%	11,26%	17,58%
Dominican Republic	14,66%	-2,84%	21,60%	12,15%	-13,48%
Egypt	50,92%	1,21%	28,06%	28,97%	-9,71%
Finland	35,74%	-3,70%	15,01%	21,73%	0,68%
France	22,70%	-0,30%	4,82%	18,71%	-1,09%
United Kingdom	22,18%	0,09%	-1,12%	22,58%	0,71%
Greece	35,01%	4,64%	5,17%	19,16%	2,96%
Guatemala	4,73%	0,53%	-1,88%	3,13%	2,95%
Honduras	6,48%	-4,07%	0,69%	8,71%	1,40%
Indonesia	98,83%	0,58%	-21,67%	107,77%	21,46%
India	40,67%	-7,02%	73,08%	9,94%	-20,49%
Israel	28,40%	2,82%	-1,01%	17,86%	7,03%
Italy	37,44%	-0,51%	1,29%	40,21%	-2,74%
Japan	56,07%	-4,81%	14,22%	38,10%	3,95%
Kenya	10,99%	-9,79%	8,93%	11,10%	1,67%
Korea, Republic of	110,29%	-2,32%	1,04%	111,24%	0,88%
Sri Lanka	46,49%	6,26%	6,14%	13,57%	14,35%
Morocco	22,29%	6,58%	0,32%	9,08%	4,85%
Madagascar	-22,75%	-0,89%	58,05%	-49,25%	-2,83%
Malawi	11,75%	10,35%	24,09%	-22,66%	5,53%
Netherlands	10,38%	-1,23%	5,44%	11,64%	-5,06%
Norway	33,08%	-2,84%	19,75%	13,84%	0,48%
New Zealand	2,81%	0,14%	1,83%	1,50%	-0,66%
Pakistan	32,35%	6,61%	47,35%	-13,39%	-2,73%
Peru	-14,52%	-10,57%	-0,09%	-1,50%	-2,88%
Philippines	11,23%	2,07%	7,94%	-3,38%	4,49%
El Salvador	-8,08%	-16,81%	0,19%	16,33%	-5,19%
Sweden	13,08%	-0,15%	6,67%	5,78%	0,36%
Syrian Arab Republic	42,64%	-0,27%	-5,88%	60,76%	-5,46%
Tunisia	35,78%	10,28%	-0,26%	15,87%	6,54%
Turkey	32,45%	3,06%	-0,06%	24,43%	3,35%
Uruguay	10,64%	2,84%	-6,62%	5,49%	9,22%
USA	9,39%	-0,33%	5,66%	9,21%	-4,89%
South Africa	8,04%	-7,38%	1,97%	12,86%	1,36%
Zimbabwe	3,76%	6,07%	1,98%	-11,51%	8,40%
Portugal	36,81%	0,84%	16,78%	22,72%	-5,33%
Mean	**22,97%**	**-0,22%**	**7,96%**	**15,30%**	**1,25%**

