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EXPLANATORY FACTORS OF LABOR PRODUCTIVITY DISTRIBUTION: A COMPARATIVE ANALYSIS ACROSS COUNTRIES AND REGIONS

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Abstract:

This dissertation aims to evaluate the growth and convergence of worldwide labor productivity. From a perspective of understanding the differences in growth patterns of these countries, we employ Data Envelopment Analysis (DEA) in order to construct a production possibilities frontier, which allows to calculate the growth of labor productivity, which in turn is decomposed into four factors, namely the variation of technical efficiency, technological variation, the accumulation of physical capital, and the accumulation of human capital. It should be noted that we use a very recent methodology for constructing a human capital index. In contrast to earlier studies, we find that efficiency change, combined with human capital accumulation, enables a multimodal distribution of labor productivity.

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1. Introduction

Badunenko et al. (2013) used the Henderson and Russel (2005) decomposition of labor productivity growth of 98 countries over the 1965-2007 period into components attributable to efficiency change (movement toward or away from the frontier), technological change (shifts in the world production frontier itself), physical and human capital accumulation (movements along the frontier). Both these authors[1] use this decomposition to analyze the evolution of the worldwide productivity distribution. Their main findings were increased productivity dispersion and the change from a unimodal distribution to a bimodal distribution over time.

Our research consists in decomposing the components of labor productivity growth and analyzing the individual and combined effects of each component in labor productivity distribution. To identify the drivers of labor productivity growth, we propose a decomposition of labor productivity growth similar to Badunenko et al. (2013). Our first conclusion is that technological progress takes place mostly in richer countries. Secondly, while efficiency change was the sole cause of bimodality in Badunenko et al. (2013), we find that efficiency change is only responsible for bimodality when combined with human capital accumulation. Furthermore, we find that the effects of the combination of technological change, physical capital accumulation, and human capital accumulation enable the multimodal distribution.

Similarly to Badunenko et al. (2013), our results suggest the possibility of a structural change in the early 2000s, enabled by the increasing contribution of technological change and human capital accumulation to labor productivity growth.

This work contributes to the literature since it uses the most recent construction of human capital indexes, available in the Penn World Tables. Furthermore, we use a larger sample of countries with a longer timeframe than previous studies. In addition, we extend the study of Badunenko et al. (2013) with a regional analysis, further confirming some of our results.

[1] Henderson and Russel (2005) had a sample of 65 countries for the period between 1965 and 1990.

2. Literature Review

2.1 What is productivity and how to account for it

Productivity can be described as a measure of performance that compares the output of a product with the input, or resources, required to produce it. As such, productivity is seen as one of the key sources of economic growth and competitiveness (Adler et al., 2017).

The Organization for Economic Co-operation and Development (OECD), has been calling increased attention to efforts to productivity as one of the main priorities for its member countries. In the OECD' view, productivity growth is strongly correlated with the improvement of per capita output and, consequently, the improvement of general living conditions.

Productivity is not the decisive factor to consider when analyzing the well-being of a country's population in the short term (see Krugman (1997)). However, in the long term, an economy's ability to increase the general level of well-being of its population objectively depends on an increase in its product per worker, which in turn is closely linked with the efficiency of productive factors.

One of the main contributions to the explanation of the determinants of economic growth was presented by Solow (1956). His seminal contribution established the roots of the neoclassical theory of economic growth, and, in his view, sustainable and long-term economic growth objectively depends on a continuous advance in more productive technologies.

In Solow's model, the total factor productivity (TFP) is measured by the residual. This represents the variation in production that isn't explained by variations in the quantity of productive factors used, namely capital and labor (Ahmed and Bhatti, 2020).

Kuznets (1971) finds evidence that a high rate of productivity growth is largely responsible for the growth of per capita output. Therefore, it can be concluded that these authors attribute to productivity growth a fundamental role in economic growth, but in these models this was considered exogenous.

Subsequently, Romer (1990) introduces an endogenous growth model, in which the technology available in a given economy is endogenized and, in turn, economic growth is driven by technological variations that emerge from decisions deliberately made by economic agents whose behavioral objective is profit maximization.

Empirically, Young (1995) finds that the accumulation of productive factors, rather than the growth of TFP, allows for the explanation of the economic growth of various Southeast Asian economies in the post-World War II period.

On the other hand, Klenow and Rodriguez-Clare (1997), find evidence that differences in the level and growth of TFP are predominant in explaining, in turn, the differences in the level of per capita output and its growth.

Hall and Jones (1999) go even further than Klenow and Rodriguez-Clare (1997) and find that differences between physical and human capital can only partially explain the differences in per capita output among countries. Furthermore, the authors find some evidence that variations in per capita income among countries have been mainly due to fluctuations in the level of TFP, rather than its growth.

2.2 Key drivers of productivity growth

2.2.1 The role of Research and Development

According to Coe and Helpman (1995), both domestic research and development (R&D) and the R&D efforts of trading partners and neighbors may influence a country's productivity in a globalized economy that involves international trade in goods and services and foreign direct investment.

In fact, domestic R&D allows for the production of traded and non-tradeable goods which promote the effective use of resources. At the same time, it enhances the economy's ability to absorb and benefit from foreign technological advancements. On the other hand, foreign R&D may enhance the ability to learn about new technologies, production processes, and materials. (Guellec and Van Pottelsberghe, 2004).

Barro and Sala-i-Martin (2004) identified two main routes of R&D effects on productivity, namely with the varieties model and the quality ladder model. The former is through an expansion of both the range of inputs available and the higher stock of knowledge available (Griliches and Lichtenberg, 1984). The latter deals with improvements in the quality of intermediate inputs (or the cost reduction of a certain input), which enables future innovators to begin their improvements from a higher quality standpoint. On the "neo-Schumpeterian" growth approach, TFP growth depends on the rate of innovation creation and the rate of adoption or diffusion of new technologies (Aghion and Howitt, 2006). As such, the process of innovation creation and the rate of adoption of new technologies may play a fundamental role in productivity and economic growth.

With this said, Hammar and Belarbi (2021) indicate that innovation, which is related to R&D, has a positive and significant effect on productivity in developed countries, but not so much in less developed countries. In fact, a recent empirical study suggests that although R&D is a key driver of productivity, the efficiency of R&D has been on a downward path over the last two decades in developed countries (Bloom et al., 2020).

2.2.2 The role of Human Capital

Personal characteristics embodied in people, such as knowledge and skill, contribute to their productive capacity, which is referred to as human capital (OECD, 2022).

Engelbrecht (2002) points out that there are two distinct ways of modeling human capital in growth regressions. The first is the "Lucas approach", in which the human capital is treated as any other factor of production, with the accumulation of human capital promoting labor productivity for a given technology (known as the level effect). The second approach is known as the "Nelson-Phelps", in which human capital affects a country's ability to innovate and absorb new technologies.

Studies based on cross-country data have produced mixed results, although it has long been found in previous literature that human capital plays a fundamental role in economic growth (Barro, 1991; Mankiw et al., 1992; Temple, 2001). Pritchett (2001) points out that these different results are caused by the impacts of education in countries with different institutions, labor markets, and education quality.

It should be noted that there are some measurement challenges in accounting for human capital, as some authors proxy it as average years of schooling (Maudos et al., 2003), PISA scores (Égert et al., 2022), or literacy (Romer, 1990).

Alongside other determinants of productivity, human capital has also been demonstrated to play a complementary role in trade openness and R&D. This highlights the importance of a qualified labor force in terms of skills, diversity, and management (Criscuolo et al., 2021).

2.2.3 The role of Institutions

North (1990, p. 1) characterizes institutions as "the rules of the game in a society or, more formally, the humanly devised constraints that shape human interaction".

Institutions, which play a crucial role in molding economic and productivity growth, are designed entities tasked with guiding the interactions between economic agents. The economic landscape of a country, which influences the distribution and redistribution of resources, is shaped by factors such as the protection of property rights, the rule of law, corruption, and economic freedom (Easterly, 2004).

Acemoglu (2008) argues that the structure of economic incentives in each society, which is influenced by economic institutions such as the structure of property rights and the presence of markets, may be important for productivity and economic growth.

Empirical studies support the idea of a positive effect of institutions on productivity growth (Barro, 1996; Alexandre et al., 2022), and a positive link between democracies and productivity (Acemoglu et al., 2019).

2.2.4 Other drivers of productivity

Fiscal and monetary policy can also be important determinants of productivity. For example, government spending may be complementary to private business investments in certain sectors, enhancing productivity in those sectors (Loko and Diouf, 2009).

Productivity may also be improved through a country's financial openness, that is, a financial system open to the rest of the world will promote exchanges of capital across countries. Kose et al. (2009) and Mishkin (2006) provide evidence that more financial liberalization provides better domestic financial markets, institutions, and macroeconomic policies, which in turn may improve the host country's productivity.

Moreover, workforce aging is expected to affect the evolution of labor productivity and TFP. Calvo-Sotomayor et al. (2019) and Aiyar et al. (2016) find a negative effect of workforce aging on the growth of labor productivity, mainly through the reduction of TPF growth.

2.3 The Data Envelopment Analysis approach

In general, and until the mid-2000s, the literature exploring the topic of TFP focused on the use of production functions, based on the Solow model, or of a non-parametric approach of index numbers (McLellan, 2004; Caves et al., 1982; Lanoie et al., 2008). However, both methodologies assume that countries are technically efficient, and therefore growth in TFP derives only from technical progress.

Indeed, according to Quah (1993), the use of parametric methodologies, such as Ordinary Least Squares (OLS) or semi-parametric ones like the Generalized Method of Moments (GMM), are not ideal for analyzing differences in TFP among economies. This argument is raised by Van Biesebroeck (2007) who indicates that the most appropriate methodology for measuring TFP is DEA. In the author's opinion, this non-parametric methodology allows for robust estimators for the level of TFP in economies with different levels of technology whose returns to scale vary over time.

Thus, it is necessary to conduct productivity analysis with methods that consider the existence of economic inefficiencies of decision-making units (DMUs). Charnes et al. (1978) introduced the DEA methodology, which doesn't assume technical efficiency of DMUs and does not require imposing a functional form for the production function.

Subsequently, Banker et al. (1984) have generalized the model of Charnes et al. (1978) to accommodate the possibility of variable returns to scale.

The DEA approach to measuring productive efficiency constructs a virtual production frontier and associated efficiency indexes of individual economies. Technically efficient countries operate on the production frontier, so, they have an efficiency index of 1, and technically inefficient economies have an index lower than 1 (Kumar and Russel, 2002).

Maudos et al. (1999) analyze the variation of TFP, using a DEA methodology, and they take into account human capital, for 22 economies belonging to the OECD. However, this article uses only the average number of years of schooling for the population over 25 years old as a proxy for human capital and does not consider the multiplier effect of human capital on the labor factor.

Kumar and Russel (2002) perform an analysis of the growth of labor productivity between 1965 and 1990 and decompose this growth into three components attributable to technological variation, variation in productive efficiency, and accumulation of physical capital. However, this article does not make any reference to the fundamental role of human capital in the country's productivity.

Henderson and Russel (2005) improved upon the article by Kumar and Russel (2002), introducing human capital as a fundamental input in the formulation and explanation of labor productivity. This article adopts a methodology that considers the multiplier role of human capital in the labor factor.

Fare et al. (2006) use DEA to construct an EU production frontier and compute a Malmquist index of TFP, which includes the decomposition of productivity growth considering human capital accumulation as a labor-augmenting factor. This study highlights the importance of policy and market reforms in influencing productivity growth.

Badunenko et al. (2013) use a methodology similar to Henderson and Russel (2005), using the newest data up until then, a larger sample of countries, and they base the construction of the human capital index on an updated version of the article by Hall and Jones (1999) in which human capital is represented by the returns on education.

Subsequently, Walheer (2016) argues that the methodology adopted by Henderson and Russel (2005) and Badunenko et al. (2013) is not ideal, as it simply ignores sector heterogeneity. Thus, this author proceeds to adopt a similar methodology, but performing a decomposition of the economy into 16 different sectors.

Mensah et al. (2023) apply the DEA approach to estimate an African production frontier, decomposing productivity changes into technological change and technological catch-up. They find that convergence within African countries is driven primarily by technological catch-up (improved efficiency with existing technologies) rather than technological change (development of new technologies).