Table 9 – Decomposition of Labor Productivity Growth for Agriculture

a) From First to Last Year

Country	Percentage Change in Output per Worker	Contribution to Percentage Change in Output per Worker of			
		Change in Efficiency	Change in Technology	Capital Deepening	Stochastic Shocks
Argentina	47,14%	23,16%	43,54%	-59,17%	103,85%
Australia	63,04%	27,59%	88,29%	-63,18%	84,32%
Austria	156,24%	12,71%	19,34%	50,87%	26,27%
Canada	192,47%	4,56%	91,98%	57,70%	-7,62%
Chile	44,82%	12,58%	35,28%	-27,27%	30,74%
Colombia	65,67%	15,04%	30,76%	-34,45%	68,02%
Costa Rica	99,72%	30,50%	23,93%	-37,24%	96,76%
Denmark	151,35%	9,79%	29,41%	44,04%	22,83%
Dominican Republic	75,75%	9,00%	30,31%	-4,36%	29,38%
Egypt	39,67%	8,10%	37,56%	-23,76%	23,20%
Finland	138,57%	6,07%	28,24%	118,11%	-19,58%
France	279,99%	26,94%	19,24%	46,53%	71,32%
United Kingdom	78,66%	6,78%	29,02%	-20,52%	63,14%
Greece	183,84%	24,96%	27,73%	-11,46%	100,84%
Guatemala	22,25%	26,79%	29,45%	-53,95%	61,74%
Honduras	15,95%	19,97%	31,94%	-41,49%	25,19%
Indonesia	93,06%	34,52%	28,68%	-39,05%	82,96%
India	42,03%	21,57%	23,87%	-35,34%	45,85%
Iran	74,37%	169,14%	-1,57%	-82,88%	284,50%
Israel	173,93%	29,24%	0,80%	13,17%	85,81%
Italy	197,22%	33,53%	8,28%	29,46%	58,78%
Japan	258,68%	18,83%	6,68%	109,66%	34,94%
Kenya	6,92%	19,24%	28,34%	-42,91%	22,37%
Korea, Republic of	395,34%	26,19%	32,55%	81,51%	63,16%
Sri Lanka	-13,25%	8,14%	30,42%	-41,93%	5,92%
Morocco	10,96%	24,08%	26,20%	-58,73%	71,72%
Madagascar	-17,99%	14,56%	26,73%	-55,55%	27,07%
Malawi	-30,59%	13,43%	19,75%	-54,84%	13,14%
Netherlands	140,19%	5,00%	10,39%	27,62%	62,37%
Norway	100,08%	5,68%	18,29%	86,79%	-14,32%
New Zealand	0,95%	0,94%	13,88%	11,51%	-21,25%
Pakistan	20,61%	11,47%	24,34%	-33,70%	31,25%
Peru	-9,33%	7,12%	29,73%	-34,48%	-0,41%
Philippines	38,81%	14,91%	29,48%	-45,28%	70,50%
El Salvador	40,37%	26,79%	28,99%	-45,92%	58,69%
Sweden	199,32%	-0,25%	36,99%	198,03%	-26,50%
Syrian Arab Republic	71,98%	37,39%	37,62%	-45,49%	66,87%
Tunisia	96,41%	33,47%	38,93%	-23,81%	39,02%
Turkey	63,49%	39,59%	30,35%	-49,57%	78,17%
Uruguay	59,25%	12,29%	34,04%	-51,67%	118,91%
USA	67,95%	11,24%	65,28%	-37,03%	45,08%
Venezuela	100,32%	23,80%	33,51%	-28,41%	69,29%
South Africa	57,51%	17,55%	37,16%	-30,78%	41,14%
Zimbabwe	-33,14%	4,51%	24,17%	-37,70%	-17,30%
Portugal	177,78%	-0,90%	32,55%	214,12%	-32,68%
Mean	89,74%	**20,61%**	**30,05%**	**-3,62%**	**47,68%**