3. Methodology

The efficiency score for each country is obtained using the Farrel-Debreu measure of technical efficiency and the "sequential production set" proposed by Diewert (1980). Then, using the methodology based on the work of Badunenko et al. (2013), labor productivity growth is decomposed into four components attributable to 1) technological change; 2) productive efficiency change; 3) accumulation of physical capital, and 4) accumulation of human capital.

Let $\{Y_{i,t}, K_{i,t}, L_{i,t}, H_{i,t}\}$ represent observations on aggregate output (Y), aggregate labor (L), aggregate physical capital (K), and human capital (H), with t=1, 2, …T and i=1, 2, …N, where T represents number of time periods and N the number of countries.

In a general sense, the macroeconomic literature indicates that human capital is a multiplicative augmentation of physical labor. As such, the observations can be presented as: $\{Y_{i,t}, K_{i,t}, \hat{L}_{i,t}\}$, where t=1, 2, … T; i=1, 2, …, N and $\hat{L}_{i,t} = L_{i,t} H_{i,t}$ represents the amount of labor measured in efficiency units in country i, at time period t.

Following Badunenko et al. (2013), we use the "sequential production set" proposed by Diewert (1980) to preclude the implosion of the frontier over time. The convex, free-disposal technological production set in period t, using all data up to that point in time, with constant returns to scale, is given by:

(1) $\boldsymbol{\mathcal{T}_t = \left\{\{Y, \hat{L}, K\} \in \Re^3_+ | Y \leq \sum_{\mathcal{T}\leq t} \sum_i z_{i\mathcal{T}} Y_{i\mathcal{T}}, \hat{L} \geq \sum_{\mathcal{T}\leq t} \sum_i z_{i\mathcal{T}} \hat{L}_{i\mathcal{T}}, K \geq \sum_{\mathcal{T}\leq t} \sum_i z_{i\mathcal{T}} K_{i\mathcal{T}}, z_{i\mathcal{T}} \geq 0 \forall i, \mathcal{T}\right\}}$, in which $\boldsymbol{z_{i\mathcal{T}}}$, τ = 1, 2, …, t, and i = 1, 2, … N, are the activity levels.

The output technical efficiency measure, for a country i at the time period t, is formulated as (Farrel, 1957; Debreu, 1951):

(2) $$\mathbf{e_{it} = E(Y_{it}, \hat{L}_{it}, K_{it} \backslash \mathcal{T}_t) = \min\{\lambda | (Y_{it}/\lambda, \hat{L}_{i,t}, K_{i,t}) \in \mathcal{T}_t\}}$$

This score is the inverse of the maximal amount that output $\mathbf{Y_{it}}$ can be expanded while remaining technologically possible, given the technology and input quantities. In our case of a scalar output, the output based efficiency score is the ratio of actual to potential output, evaluated at the actual input quantities.

Under the assumption of constant return to scale, the production frontier can be represented in $\{\hat{\mathbf{k}}, \widehat{\mathbf{y}}\}$ space by a function $\hat{\mathbf{y}}(\hat{\mathbf{k}})$, where $\hat{\mathbf{y}} = \mathbf{Y}/\hat{\mathbf{L}}$ and $\hat{\mathbf{k}} = \mathbf{K}/\hat{\mathbf{L}}$ represent the ratios of output and capital to effective labor. The potential output per efficiency unit of labor in the base and current period are, respectively, $\bar{\mathbf{y}}_{\mathbf{b}}(\hat{\mathbf{k}}_{\mathbf{b}}) = \hat{\mathbf{y}}_{\mathbf{b}}/\mathbf{e}_{\mathbf{b}}$ and $\bar{\mathbf{y}}_{\mathbf{c}}(\hat{\mathbf{k}}_{\mathbf{c}}) = \hat{\mathbf{y}}_{\mathbf{c}}/\mathbf{e}_{\mathbf{c}}$, where $\mathbf{e}_{\mathbf{b}}$ and $\mathbf{e}_{\mathbf{c}}$ are the values of the efficiency score in the respective periods. Alternatively, the ratio of output to effective labor can be expressed as a function of the potential output per efficiency unit of labor in the base and current period as follows: $\widehat{\boldsymbol{y}}_{\mathbf{b}} = \bar{\boldsymbol{y}}_{\boldsymbol{b}}(\hat{\mathbf{k}}_{\mathbf{b}})\mathbf{e}_{\mathbf{b}}$ and $\widehat{\boldsymbol{y}}_{\mathbf{c}} = \bar{\boldsymbol{y}}_{\boldsymbol{c}}(\hat{\mathbf{k}}_{\mathbf{c}})\mathbf{e}_{\mathbf{c}}$.

Dividing $\widehat{\boldsymbol{y}}_{\mathbf{b}}$ by $\widehat{\boldsymbol{y}}_{\mathbf{c}}$ yields:

$$(3)\ \frac{\hat{\mathbf{y}}_{\mathbf{c}}}{\hat{\mathbf{y}}_{\mathbf{b}}} = \frac{\mathbf{e}_{\mathbf{c}}}{\mathbf{e}_{\mathbf{b}}} * \frac{\bar{\mathbf{y}}_{\mathbf{c}}(\hat{\mathbf{k}}_{\mathbf{c}})}{\bar{\mathbf{y}}_{\mathbf{b}}(\hat{\mathbf{k}}_{\mathbf{b}})}$$

Let $\tilde{\mathbf{k}}_{\mathbf{c}} = \mathbf{k}_{\mathbf{c}}/(\mathbf{L}_{\mathbf{c}} * \mathbf{H}_{\mathbf{b}})$ be the ratio of capital to labor, measured in efficient units, under the assumption that human capital did not change since the base period. In the same sense, let $\tilde{\mathbf{k}}_{\mathbf{b}} = \mathbf{k}_{\mathbf{b}}/(\mathbf{L}_{\mathbf{b}} * \mathbf{H}_{\mathbf{c}})$ the ratio of capital to labor, measured in efficient units, under the assumption that human capital was the same as the current period.

Therefore, $\bar{\mathbf{y}}_{\mathbf{b}}(\tilde{\mathbf{k}}_{\mathbf{c}})$ and $\bar{\mathbf{y}}_{\mathbf{c}}(\tilde{\mathbf{k}}_{\mathbf{b}})$ represent the potential output per efficient labor unit, using the technologies available in the base and current period, respectively. Multiplying equation (3) first by: $\bar{\mathbf{y}}_{\mathbf{b}}(\hat{\mathbf{k}}_{\mathbf{c}})\bar{\mathbf{y}}_{\mathbf{b}}(\tilde{\mathbf{k}}_{\mathbf{c}})$ and then dividing by $\bar{\mathbf{y}}_{\mathbf{c}}(\hat{\mathbf{k}}_{\mathbf{b}})\bar{\mathbf{y}}_{\mathbf{c}}(\tilde{\mathbf{k}}_{\mathbf{b}})$, we obtain the following alternative decompositions the growth of $\hat{\mathbf{y}}$:

$$(4)\ \frac{\hat{\mathbf{y}}_{\mathbf{c}}}{\hat{\mathbf{y}}_{\mathbf{b}}} = \frac{\mathbf{e}_{\mathbf{c}}}{\mathbf{e}_{\mathbf{b}}} * \frac{\bar{\mathbf{y}}_{\mathbf{c}}(\hat{\mathbf{k}}_{\mathbf{c}})}{\bar{\mathbf{y}}_{\mathbf{b}}(\hat{\mathbf{k}}_{\mathbf{c}})} * \frac{\bar{\mathbf{y}}_{\mathbf{b}}(\tilde{\mathbf{k}}_{\mathbf{c}})}{\bar{\mathbf{y}}_{\mathbf{b}}(\hat{\mathbf{k}}_{\mathbf{b}})} * \frac{\bar{\mathbf{y}}_{\mathbf{b}}(\hat{\mathbf{k}}_{\mathbf{c}})}{\bar{\mathbf{y}}_{\mathbf{b}}(\tilde{\mathbf{k}}_{\mathbf{c}})}$$

$$(5)\ \frac{\hat{\mathbf{y}}_{\mathbf{c}}}{\hat{\mathbf{y}}_{\mathbf{b}}} = \frac{\mathbf{e}_{\mathbf{c}}}{\mathbf{e}_{\mathbf{b}}} * \frac{\bar{\mathbf{y}}_{\mathbf{c}}(\hat{\mathbf{k}}_{\mathbf{b}})}{\bar{\mathbf{y}}_{\mathbf{b}}(\hat{\mathbf{k}}_{\mathbf{b}})} * \frac{\bar{\mathbf{y}}_{\mathbf{c}}(\hat{\mathbf{k}}_{\mathbf{c}})}{\bar{\mathbf{y}}_{\mathbf{c}}(\tilde{\mathbf{k}}_{\mathbf{b}})} * \frac{\bar{\mathbf{y}}_{\mathbf{c}}(\tilde{\mathbf{k}}_{\mathbf{b}})}{\bar{\mathbf{y}}_{\mathbf{c}}(\hat{\mathbf{k}}_{\mathbf{b}})}.$$

Additionally, labor productivity ($\mathbf{y}_{\mathbf{t}} = \mathbf{Y}_{\mathbf{t}}/\mathbf{L}_{\mathbf{t}}$) can be expressed as $\mathbf{y}_{\mathbf{t}} = \boldsymbol{H}_{\boldsymbol{t}}\widehat{\boldsymbol{y}}_{\boldsymbol{t}}$. Dividing labor productivity in the current period by the productivity in the base period yields:

$$(6)\ \frac{\mathbf{y}_{\mathbf{c}}}{\mathbf{y}_{\mathbf{b}}} = \frac{\mathbf{H}_{\mathbf{c}}}{\mathbf{H}_{\mathbf{b}}} * \frac{\hat{\mathbf{y}}_{\mathbf{c}}}{\hat{\mathbf{y}}_{\mathbf{b}}}.$$

Expression (6) shows the decomposition of labor productivity growth into two components: the growth of human capital and the growth of output per efficiency units of labor. Combining (4) with (6) and (5) with (6), we obtain two decompositions of labor productivity growth:

$$(7)\ \frac{\mathbf{y_c}}{\mathbf{y_b}} = \frac{\mathbf{e_c}}{\mathbf{e_b}} * \frac{\bar{\mathbf{y}}_\mathbf{c}(\hat{\mathbf{k}}_\mathbf{c})}{\bar{\mathbf{y}}_\mathbf{b}(\hat{\mathbf{k}}_\mathbf{c})} * \frac{\bar{\mathbf{y}}_\mathbf{b}(\tilde{\mathbf{k}}_\mathbf{c})}{\bar{\mathbf{y}}_\mathbf{b}(\hat{\mathbf{k}}_\mathbf{b})} * [\frac{\bar{\mathbf{y}}_\mathbf{b}(\hat{\mathbf{k}}_\mathbf{c})}{\bar{\mathbf{y}}_\mathbf{b}(\tilde{\mathbf{k}}_\mathbf{c})} * \frac{\mathbf{H_c}}{\mathbf{H_b}}] = \mathbf{EFF} * \mathbf{TECH^c} * \mathbf{KACC^b} * \mathbf{HACC^b}$$

$$(8)\ \frac{\mathbf{y_c}}{\mathbf{y_b}} = \frac{\mathbf{e_c}}{\mathbf{e_b}} * \frac{\bar{\mathbf{y}}_\mathbf{c}(\hat{\mathbf{k}}_\mathbf{b})}{\bar{\mathbf{y}}_\mathbf{b}(\hat{\mathbf{k}}_\mathbf{b})} * \frac{\bar{\mathbf{y}}_\mathbf{c}(\hat{\mathbf{k}}_\mathbf{c})}{\bar{\mathbf{y}}_\mathbf{c}(\tilde{\mathbf{k}}_\mathbf{b})} * [\frac{\bar{\mathbf{y}}_\mathbf{c}(\tilde{\mathbf{k}}_\mathbf{b})}{\bar{\mathbf{y}}_\mathbf{c}(\hat{\mathbf{k}}_\mathbf{b})} * \frac{\mathbf{H_c}}{\mathbf{H_b}}] = \mathbf{EFF} * \mathbf{TECH^b} * \mathbf{KACC^c} * \mathbf{HACC^c}.$$

The decomposition of labor productivity growth in (7) measures technological change by the shift in the production frontier evaluated at the current-period ratio of capital to effective labor and physical and human capital accumulation components are computed along the base-period frontier. In contrast, decomposition in (8) measures technological change by the shift in the production frontier computed at the base-period ratio of capital to effective labor and the effects of physical and human capital accumulation are evaluated along the current-period production frontier.

Given that decompositions in (7) and (8) yield, in general, different results, Badunenko *et al.* (2013) proposes that the decomposition of labor productivity growth is given as the geometric means of (7) and (8):

$$(9)\ \frac{\mathbf{y_c}}{\mathbf{y_b}} = \mathbf{EFF} * (\mathbf{TECH^b} * \mathbf{TECH^c})^{1/2} * (\mathbf{KACC^b} * \mathbf{KACC^c})^{1/2} * (\mathbf{HACC^b} * \mathbf{HACC^c})^{1/2} = \mathbf{EFF} * \mathbf{TECH} * \mathbf{KACC} * \mathbf{HACC}.$$

In this way, labor productivity growth is decomposed into components attributable to efficiency change (EFF), technological change (TECH), accumulation of physical capital (KACC), and lastly, accumulation of human capital (HACC).

In the DEA approach, we use the *teradial* STATA package developed by Badunenko and Mozharovskyi (2016).

4. Data

For our analysis, the data selected for output, physical capital, labor, and human capital are obtained from the Penn World Tables, version 10.01 (Feenstra, Inklaar and Timmer, 2015), where both GDP and physical capital are measured in current PPP's, in 2017 US$.

For labor, we use the number of persons engaged in the labor market, and, for human capital, we depart from previous studies and employ a variable that represents the returns to education, based on the average number of years of education, per worker. The human capital index is based on the education data in Barro and Lee (2013).

Our sample includes a longer time period than previous studies and a larger worldwide representation with 103 countries. Due to space restrictions, the descriptive statistics of the variables are presented only for the years of 1975 and 2019 (Tables 1 and 2).

Table 1: Descriptive statistics-1975

	N	Mean	Min	Max	SD	Median
Y	103	2.266e+11	1.347e+09	6.134e+12	6.725e+11	4.593e+10
K	103	7.468e+11	9.469e+08	2.485e+13	2.654e+12	7.088e+10
L	103	13812489	82100	4.198e+08	47517293	3394333.8
hc	103	5.059	1.691	8.68	1.534	4.927
lab	103	61907638	502295.19	1.477e+09	1.786e+08	13672422
y	103	3821.882	544.451	10366.872	2657.606	2992.509
k	103	11525.753	190.667	51354.207	12099.992	6138.224
yl	103	21362.777	1525.75	70638.414	17770.33	14524.654
kl	103	66493.17	491.61	275231.13	77271.579	33173.043

Note: Y is the GDP measured in PPP's, in 2017 US$. K is the physical capital stock measured in PPP, in 2017 US$. L is the number of persons engaged. hc is the human capital index per worker. lab is the labor input in efficiency units (L*hc). y is the output per efficiency unit of labor (Y/lab). k is the physical capital stock per efficiency unit of labor (K/lab). yl is the output per effective unit of labor (Y/L). kl is the physical capital stock per effective unit of labor (K/L).

Table 2: Descriptive statistics-2019

	N	Mean	Min	Max	SD	Median
Y	103	1.101e+12	3.578e+09	2.057e+13	2.997e+12	2.835e+11
K	103	4.680e+12	2.239e+10	9.946e+13	1.275e+13	1.127e+12
L	103	29674852	132258.63	7.988e+08	93537509	8180496
hc	103	6.383	2.809	11.921	1.608	6.388
lab	103	1.733e+08	816893.94	3.870e+09	4.926e+08	44633472
y	103	7343.082	572.179	31915.057	5974.365	5100.117
k	103	31800.381	589.446	116088.86	29624.788	21995.996
yl	103	49108.965	2733.814	219595.2	40777.975	39429.195
kl	103	212461.46	2816.315	798762.69	200117.98	135056.13

Note: Y is the GDP measured in PPP's, in 2017 US$. K is the physical capital stock measured in PPP, in 2017 US$. L is the number of persons engaged. hc is the human capital index per worker. lab is the labor input in efficiency units (L*hc). y is the output per efficiency unit of labor (Y/lab). k is the physical capital stock per efficiency unit of labor (K/lab). yl is the output per effective unit of labor (Y/L). kl is the physical capital stock per effective unit of labor (K/L).

5. Empirical Results

5.1 Efficiency Scores and Production Frontiers

Figures 1 and 2 depict the estimated best practice frontier in the base and current period of our sample. Countries in the dotted line are those that define the world production frontier. Furthermore, Table 3 presents the country-specific efficiency scores of our base (1975) and most recent (2019) period under the assumption of constant returns to scale (CRS). There are several conclusions that we can draw from the information in both Figures 1 and 2, and from Table 3.

In 1975, Switzerland, Gabon, Rwanda, Trinidad and Tobago, Iraq, Egypt, and Bulgaria were on the frontier, but at different capitalization levels. The frontier at a low capitalization level was defined by Bulgaria, Egypt, and Rwanda, while the mid-level was defined by Iraq, Gabon, and Trinidad and Tobago. Switzerland's productivity determines the frontier at high levels of capitalization.

Figure 1: Estimated world production frontier in 1975

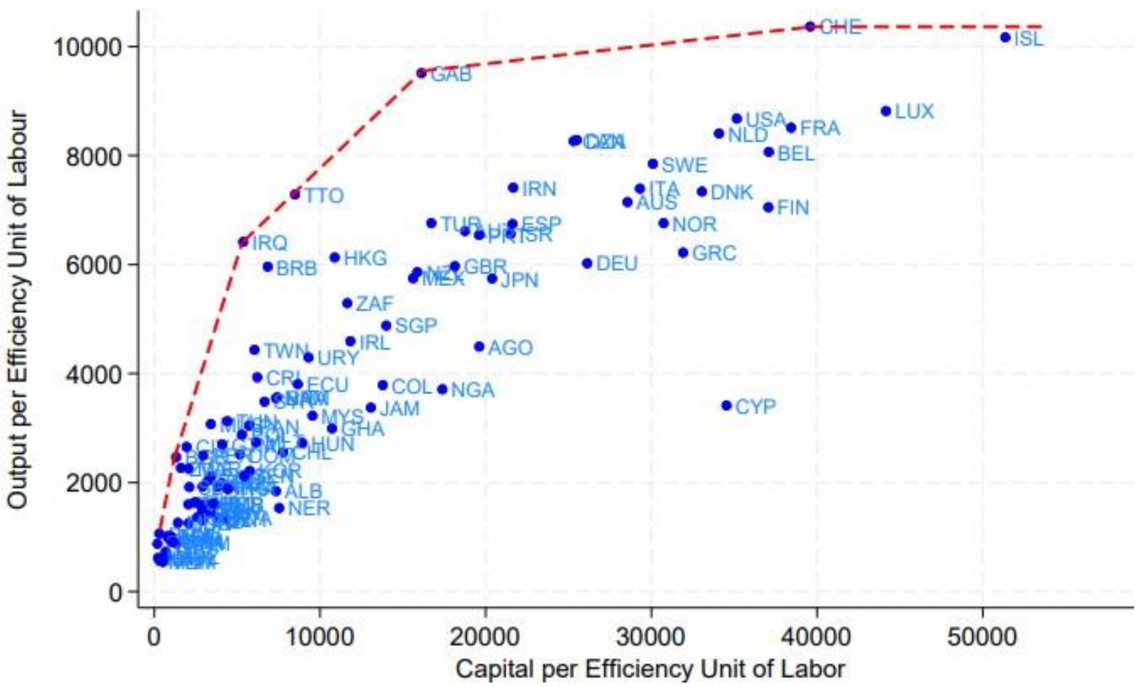


Figure 2: Estimated world production frontier in 2019

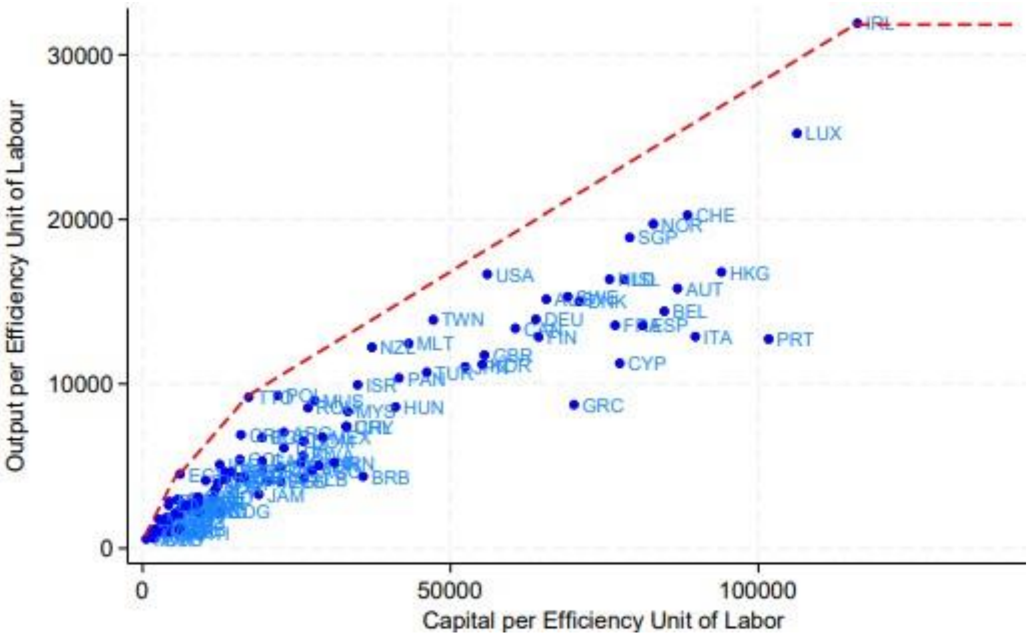
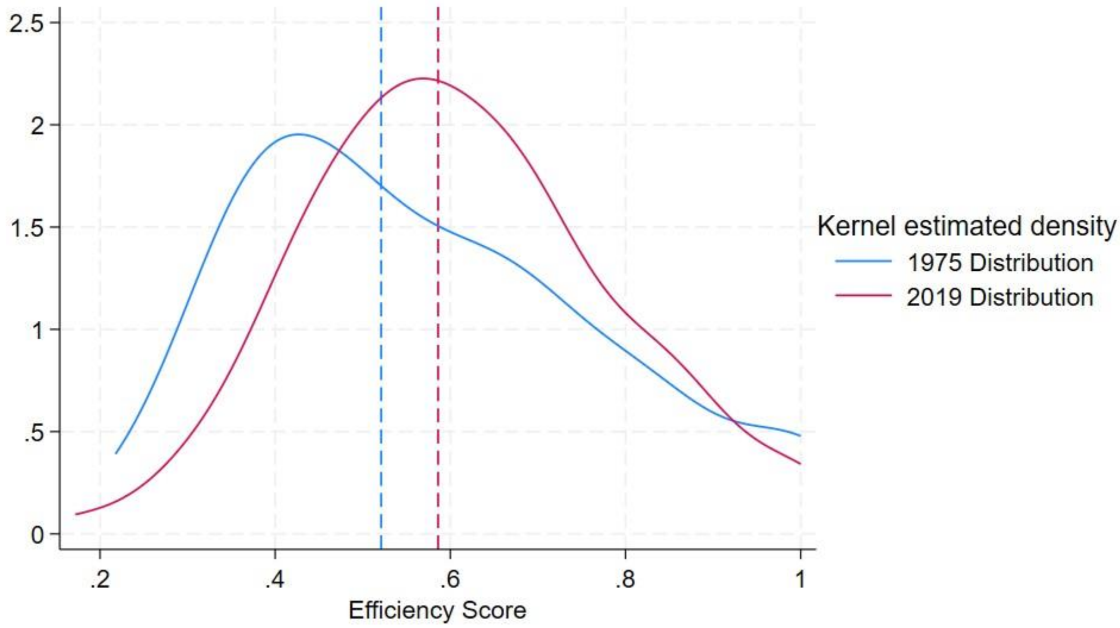