b) From First to Last 13-years Period

Country	Percentage Change in Output per Worker	Contribution to Percentage Change in Output per Worker of			
		Change in Efficiency	Change in Technology	Capital Deepening	Stochastic Shocks
Argentina	25,35%	10,39%	45,95%	-33,42%	16,84%
Australia	15,65%	7,88%	93,18%	-44,71%	0,37%
Austria	64,58%	7,52%	20,71%	20,04%	5,64%
Canada	56,87%	-1,84%	85,72%	26,20%	-31,81%
Chile	18,99%	5,75%	36,13%	-14,60%	-3,22%
Colombia	16,92%	9,06%	30,55%	-36,21%	28,73%
Costa Rica	21,74%	12,12%	25,20%	-26,62%	18,19%
Denmark	75,35%	5,27%	29,96%	30,05%	-1,45%
Dominican Republic	29,34%	4,55%	30,06%	-7,34%	2,65%
Egypt	4,10%	4,24%	38,84%	-27,96%	-0,15%
Finland	69,22%	5,25%	26,92%	57,48%	-19,56%
France	102,29%	14,61%	18,96%	20,86%	22,76%
United Kingdom	33,80%	4,31%	27,31%	-14,35%	17,64%
Greece	72,30%	12,75%	27,82%	-5,90%	27,05%
Guatemala	-0,87%	13,10%	29,30%	-42,73%	18,37%
Honduras	4,31%	15,19%	31,28%	-41,42%	17,75%
Indonesia	37,71%	16,56%	25,71%	-31,28%	36,76%
India	15,63%	12,25%	21,39%	-27,07%	16,36%
Iran	21,84%	87,68%	3,16%	-65,56%	82,75%
Israel	67,11%	17,78%	-0,65%	0,77%	41,73%
Italy	74,99%	19,25%	7,71%	13,89%	19,62%
Japan	97,86%	10,53%	8,34%	51,35%	9,17%
Kenya	2,22%	10,87%	26,83%	-29,49%	3,10%
Korea, Republic of	107,34%	10,57%	36,94%	26,32%	8,40%
Sri Lanka	0,39%	5,83%	31,10%	-25,67%	-2,66%
Morocco	1,26%	11,96%	24,47%	-42,27%	25,88%
Madagascar	-10,56%	8,54%	24,85%	-39,03%	8,25%
Malawi	-10,68%	10,44%	21,56%	-37,93%	7,20%
Netherlands	51,90%	2,62%	11,24%	18,28%	12,49%
Norway	45,65%	3,54%	17,61%	45,87%	-18,00%
New Zealand	0,81%	-1,16%	16,22%	42,90%	-38,58%
Pakistan	6,28%	8,36%	23,76%	-30,60%	14,18%
Peru	-2,07%	3,98%	30,06%	-17,77%	-11,94%
Philippines	19,02%	9,54%	30,23%	-34,62%	27,61%
El Salvador	8,23%	14,79%	29,84%	-38,07%	17,25%
Sweden	86,15%	0,34%	35,50%	81,81%	-24,69%
Syrian Arab Republic	46,83%	24,98%	37,25%	-36,16%	34,09%
Tunisia	21,94%	14,76%	38,64%	-23,93%	0,75%
Turkey	33,00%	19,65%	31,31%	-28,29%	18,05%
Uruguay	20,16%	5,58%	35,77%	-35,19%	29,35%
USA	21,48%	3,35%	66,08%	-21,64%	-9,69%
Venezuela	53,90%	12,51%	34,38%	-20,48%	28,01%
South Africa	49,35%	10,07%	37,94%	-11,98%	11,75%
Zimbabwe	-12,11%	8,09%	23,03%	-32,93%	-1,46%
Portugal	27,94%	-2,83%	31,22%	64,67%	-39,06%
Mean	33,19%	**10,90%**	**30,21%**	**-9,44%**	**9,48%**