Table 3: Efficiency scores, 1975-2019

#	Country	TEb	TEc	#	Country	TEb	TEc
1	Albania	0.26	0.38	**43**	Iceland	0.98	0.70
2	Algeria	0.84	0.47	**44**	India	0.33	0.45
3	Angola	0.47	0.41	**45**	Indonesia	0.39	0.43
4	Argentina	0.39	0.67	**46**	Iran	0.76	0.42
5	Australia	0.72	0.75	**47**	Iraq	**1.00**	0.71
6	Austria	0.69	0.63	**48**	Ireland	0.56	**1.00**
7	Bangladesh	0.54	0.42	**49**	Israel	0.68	0.75
8	Barbados	0.87	0.33	**50**	Italy	0.74	0.50
9	Belgium	0.79	0.58	**51**	Jamaica	0.39	0.34
10	Bolivia	0.33	0.65	**52**	Japan	0.59	0.64
11	Botswana	0.28	0.50	**53**	Jordan	0.33	0.53
12	Brazil	0.51	0.49	**54**	Kenya	0.32	0.59
13	Bulgaria	**1.00**	0.70	**55**	Luxembourg	0.85	0.85
14	Burkina Faso	0.58	0.67	**56**	Madagascar	0.49	0.57
15	Cambodia	0.35	0.52	**57**	Malawi	0.50	**1.00**
16	Cameroon	0.37	0.54	**58**	Malaysia	0.42	0.64
17	Canada	0.84	0.70	**59**	Mali	0.51	0.88
18	Chile	0.36	0.58	**60**	Malta	0.41	0.82
19	China	0.46	0.47	**61**	Mauritius	0.68	0.77
20	Hong Kong SAR	0.77	0.63	**62**	Mexico	0.61	0.56
21	Colombia	0.43	0.63	**63**	Morocco	0.71	0.41

22	Congo	0.47	0.31	**64**	Mozambique	0.39	0.43
23	Costa Rica	0.59	0.80	**65**	Myanmar	0.67	0.52
24	Cyprus	0.34	0.49	**66**	Namibia	0.51	0.55
25	Cote d'Ivoire	0.86	0.71	**67**	Netherlands	0.83	0.72
26	D.R. of the Congo	0.38	0.41	**68**	New Zealand	0.62	0.89
27	Denmark	0.72	0.70	**69**	Niger	0.22	0.31
28	Dominican Republic	0.41	0.58	**70**	Nigeria	0.39	0.49
29	Ecuador	0.52	0.39	**71**	Norway	0.67	0.81
30	Egypt	**1.00**	**1.00**	**72**	Pakistan	0.50	0.87
31	El Salvador	0.46	0.51	**73**	Panama	0.47	0.70
32	Ethiopia	0.47	0.64	**74**	Paraguay	0.48	0.58
33	Finland	0.69	0.64	**75**	Peru	0.62	0.51
34	France	0.82	0.59	**76**	Philippines	0.45	0.54
35	Gabon	**1.00**	0.55	**77**	Poland	0.45	0.90
36	Germany	0.61	0.70	**78**	Portugal	0.68	0.44
37	Ghana	0.38	0.54	**79**	Republic of Korea	0.34	0.62
38	Greece	0.62	0.41	**80**	Romania	0.47	0.75
39	Guatemala	0.52	0.56	**81**	Rwanda	**1.00**	0.74
40	Haiti	0.25	0.17	**92**	Thailand	0.34	0.58
41	Honduras	0.39	0.38	**93**	Trinidad and Tobago	**1.00**	**1.00**
42	Hungary	0.37	0.59	**94**	Tunisia	0.57	0.66
82	Senegal	0.33	0.47	**95**	Turkey	0.71	0.68
83	Singapore	0.55	0.81	**96**	Tanzania	0.38	0.45
84	South Africa	0.64	0.48	**97**	Uganda	0.41	0.65
85	Spain	0.69	0.57	**98**	United Kingdom	0.62	0.65
86	Sri Lanka	0.46	0.61	**99**	United States	0.85	0.92
87	Sudan	0.59	0.82	**100**	Uruguay	0.57	0.58
88	Sweden	0.78	0.73	**101**	Viet Nam	0.40	0.53
89	Switzerland	**1.00**	0.79	**102**	Zambia	0.35	0.27
90	Syria	0.51	0.48	**103**	Zimbabwe	0.83	0.85
91	Taiwan	0.67	0.86		**Median**	**0.52**	**0.59**

Figure 3: Distribution of efficiency scores, 1975 and 2019.



Note: The dotted vertical lines represent the median efficiency scores in each period.

The 2019 technological frontier is defined by Ireland, Trinidad and Tobago, Malawi, and Egypt, but the frontier at low levels of capitalization is determined, primarily, by observations from Egypt, Malawi, and Trinidad and Tobago. At high capitalization levels, the frontier is defined by the observation of Ireland's productivity. The 10 most efficient economies in 2019 are, in descendent order, Ireland, Trinidad and Tobago, Malawi, Egypt, the United States, Poland, New Zealand, Mali, and Taiwan. Of this list, only the first 4 countries identify the frontier.

Another conclusion that emerges from Figures 1 and 2 is that technological change occurs mostly in richer countries. This is, up to a capital-labor ratio of about 8000, the 1975 and 2019 frontiers are coincident, although, for higher levels of capitalization, the 2019 frontier shifts upward in a dramatic way. Since technological change is rather intensive in physical and human capital, almost no technological progress occurs at lower levels of capitalization.

The previous conclusion is consistent with the results of Badunenko et al. (2013), which in turn confirms the Henderson and Russel (2005) finding that technological change takes place mostly in richer countries.

Figure 3 plots the distribution of the efficiency scores in 1975 and 2019, with a Gaussian kernel, and shows a slight increase in the median of the efficiency scores between 1975 and

2019. The shift of the distribution towards the right over time indicates a predominant tendency of these economies towards the frontier, which may be due to the occurrence of technological transfer from rich to poor countries, enabling higher efficiency. This result differs from Badunenko et al. (2013), as this study shows a slight decline in efficiency median from 1965 to 2007.

5.2 Quadripartite decomposition

Table 4 presents the country-specific components of the decomposition of the growth rate of output per worker, between 1975 and 2019. The first column shows the productivity growth rate of each country, and the other four present contributions of each component to productivity growth: efficiency change, technological change, physical capital accumulation, and human capital accumulation. We should note that percentages are obtained by subtracting 1 from the index and multiplying by 100. The contributions of individual components, because of compounding, do not sum to the total productivity change.

The median contribution of both efficiency change and physical capital accumulation to labor productivity is rather small, while that of technological change and human capital accumulation is quite significant.

Technological change has contributed to a significant movement of the world production frontier (94%), improving the growth rate of output per worker (128%), with most countries registering a small approximation to the new estimated best-practice frontier (9%). The difference in accumulation of physical (8%) and human capital (59%) means that the effect of human capital accumulation had a much stronger contribution to productivity growth than physical capital accumulation.

Table 4: Percentage change of quadripartite decomposition indexes, 1975-2019

#	Country	PRDCH	EFFCH	TECH	KACC	HACC
1	Albania	297.96	43.09	199.34	1.26	87.85
2	Algeria	-36.73	-43.68	-63.47	-66.61	192.15
3	Angola	76.51	-12.21	0.36	-53.42	231.49
4	Argentina	305.85	71.43	401.63	132.71	-40.40
5	Australia	103.53	4.00	235.64	51.45	-58.36
6	Austria	161.28	-8.95	237.96	-7.63	-23.79
7	Bangladesh	195.27	-22.96	-3.64	-56.92	447.94
8	Barbados	-35.30	-62.67	-73.56	-86.38	570.67
9	Belgium	108.59	-25.71	137.06	-24.81	-13.06

10	Bolivia	203.50	96.96	162.15	114.01	6.55
11	Botswana	649.04	80.40	514.34	59.15	38.21
12	Brazil	125.67	-4.40	8.20	-54.09	334.34
13	Bulgaria	261.78	-30.50	27.10	-62.57	428.54
14	Burkina Faso	181.84	15.73	-8.37	-45.60	554.35
15	Cambodia	232.06	48.33	112.69	46.09	58.51
16	Cameroon	121.71	46.85	19.38	-2.59	179.99
17	Canada	65.31	-16.78	93.90	-14.76	-16.77
18	Chile	145.47	60.08	347.45	164.71	-66.82
19	China	675.37	2.30	300.93	-17.40	139.53
20	Hong Kong SAR	261.99	-18.28	225.33	-42.32	57.65
21	Colombia	39.88	46.58	86.79	98.78	-44.78
22	Congo	52.39	-33.93	-51.17	-74.76	717.05
23	Costa Rica	77.22	35.12	88.09	46.92	-13.34
24	Cyprus	189.13	45.61	713.48	265.00	-85.82
25	Cote d’Ivoire	110.74	-17.85	-47.72	-71.36	1056.41
26	D.R. of the Congo	-44.29	7.16	-82.20	-73.25	1153.61
27	Denmark	142.61	-3.75	219.56	13.43	-35.58
28	Dominican Republic	144.10	42.66	208.78	72.80	-34.74
29	Ecuador	-4.31	-24.55	-27.75	-44.49	80.01
30	Egypt	703.54	0.00	86.56	-49.38	750.96
31	El Salvador	415.88	12.18	216.58	24.26	47.12
32	Ethiopia	243.98	37.43	93.16	31.46	86.17
33	Finland	152.97	-6.40	174.36	-6.62	-7.58
34	France	100.94	-28.09	98.62	-35.74	13.20
35	Gabon	47.77	-45.32	-70.69	-89.52	2530.12
36	Germany	147.05	14.63	291.76	58.56	-54.41
37	Ghana	17.79	43.38	-28.04	-13.24	170.54
38	Greece	90.65	-33.58	49.42	-53.59	82.61
39	Guatemala	99.62	7.70	13.27	-31.70	177.93
40	Haiti	-4.01	-30.89	-68.69	-75.53	765.81
41	Honduras	58.46	-1.95	-9.57	-30.99	148.99
42	Hungary	339.75	60.09	426.50	69.18	-20.97
43	Iceland	93.84	-28.23	121.22	-22.53	-18.82
44	India	316.73	38.94	121.69	-7.50	182.35
45	Indonesia	293.75	9.30	241.78	20.87	4.18
46	Iran	25.23	-44.88	-55.89	-81.85	762.28
47	Iraq	54.75	-29.30	-59.07	-81.10	1314.10
48	Ireland	577.11	80.13	1908.23	309.83	-85.18
49	Israel	67.74	11.01	96.57	19.43	-20.68
50	Italy	121.40	-32.72	102.61	-47.32	39.56
51	Jamaica	-4.57	-12.34	-21.02	-27.76	46.62
52	Japan	117.64	7.53	170.21	13.82	-23.91
53	Jordan	265.99	59.69	163.42	33.27	66.49

54	Kenya	81.52	82.11	33.36	42.85	73.53
55	Luxembourg	141.97	-0.05	488.94	117.73	-81.14
56	Madagascar	-10.20	16.10	-60.36	-44.57	374.57
57	Malawi	-22.89	99.88	-53.56	7.88	207.64
58	Malaysia	247.32	52.38	292.24	56.21	-13.62
59	Mali	332.93	70.82	115.83	40.03	144.70
60	Malta	336.94	98.72	802.32	253.54	-72.78
61	Mauritius	167.62	13.15	171.87	26.39	-11.88
62	Mexico	9.64	-7.97	12.74	-15.36	5.75
63	Morocco	128.16	-41.44	-22.83	-72.96	540.43
64	Mozambique	56.78	9.49	-18.89	-18.15	158.58
65	Myanmar	563.89	-22.21	46.64	-60.33	787.82
66	Namibia	44.20	8.76	2.15	-21.76	96.23
67	Netherlands	81.17	-12.67	185.01	22.49	-54.68
68	New Zealand	92.79	42.72	229.56	110.25	-60.29
69	Niger	-11.76	42.22	-39.39	-10.67	131.77
70	Nigeria	17.15	26.00	-28.60	-25.44	177.28
71	Norway	202.08	20.58	495.84	106.75	-70.43
72	Pakistan	159.34	72.70	69.79	43.94	83.26
73	Panama	185.78	49.67	391.11	124.43	-61.19
74	Paraguay	181.54	20.51	104.26	11.40	49.10
75	Peru	63.69	-17.65	1.23	-34.71	103.97
76	Philippines	149.30	21.90	49.55	-5.45	114.93
77	Poland	380.74	98.33	418.38	110.03	-12.43
78	Portugal	165.70	-34.44	112.96	-58.99	99.45
79	Republic of Korea	456.18	84.01	888.09	172.41	-61.98
80	Romania	533.86	59.89	444.17	54.68	20.41
81	Rwanda	142.07	-25.94	-67.03	-82.72	3046.54
82	Senegal	-1.32	41.40	-13.33	25.16	28.62
83	Singapore	467.93	47.17	703.51	63.43	-36.35
84	South Africa	32.69	-24.63	-45.76	-68.27	481.16
85	Spain	157.93	-18.44	154.86	-34.25	25.54
86	Sri Lanka	218.96	32.74	156.87	43.19	15.12
87	Sudan	88.99	39.54	6.21	-1.94	153.20
88	Sweden	139.89	-7.42	183.55	-3.15	-19.12
89	Switzerland	90.92	-20.76	186.08	6.08	-50.15
90	Syria	43.52	-5.76	-45.00	-64.22	587.24
91	Taiwan	344.72	28.71	313.32	1.55	36.37
92	Thailand	364.29	70.52	346.68	70.45	3.98
93	Trinidad and Tobago	34.00	0.40	8.06	-16.20	48.59
94	Tunisia	146.55	15.55	6.16	-46.37	400.36
95	Turkey	176.71	-4.72	81.05	-48.02	180.18
96	Tanzania	19.18	18.24	-38.43	-31.37	233.53
97	Uganda	76.15	55.98	-32.77	-34.65	525.41

98	United Kingdom	136.34	4.87	169.41	-1.68	-6.43
99	United States	91.20	8.31	213.98	65.64	-60.18
100	Uruguay	84.88	1.66	74.23	-12.90	23.85
101	Viet Nam	540.28	31.50	225.23	27.87	102.47
102	Zambia	42.19	-22.95	-64.93	-77.60	1294.45
103	Zimbabwe	-23.40	2.52	-78.11	-71.17	1144.40
	Median	**128.16**	**8.76**	**93.90**	**7.50**	**58.51**

The overall results indicate that the economic evolution of the last twenty years translates in a significant change in the contribution of these components to labor productivity. For example, Badunenko et al. (2013) estimate for the period between 1965 and 2007 that the contribution of physical and human capital accumulation is, on average, 38,5 and 25,9 respectively, while Henderson and Russel (2005) estimate for the period between 1965 and 1990 a contribution of 29,5 and 14,7. Regarding these components, we can conclude that, with the inclusion of more recent data, worldwide labor productivity growth appears to rely more heavily on the contribution of technology change and human capital accumulation, rather than on physical capital accumulation.

Table 5: Median percentage change of the quadripartite decomposition indexes, 1975-2019

Country Group	TEb	TEc	PRDCH	EFFCH	TECH	KACC	HACC
OECD[2]	0.87	0.71	136.34	-16.28	160.98	-9.19	-9.62
Latin and Central America[3]	0.58	0.64	84.88	-9.05	55.54	-19.43	41.34
Africa[4]	0.56	0.63	54.58	-1.11	-26.28	-42.55	219.18
Asia[5]	0.67	0.75	168.02	19.11	57.72	-13.23	161.32
East Asia[6]	0.80	0.89	344.72	0.04	231.75	-3.13	54.60

Table 5 shows the technical efficiency scores for five groups of countries, the median percentage change in labor productivity, and the respective four components. For the OECD countries, we can observe a decrease in the efficiency scores, indicating that these countries

[2] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.
[3] Argentina, Bolivia, Brazil, Barbados, Chile, Costa Rica, Colombia, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Panama, Paraguay, Peru, Trinidad and Tobago, Uruguay.
[4] Algeria, Angola, Botswana, Burkina Faso, Cameroon, Congo, Cote d'Ivoire, D.R. of the Congo, Egypt, Ethiopia, Gabon, Ghana, Kenya, Madagascar, Malawi, Mali, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, South Africa, Sudan, Tunisia, Tanzania, Uganda, Zambia, Zimbabwe.
[5] Bangladesh, India, Iran, Iraq, Israel, Jordan, Myanmar, Pakistan, Philippines, Sri Lanka, Syria, Turkey.
[6] China, Cambodia, Hong Kong SAR, Indonesia, Japan, Malaysia, Korea, Singapore, Taiwan, Thailand, Viet Nam.

moved further away from the world production frontier between 1975 and 2019. The median productivity change is slightly higher than the world median, primarily because of an expressive contribution of technological change.

Latin and Central American countries present lower labor productivity growth when compared to the worldwide median and other groups of countries (except Africa), even though their human capital accumulation is higher than the OECD countries. The major contributions to their labor productivity growth are estimated to be technological change and human capital accumulation.

Regarding Africa, labor productivity growth has been lower than the worldwide median being the group of countries with the lowest labor productivity growth. Efficiency change is almost zero, and the negative effect of physical capital accumulation heavily contributed to this result. We should also note that in Africa human capital accumulation, compared to the other country groups, contributes most to the growth of labor productivity.

Estimations for the Asian countries reveal that their labor productivity growth is greater than that of the world median, mainly due to the positive contributions of efficiency change, technological change, and human capital accumulation. There is a negative contribution of physical capital accumulation to the labor productivity growth in these countries.

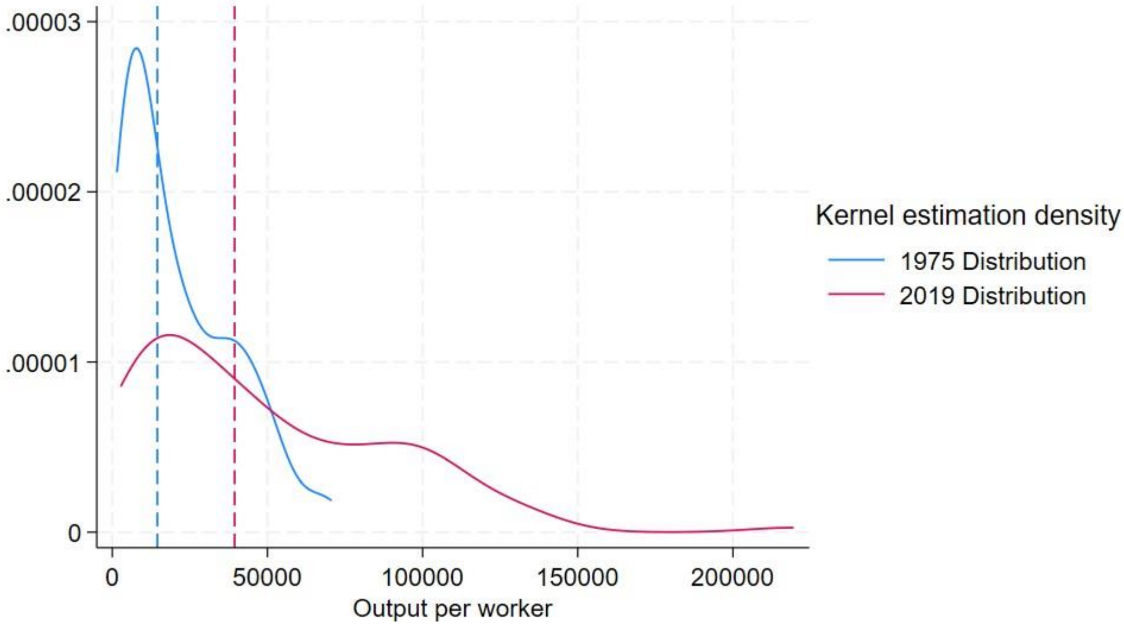
The group of East Asian economies outperforms the other groups in terms of productivity growth. This result is attributable to the exceptional performance of China (675%), Vietnam (540%), and Korea (456%) in terms of labor productivity growth. These results can be attributable to substantial technological change in these countries.

5.3 Analysis of the world distribution of output per worker

5.3.1 The 1975-2019 period

Figure 4 presents the distribution of the output per worker of the 103 countries in 1975 and 2019. The distributions seem to be unimodal, yet there is a slight possibility of a bimodal distribution both in 1975 and 2019. A second aspect of these distributions is the increased dispersion of productivity across the world, as the right-hand tail of the 2019 distribution is significantly wider than the one in 1975.

Figure 4: Distribution of output per worker



Note: The dotted vertical lines represent the median of each distribution.

The bootstrapped Silverman (1981) test for multimodality, presented in the first two rows in Table 6, rejects the null hypothesis that there is one mode in 2019 (at least for a 10% significance level) but fails to reject unimodality in 1975.

These findings are similar to those presented by Badunenko et al. (2013) where the output per worker distribution is found to be unimodal in 1965 and multimodal in 2007. Similarly, the results in Henderson and Russel (2005) indicate unimodalility in 1965 and bimodality in 1990.

Following Badunenko et al. (2013), we can further explore the effects of each of the four components in the quadripartite decomposition on the change in the distribution of output per worker between 1975 and 2019. For this purpose, let:

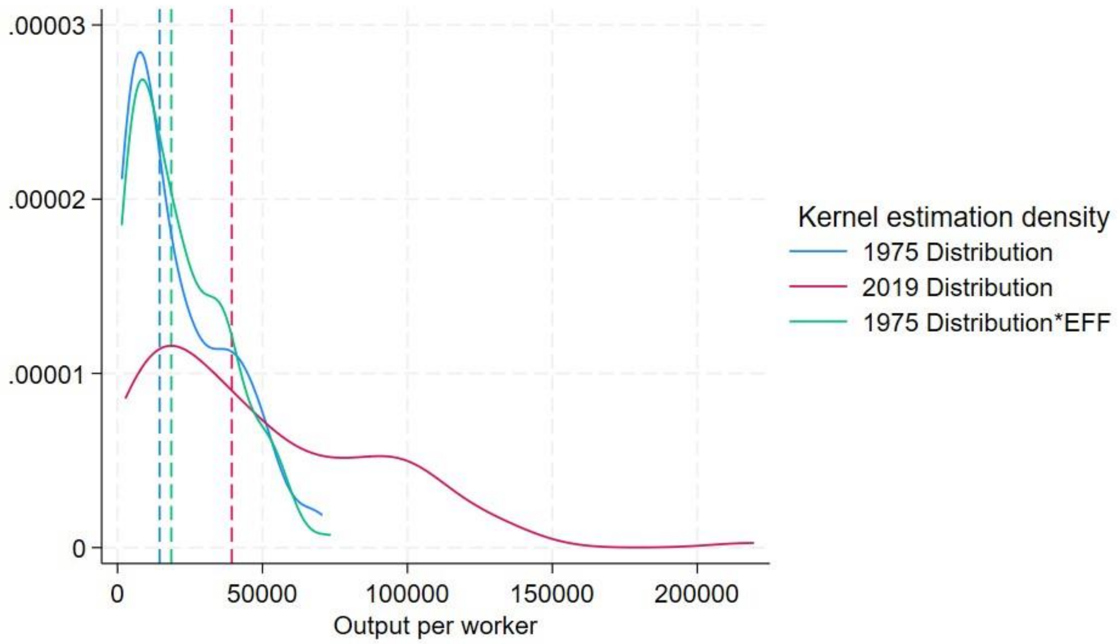
(10) $$y_c = (EFF * TECH * KACC * HACC) * y_b.$$

Labor productivity distribution in the current period can be constructed by multiplying the labor productivity in the base period by each of the four components. Given that we want to explore the impact of each component separately, we introduce each component in a sequential way.

In order to assess the shift of labor productivity distribution attributable solely to efficiency change, we consider the counterfactual distribution of $y^E = EFF * y_b$. The variable y^E assumes no technological change, no capital deepening and no human capital accumulation.

Figure 5 presents the counterfactual distribution of y^E as well as the actual distributions in both the base and 2019 periods.

Figure 5: Effect of efficiency change



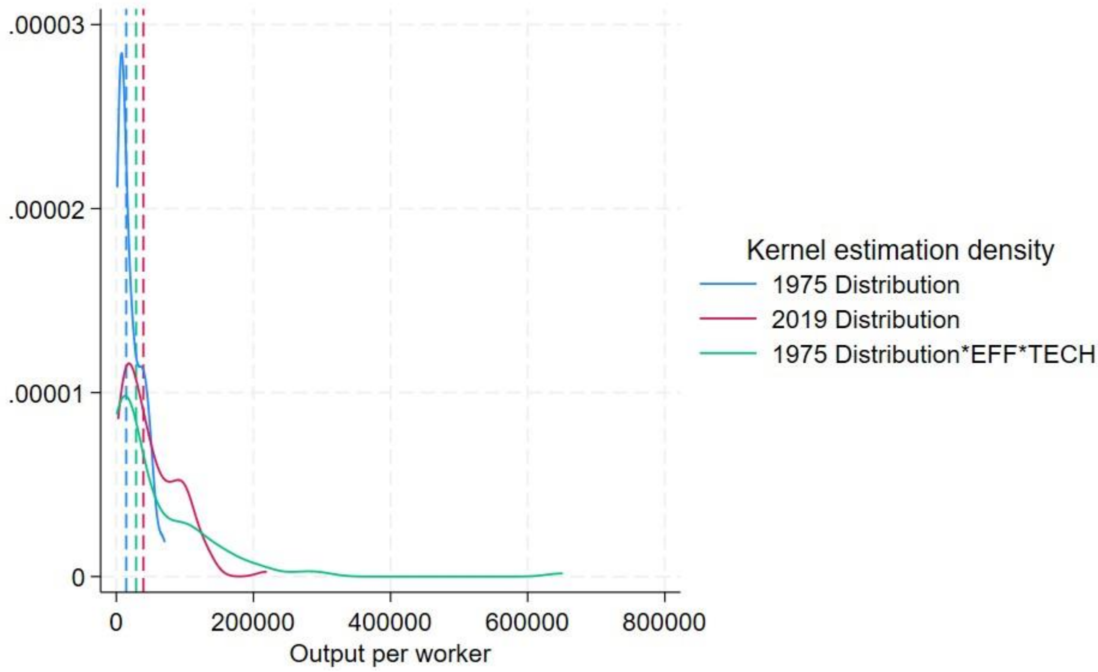
Note: The dotted vertical lines represent the median of each distribution.