Figure 4 – Counterfactual Distributions of Output per Worker for the Economy

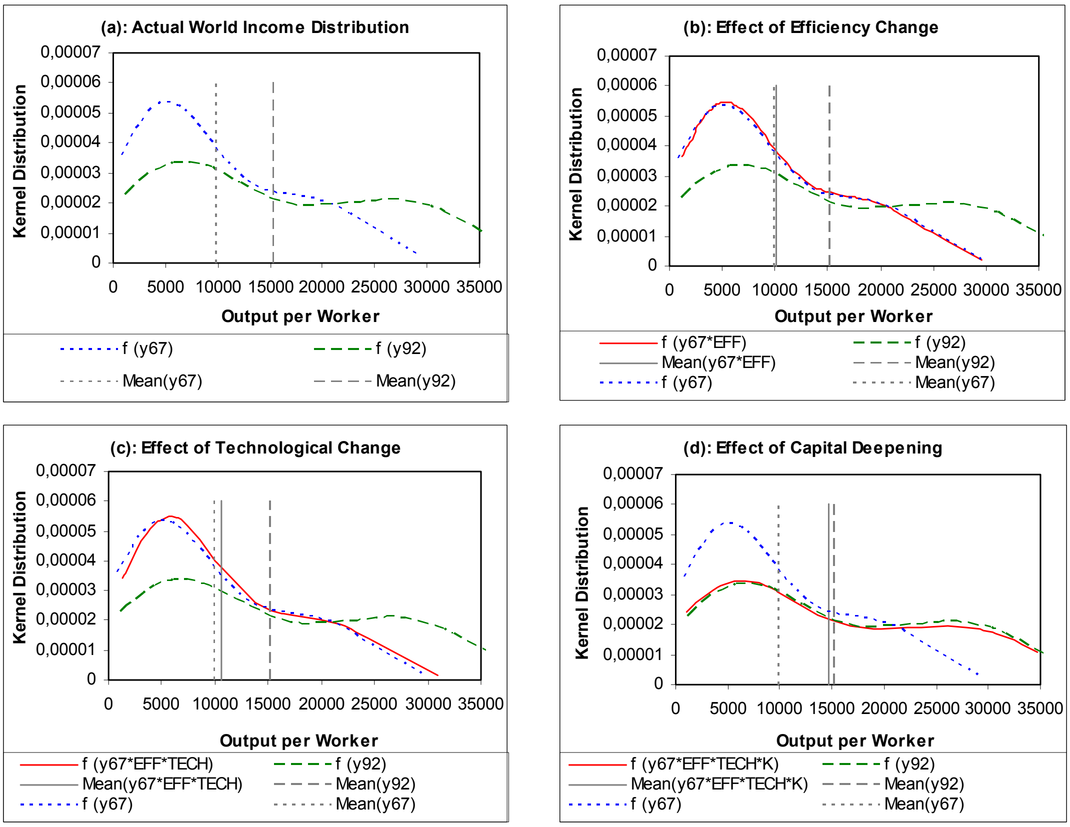


Figure 5 – Counterfactual Distributions of Output per Worker for the Economy

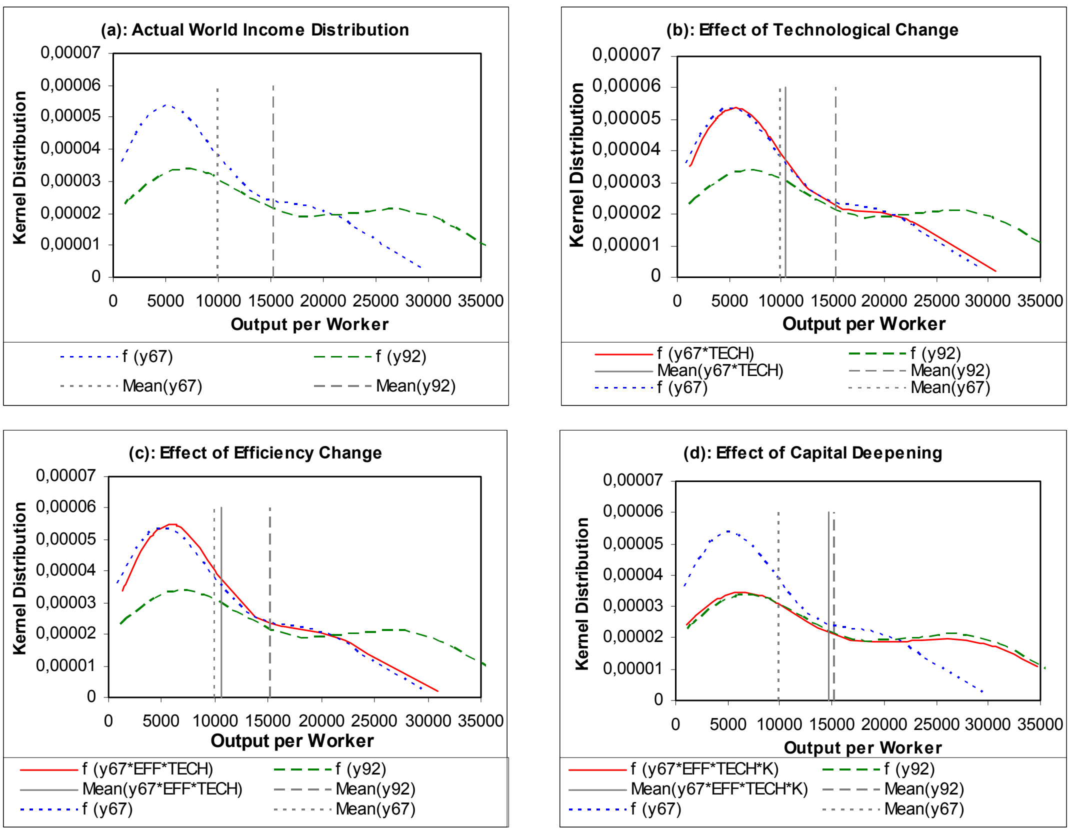


Figure 6 – Counterfactual Distributions of Output per Worker for the Economy

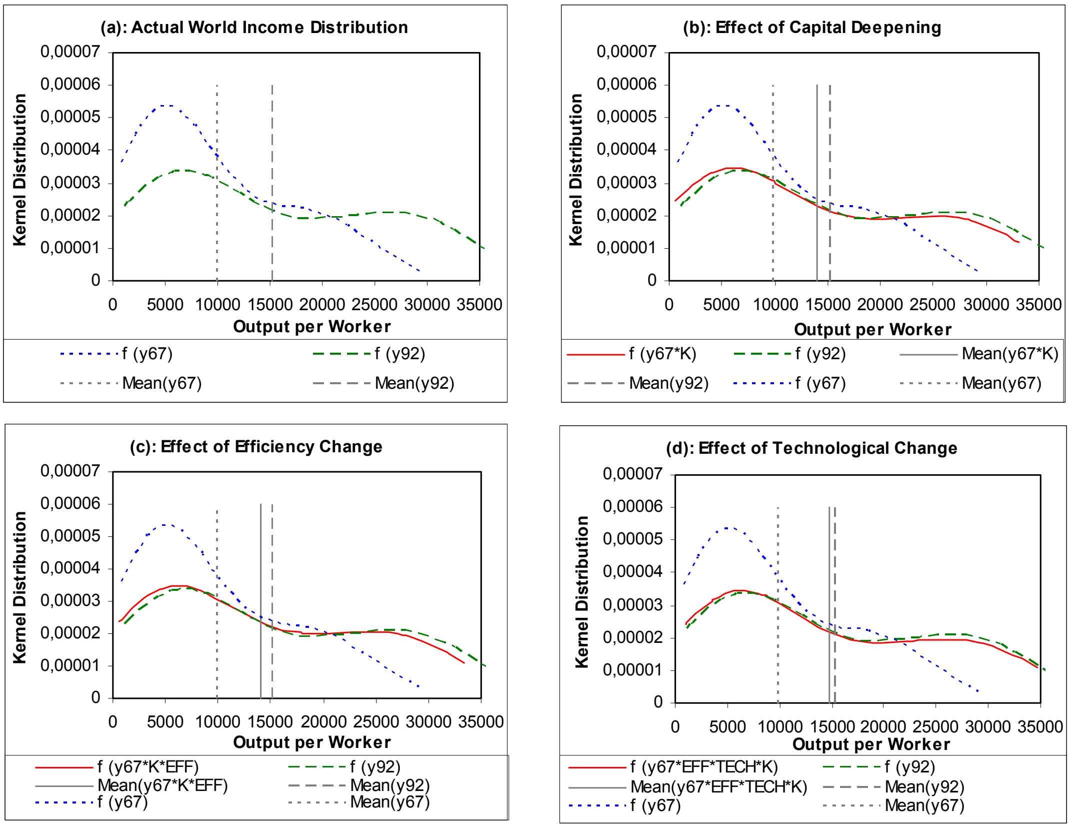


Figure 7 –Counterfactual Distributions of Output per Worker for Agriculture

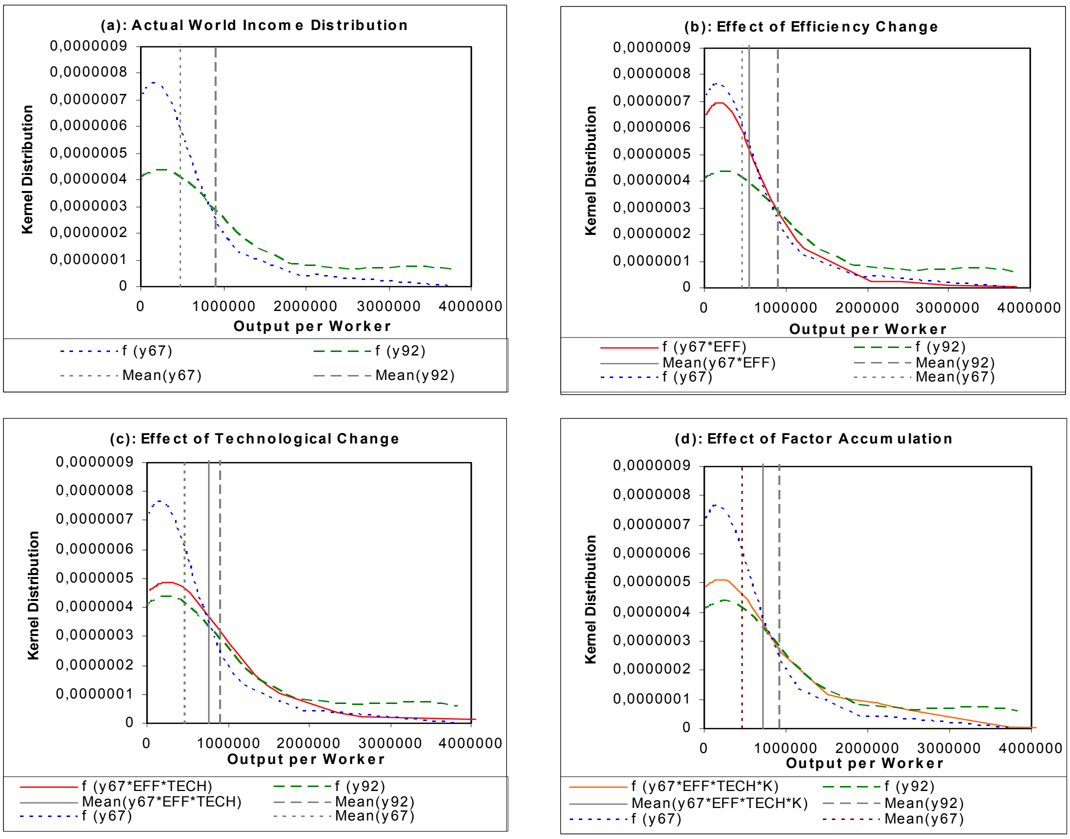


Figure 8 – Counterfactual Distributions of Output per Worker for Agriculture

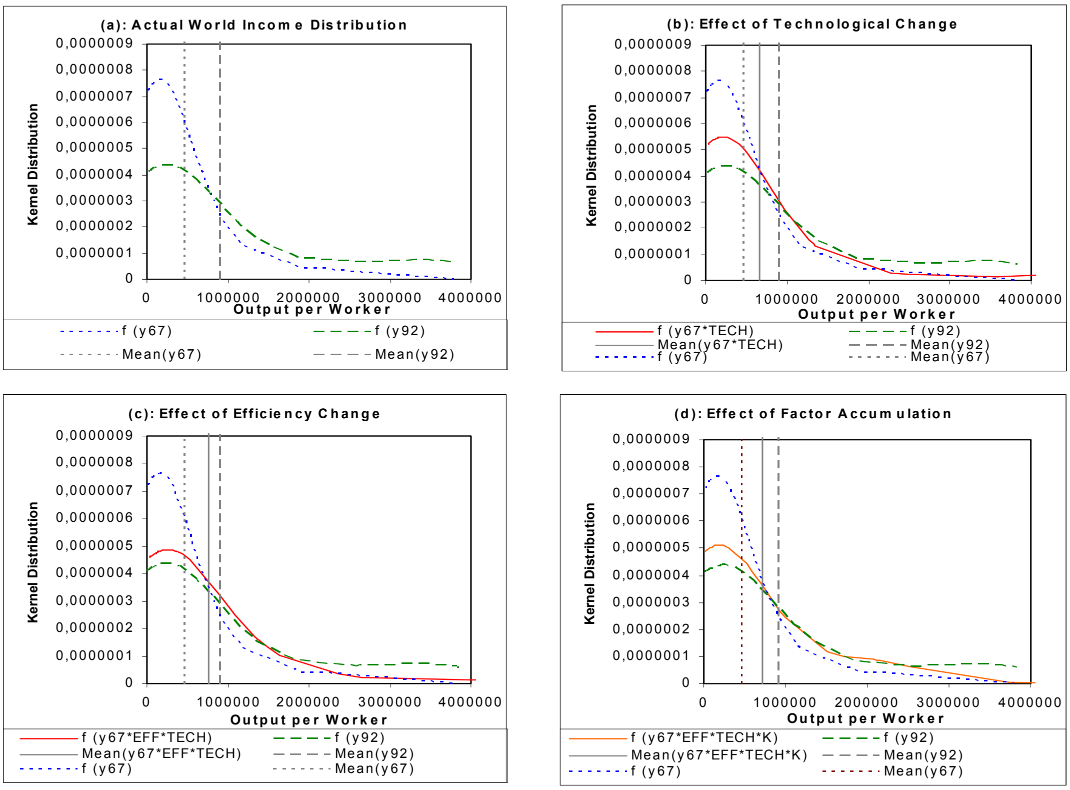