The isolated effect of efficiency change alters the 1975 distribution of output per worker, especially for economies that are above the median of the distribution. There is a movement towards a concentration of the probability mass from the top and the bottom in 1975 to the middle of the distribution in 2019. The bootstrapped Silverman test in line 3 of Table 6 fails to reject the null hypothesis of unimodality, implying that efficiency change does not change the 1975 distribution from unimodal to bimodal.

Furthermore, this may indicate that countries in the middle-income group may benefit more from gains in efficiency, rather than those at the left and right tail of the distribution. This analysis confirms the results presented in Table 5, where OECD economies that are mostly at the right-hand tail of the distribution don't show large efficiency gains. In this sense, the economies of Asia and East Asia, most of them in the middle-income group, benefit more from changes in efficiency than the other country groups.

The statistical results from the Silverman test applied to the isolated effect of each of the other three components in the quadripartite decomposition (technological change, capital accumulation, and human capital accumulation) are similar to the isolated effect of the efficiency change on the 1975 distribution. Lines 4-6 in Table 6 indicate that the isolated effect of each of those components doesn't change the pattern of the 1975 distribution from unimodal to bimodal.

Figure 6: Effect of technological change and efficiency change

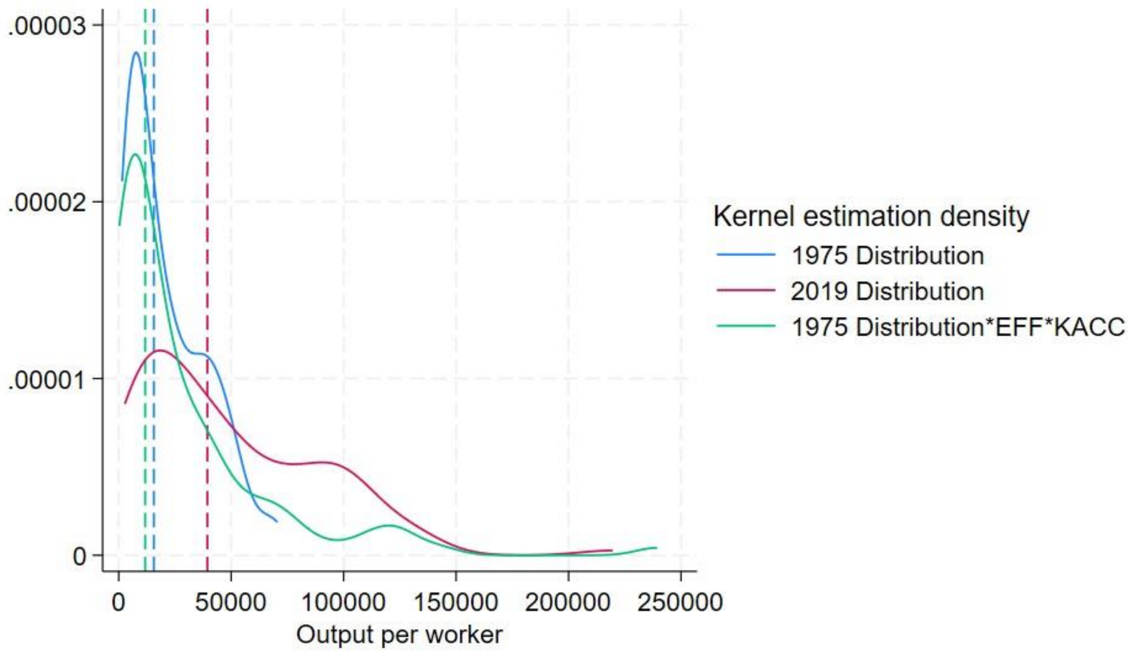


Note: The dotted vertical lines represent the median of each distribution.

Figure 6 presents the counterfactual distribution of the joint effects of technological change and efficiency change on the 1975 distribution. As technological change is the quadripartite component that contributes the most to labor productivity growth, this component shifts a substantial proportion of the probability mass from both tails of the 1975 distribution to the right-tail and increases the median of the distribution. The elongated effect from this counterfactual distribution arises, primarily, from countries with very high output per worker, such as Ireland, with technological change contributing 1908% to labor productivity growth, and Luxembourg with a 488% contribution of technological change to labor productivity growth.

The modality test (line 7 in Table 6) fails to reject that the counterfactual distribution is unimodal and thus, it does not change the 1975 distribution from unimodal to bimodal.

Figure 7: Effect of capital deepening and efficiency change



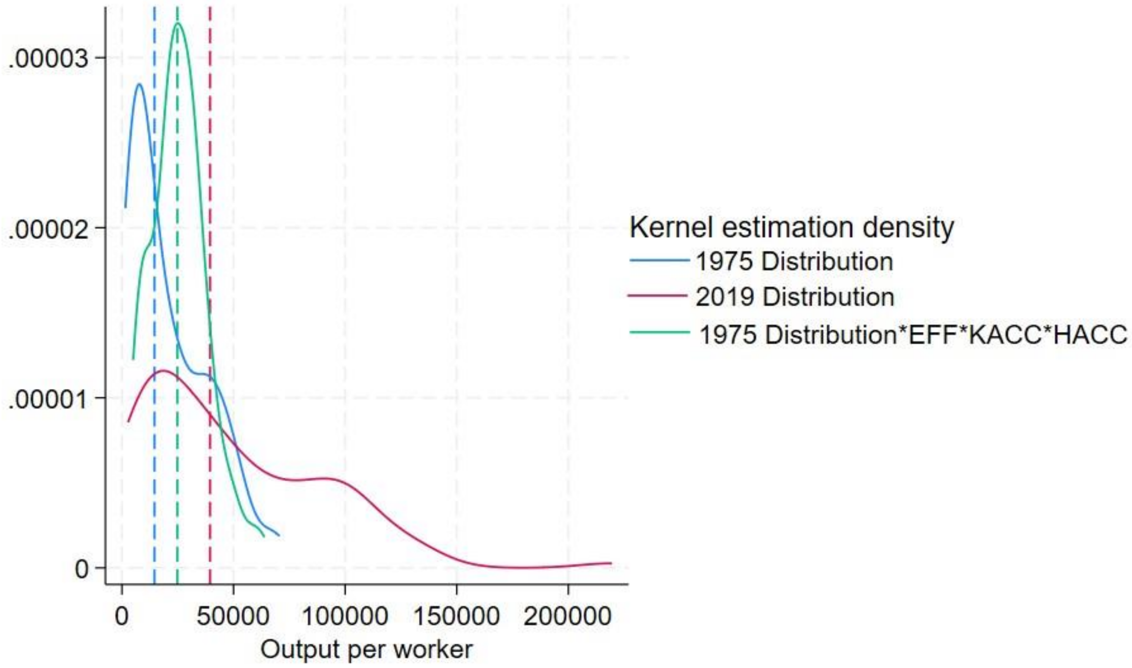
Note: The dotted vertical lines represent the median of each distribution.

Figure 7 presents the counterfactual distribution of the joint effects of capital deepening and efficiency change on the 1975 distribution. The additional effect of physical capital accumulation shifts a substantial proportion of the probability mass from the left-tail and the middle of 1975 distribution to the right-tail and increases the median of the distribution. The modality test (line 8 in Table 6) fails to reject unimodality. Thus, the additional effect of capital deepening doesn't change the pattern of the 1975 distribution of output per worker from unimodal to bimodal.

This further verifies the results presented in Table 5, that physical capital accumulation plays a less negative contribution (except in East Asia) to the growth of labor productivity in countries on the right tail of the distribution (e.g OECD), than in countries on the left-side tail (e.g. Africa). For example, along with the expressive growth of efficiency change in Ireland (80%), capital accumulation (309%) played a greater role in the productivity growth of this country (577%). On the other side of the distribution, Algeria's negative productivity growth (-36%) can be primarily explained by the negative contribution of physical capital accumulation (-66%).

The most important conclusion that arises from this counterfactual distribution is the effect of capital accumulation on labor productivity dispersion across countries. This may indicate that capital deepening plays a significant role in the explanation of the development of countries that are on the left-hand tail of the distribution of output per worker. Poorer countries from Africa and Asia experience a negative growth in physical capital accumulation, which may in turn explain why these countries are still at the left-hand tail of the distribution.

Figure 8: Effect of human capital accumulation, capital deepening, and efficiency change



Note: The dotted vertical lines represent the median of each distribution.

Figure 8 shows the effect of human capital accumulation on the distribution of worldwide output per worker. The effect of this productivity component significantly changes to the right the output per worker distribution, but not its length. This result indicates that human capital plays a truly expressive role in augmenting productivity growth in less developed countries (e.g. Africa), and not so much in developed countries (e.g. OECD). The statistical results from the Silverman test confirm that human capital accumulation is the only quadripartite component that enables multimodality of the distribution but only when combined with efficiency change (Line 9, Table 6) and the combination of technological change and physical capital accumulation (Line 16, Table 6).

Table 5 presents this result in another view, that is, the median growth of human capital accumulation for poorer African and Asian countries is approximately 219% and 161% respectively, which in turn is clearly above the worldwide median of 51%.

Table 6: Modality tests (*p values*)

	Distribution	H0: One mode H1: More than one mode
1	f(y2019)	0.0700
2	f(y1975)	0.4350
3	f(y1975*EFF)	0.5230
4	f(y1975*TECH)	0.8420
5	f(y1975*KACC)	0.9170
6	f(y1975*HACC)	0.7170
7	f(y1975*EFF*TECH)	0.7350
8	f(y1975*EFF*KACC)	0.6930
9	f(y1975*EFF*HACC)	0.0340
10	f(y1975*TECH*HACC)	0.7860
11	f(y1975*TECH*KACC)	0.1480
12	f(y1975*KACC*HACC)	0.0800
13	f(y1975*EFF*TECH*KACC)	0.1330
14	f(y1975*EFF*TECH*HACC)	0.7170
15	f(y1975*EFF*KACC*HACC)	0.5670
16	f(y1975*TECH*KACC*HACC)	0.0010

Notes: The bootstrapped Silverman (1981) test for multimodality is used as described in Izenman and Sommer (1988), with 1000 bootstrap replications.

Table 7: Distribution hypothesis tests (*p values*)

	H0: Distributions are equal H1: Distributions are not equal	KS *p value*	GK p v*alue*
1	g(y2019) vs. f(y1975)	0.0000	0.0001
2	g(y2019) vs. f(y1975*EFF)	0.0000	0.0001
3	g(y2019) vs. f(y1975*TECH)	0.0010	0.0001
4	g(y2019) vs. f(y1975*KACC)	0.0120	0.0001
5	g(y2019) vs. f(y1975*HACC)	0.0000	0.0001
6	g(y2019) vs. f(y1975*EFF*TECH)	0.0000	0.0001
7	g(y2019) vs. f(y1975*EFF*KACC)	0.1120	0.0246
8	g(y2019) vs. f(y1975*EFF*HACC)	0.0000	0.0001
9	g(y2019) vs. f(y1975*TECH*KACC)	0.0000	0.0001
10	g(y2019) vs. f(y1975*TECH*HACC)	0.8690	0.3680
11	g(y2019) vs. f(y1975*KACC*HACC)	0.0060	0.0001
12	g(y2019) vs. f(y1975*EFF*TECH*KACC)	0.0000	0.0001
13	g(y2019) vs. f(y1975*EFF*TECH*HACC)	0.0120	0.0001
14	g(y2019) vs. f(y1975*EFF*KACC*HACC)	0.0000	0.0001
15	g(y2019) vs. f(y1975*TECH*KACC*HACC)	0.0390	0.0008

Notes: The functions g(.) and f(.) are (kernel) distribution functions. The Kolmogorov-Smirnov and the Goldman and Kaplan (2018) tests is used with 1000 bootstrap replications and the Silverman (1986) adaptive rule-of-thumb bandwidth.