Figure 9 – Counterfactual Distributions of Output per Worker for Agriculture

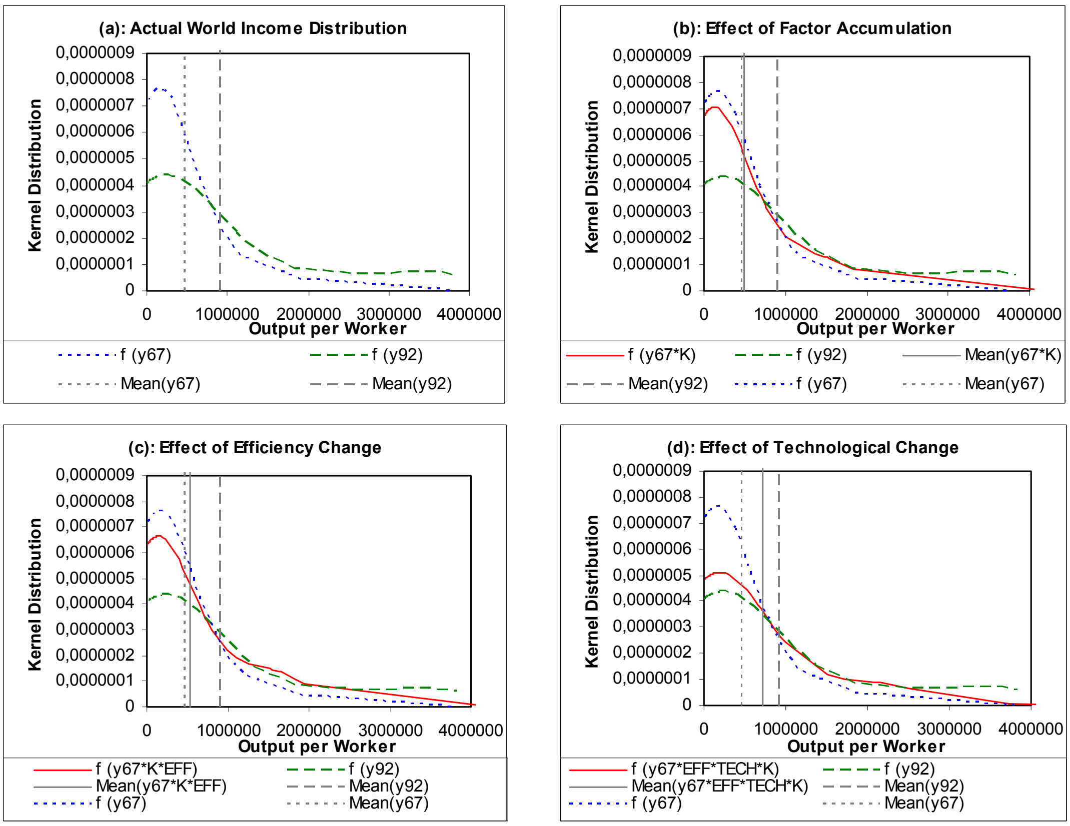


Table 10 – Li's Distribution Hypothesis Tests for the Economy

Null Hypothesis (H_0)	T-test	Ten percent significance level (critical value: 1.28)	Five percent significance level (critical value: 1.64)
$f(y_{92}) = g(y_{67})$	2.398	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * Eff)$	2.639	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * Tech)$	2.412	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * FAcc)$	-0.073	**H_0 not rejected**	**H_0 not rejected**
$f(y_{92}) = g(y_{67} * Eff * Tech)$	2.643	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * Eff * FAcc)$	-0.020	**H_0 not rejected**	**H_0 not rejected**
$f(y_{92}) = g(y_{67} * Tech * FAcc)$	-0.026	**H_0 not rejected**	**H_0 not rejected**
$f(y_{92}) = g(y_{67} * Eff * Tech * FAcc)$	-0.009	**H_0 not rejected**	**H_0 not rejected**

Table 11 – Li's Distribution Hypothesis Tests for Agriculture

Null Hypothesis (H_0)	T-test	Ten percent significance level (critical value: 1.28)	Five percent significance level (critical value: 1.64)
$f(y_{92}) = g(y_{67})$	5.842	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * Eff)$	4.336	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * Tech)$	1.832	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * FAcc)$	4.686	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * Eff * Tech)$	0.982	**H_0 not rejected**	**H_0 not rejected**
$f(y_{92}) = g(y_{67} * Eff * FAcc)$	3.719	H_0 rejected	H_0 rejected
$f(y_{92}) = g(y_{67} * Tech * FAcc)$	1.350	H_0 rejected	**H_0 not rejected**
$f(y_{92}) = g(y_{67} * Eff * Tech * FAcc)$	0.774	**H_0 not rejected**	**H_0 not rejected**