The next step of our analysis explores a non-parametric approach to formally test statistical differences between the actual 2019 distribution and the counterfactual distributions considered previously. Table 7 presents the results of Goldman and Kaplan (2018) and Kolmogorov-Smirnov tests. As the test formulated by Goldman and Kaplan (2018) is recognized as a more powerful test than the Kolmogorov-Smirnov one, we will follow the statistics provided by this test as a reference.

Firstly, the results in line 1, Table 7, show a statistically significant difference between the base and 2019 distributions, which may reflect the increased dispersion of the distribution of worldwide output per worker during the period.

With the isolated effects of the quadripartite components (lines 2-5, Table 7), there are statistical differences between the actual and counterfactual distributions, indicating that the individual effect of each component change the pattern of the distribution of output per worker.

An interesting result from both tests is presented in line 10 of Table 7, in which the combined effect of technological change and human capital accumulation on the 1975 distribution of output per worker does not statistically differ from the 2019 distribution. This further confirms the quadripartite decomposition results, in which the components of technological change and human capital accumulation play a significant role on the growth of productivity per worker.

In contrast, Badunenko et al. (2013) find that the combined effects of technological change and human capital accumulation on the 1965 distribution statistically differ from the 2007 distribution of income per worker[7].

Badunenko et al. (2013) only find the possibility of equality between the 1965 and 2007 distributions with the combined effects of technological change, physical capital accumulation, and human capital accumulation. In our estimations, with these joint effects, we reject the possibility that the actual and counterfactual distributions are statistically equal.

Concerning the other comparisons between the actual and counterfactual distributions (lines 11-14, Table 7) we find significant statistical differences between the distributions.

[7] It is important to note that Badunenko et al. (2013) used the bootstrapped Li (1996) test with 5000 bootstrap replications and the Sheather and Jones (1991) bandwidth.

This interesting comparison may suggest the possibility of a structural change in the first decade of the 2000s, one in which technological change and human capital accumulation become the most important contributors to the evolution of labor productivity distribution.

Further analysis is provided in Appendixes A through E to verify if the effects of each one of these components could alter the 1975 distribution for each group of countries presented in Table 5. Also, we provide both modality and distribution hypothesis tests in each appendix. The discussion of the results is presented below.

For OECD countries, the effect of efficiency change does not significantly alter the pattern of the 1975 output distribution per worker and further confirms the lack of efficiency improvements in these groups of countries (Appendix A). Capital deepening appears to elongate the distribution, meaning that some countries have benefited more (Ireland, 309%; Korea, 172%) from capital accumulation than others (Greece, -59%; Spain, -34%). Human capital accumulation played a negative and significant role in lowering the average output per worker in OECD countries, which confirms previous results of a clear absence of the contribution of human capital accumulation contribution to productivity growth.

When accounting for both the modality and distribution hypothesis tests, OECD countries show a unimodal distribution of output per worker in 1975, but not in 2019. These distributions statistically differ from each other. Technological change appears to be the only component with enough power to change the distribution from the base to the 2019 period.

Interestingly, the mixed effect of technological change, physical capital deepening, and human capital accumulation on the base period distribution doesn't statistically differ from the current period distribution, further confirming the expressive contribution of technological change to the productivity distribution in OECD countries.

Efficiency change in Latin and Central American countries proves to contribute positively to augmenting the average output per worker and smoothing the distribution of income, as compared to 1975 (Appendix B). Furthermore, physical capital accumulation benefited the productivity of these countries, increasing the average output per worker significantly and elongating the base period distribution of income. Human capital accumulation also smooths the distribution of output per worker and increases the average output per worker of these countries, as compared to 1975.

Regarding Latin and Central American countries (Appendix B), the distribution of output per worker in both periods remains unimodal but statistically different. Only the combined effect of physical capital accumulation and human capital accumulation appears to contribute to the multimodality of the distribution, but this distribution remains statistically different from the 2019 distribution. Furthermore, the combined effect of technological change, physical capital deepening, and human capital accumulation appear to change the distribution, but not the modality during the period.

Relatively to Africa, efficiency change shows no conclusive changes to the base period distribution, meaning that efficiency change does not play a positive contribution to increasing productivity growth (Appendix C). Capital deepening shows a negative effect on productivity growth, that is, African countries' productivity does not benefit from physical capital accumulation, as compared to other regions of the world[8]. On the other hand, human capital accumulation plays a decisive role in increasing productivity, increasing the average output per worker even further than the current period distribution, with Rwanda (3046%), Gabon (2530%), Zambia (1294%), and Zimbabwe (1144%) experiencing truly significant positive effects from human capital accumulation.

Concerning both the modality and distribution hypothesis tests, African countries show a clear multimodal distribution in 1975, but not in 2019 (at least for a 5% significance level), and the distribution in the two dates remains statistically different from each other. Efficiency change appears to be the single component that enables multimodality of the base period distribution, but only in combination with technological change. Interestingly, none of the isolated components and their combined effects enable African countries to have a statistically significant equal distribution in the base and current periods.

Asian countries' efficiency change contributes positively to the increase in the average income per worker, even though some countries have benefited more (Jordan 59%; India, 38%) than others (Iran, -44%; Bangladesh -22%) (Appendix D). Although capital deepening has a negative median contribution to labor productivity growth in these countries, the effects on the base period distribution show a slightly higher median output per worker. This result indicates that there are some countries in this group that may have benefited more from physical capital accumulation if they were below the median of the output per worker

[8] We should note the positive effect of capital deepening in Botswana (59%), Kenya (42%) and Mali (40%)

(Pakistan, 43%), and those with an output per worker higher than the median benefited less (Iran, -81%). Human capital accumulation has an extremely positive effect on the growth of labor productivity distribution in these countries, increasing the median output per worker even further than the current period distribution, with Iraq (1314%), Myanmar (787%), and Iran (762%) having phenomenal contributions of human capital accumulation on labor productivity growth.

About the Asian countries of our sample, both the 1975 and 2019 distribution of output per worker are statistically unimodal and equal, even though we observe a clear elongating pattern to the right of the current period distribution. The individual and combined effect of each component does not modify the modality of the base period distribution. Even though we observed a significant role of human capital accumulation in the productivity growth of these countries, this component doesn't have the statistical power to solely change the distribution of output per worker during the period.

Regarding East Asia countries, efficiency change does not significantly alter the 1975 distribution of output per worker (Appendix E). Capital deepening shows a similar pattern to the effects of efficiency change, with just a marginal increase in the median output per worker relative to the effect of efficiency change. Human capital accumulation appears to create a double peak distribution of output per worker, and an increase in the median output per worker but doesn't significantly change the base period distribution.

The base and current period distributions are unimodal, but there are statistical differences between them. Only the combined effects of efficiency change alongside the accumulation of both physical and human capital appear to lead to a multimodal distribution. Furthermore, when the effects of technological change are accounted for, this is the sole component responsible for not rejecting the possibility that the 2019 distribution is equal to the one of 1975, confirming the significant role that this component had on the productivity growth of these countries.

5.3.2 The 2007 to 2019 period

Since our modality results slightly differ from those of Badunenko et al. (2013), this section aims to investigate whether the financial crisis has significantly impacted the worldwide distribution of output per worker. For this purpose, we conduct a similar analysis as in the last section, but for the period between 2007 and 2019. Figures and tables for actual and counterfactual distributions are presented in Appendix F.

From the distribution hypothesis test, we can reject the possibility that the 2007 and 2019 distributions of output per worker are equal. Furthermore, the modality test doesn't reject that the 2007 distribution of output per worker is unimodal, but for a 10% significance level, the 2019 distribution of output per worker is bimodal.

With respect to efficiency change, this quadripartite component enables multimodality of the 2007 distribution of output per worker. Similarly, and alongside efficiency change, technological change and human capital accumulation also enable multimodality of the 2007 distribution.

Interestingly, and in contrast to Badunenko et al. (2013), we find that the isolated effect of efficiency change does not induce a multimodal distribution of output per worker. The sole effect of each quadripartite component induces multimodality, with the exception of physical capital accumulation.

Regarding the equality of distributions, we find that we can't reject equality between the 2007 and 2019 distributions when we account for the individual effects of technological change.

The previous statements further confirm our previous conclusion regarding the growing importance of technological change in the growth of labor productivity.

6. Conclusion

This dissertation allows us to understand the recent worldwide trends of labor productivity growth and its dispersion.

We extend previous studies of both Badunenko et al. (2013) and Henderson and Russel (2005) and with a sample of 103 countries, an extension of data up until 2019, the most recent data on educational attainment from Barro and Lee (2013), and an extensive analysis between regions of the world.

In our first step, we follow the decomposition of labor productivity growth of Badunenko et al. (2013) and decompose labor productivity growth into components attributable to efficiency change, technological change, and physical and human capital accumulation.

With regards to to our efficiency scores results, we confirm the results of Badunenko et al. (2013) and Henderson and Russel (2005) that technological change takes place mostly in richer countries.

Furthermore, the shift of the efficiency scores distribution towards the right indicates the probable occurrence of technological transfer from rich to poor countries, which in turn enables higher efficiency.

The quadripartite decomposition allows to observe the different contributions of each component to labor productivity growth in each country of our sample. Our results show that technological change has contributed to a significant movement of the world production frontier. Contrary to earlier studies (e.g. Henderson and Russel (2005)), we find that human capital accumulation had a much stronger contribution to productivity growth than physical capital accumulation

We conclude that East Asian countries had the most expressive labor productivity growth, driven primarily by technological changes and human capital accumulation. While African countries had the lowest labor productivity growth between 1975 and 2019, it is important to note that the contribution of human capital accumulation to labor productivity growth was the highest in all country groups.

Furthermore, we find concrete evidence of a structural shift in the early 2000s, driven primarily by the increased contribution of technological change and human capital accumulation to labor productivity growth.

While the study of Badunenko et al. (2013) finds that efficiency change was the only cause of a multimodal labor productivity distribution, we find that efficiency change, only when combined with human capital accumulation, is crucial for the emergence of a multimodal labor productivity distribution.

Further research may delve into studying the causes of differences in efficiency scores between countries using statistical data with the use of Simar and Wilson (2007) algorithm, for the period between 1975 and 2019. Furthermore, it would be highly pertinent to use the methodology of Walheer (2016) of the decomposition of the economy into sectors to analyze differences in labor productivity growth between sectors and the component's contribution in each sector.

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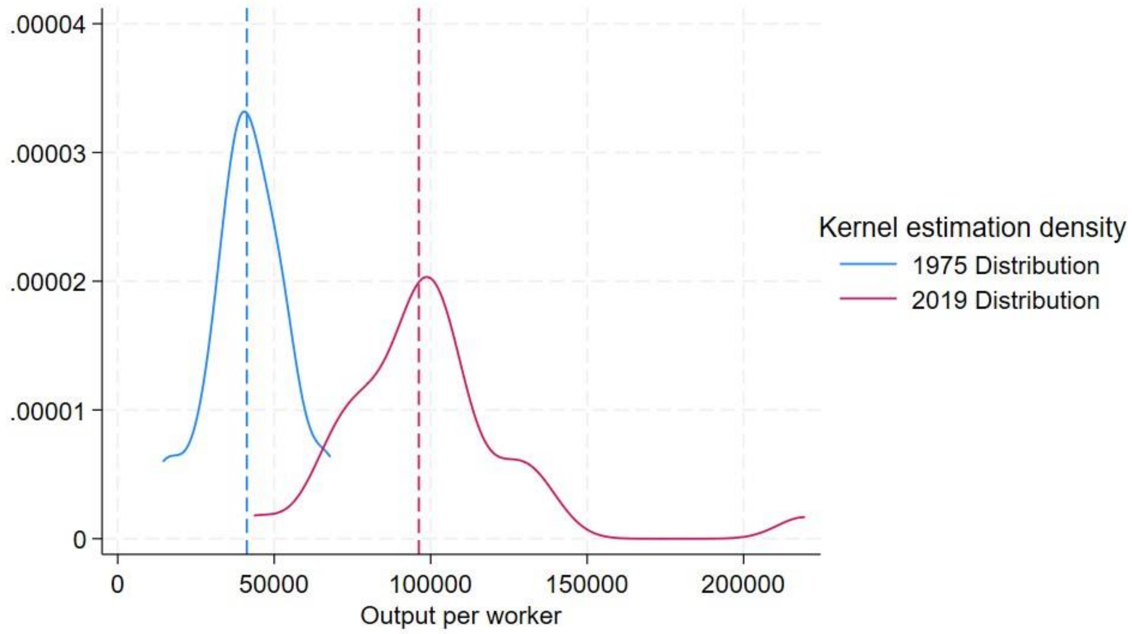
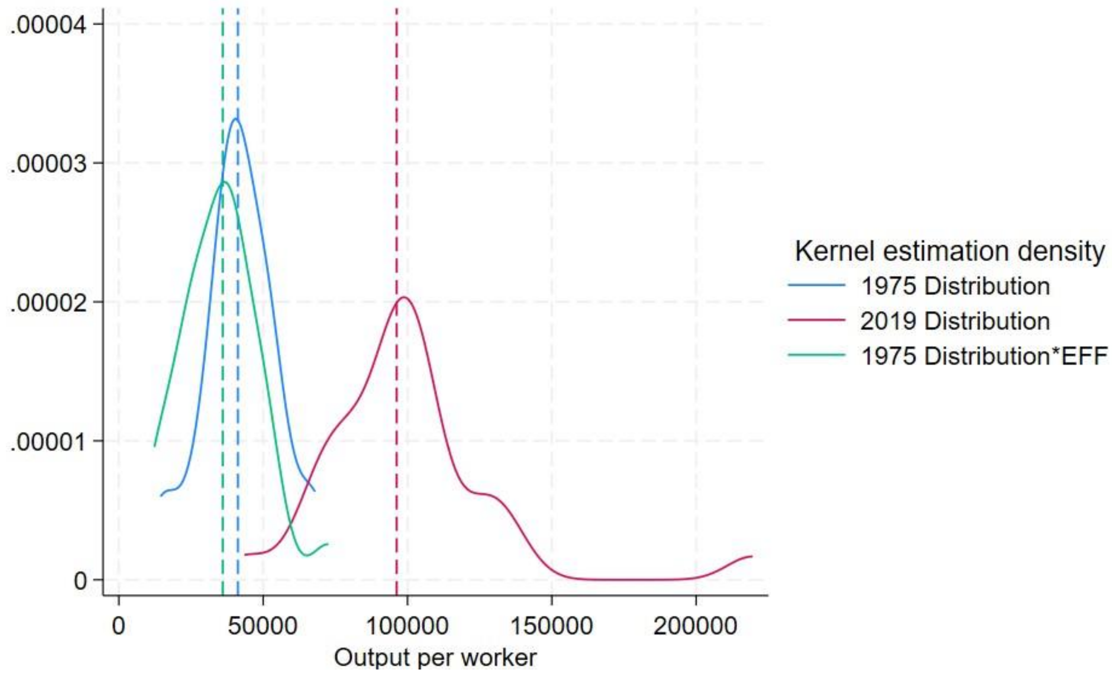
Appendix A. Analysis of the distribution of output per worker in OECD countries: 1975-2019.

Figure A.1: Output per worker distribution in OECD countries



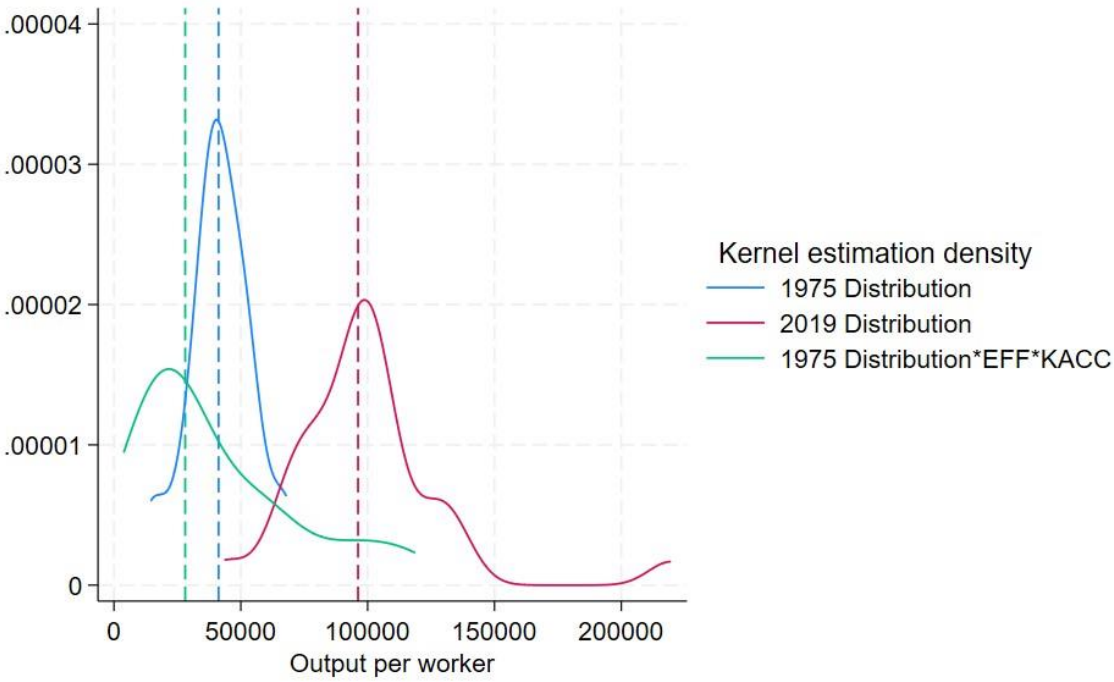
Note: The dotted vertical lines represent the median of each distribution.

Figure A.2: Effect of Efficiency Change in OECD countries



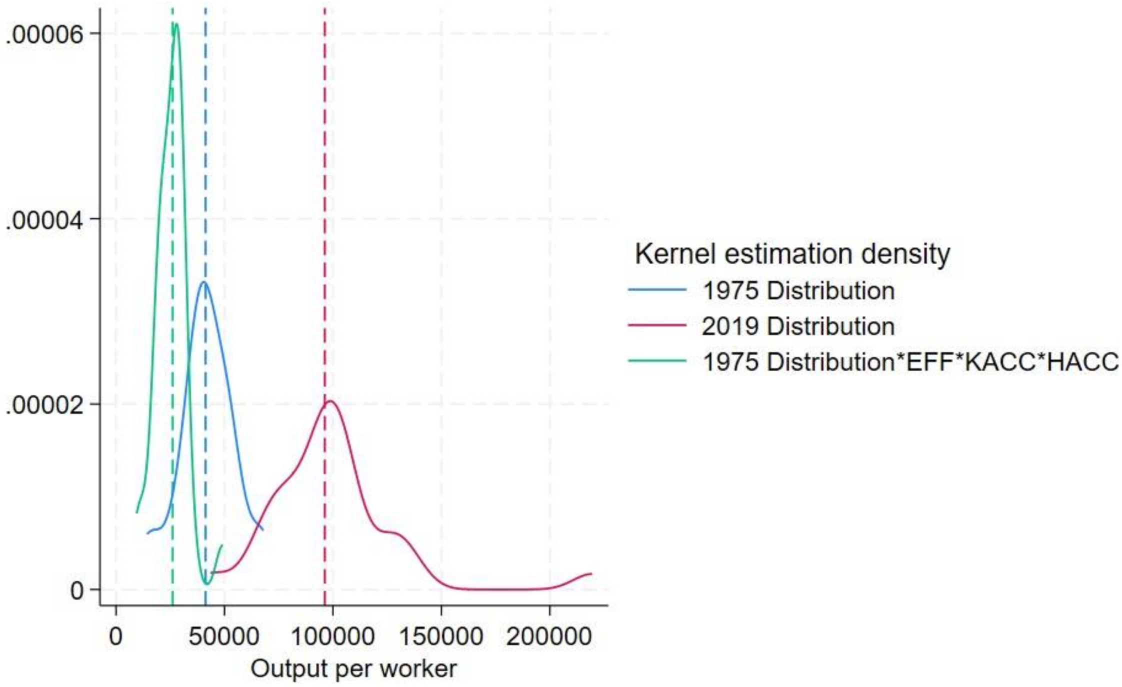
Note: The dotted vertical lines represent the median of each distribution.

Figure A.3: Effect of Capital Deepening in OECD countries



Note: The dotted vertical lines represent the median of each distribution.

Figure A.4: Effect of Human Capital Accumulation in OECD countries



Note: The dotted vertical lines represent the median of each distribution.

Table A.1: OECD: Modality tests (*p values*)

	Distribution	H0: One mode H1: More than one mode
1	f(y2019)	0.0210
2	f(y1975)	0.5390
3	f(y1975*EFF)	0.2500
4	f(y1975*TECH)	0.1810
5	f(y1975*KACC)	0.5950
6	f(y1975*HACC)	0.1410
7	f(y1975*EFF*TECH)	0.1420
8	f(y1975*EFF*KACC)	0.5570
9	f(y1975*EFF*HACC)	0.0400
10	f(y1975*TECH*HACC)	0.0920
11	f(y1975*TECH*KACC)	0.6110
12	f(y1975*KACC*HACC)	0.6950
13	f(y1975*EFF*TECH*KACC)	0.5590
14	f(y1975*EFF*TECH*HACC)	0.0480
15	f(y1975*EFF*KACC*HACC)	0.0670
16	f(y1975*TECH*KACC*HACC)	0.0680

Notes: The bootstrapped Silverman (1981) test for multimodality is used as described in Izenman and Sommer (1988), with 1000 bootstrap replications.

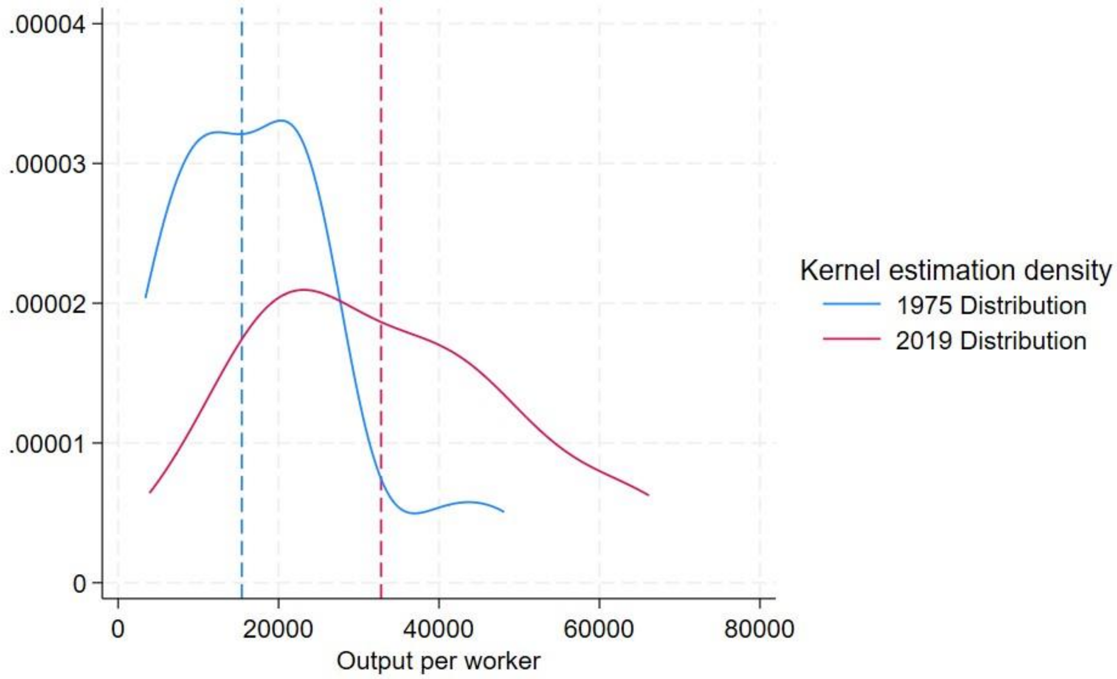
Table A.2: OECD: Distribution hypothesis tests (*p values*)

	H0: Distributions are equal H1: Distributions are not equal	KS *p value*	GK *p value*
1	g(y2019) vs. f(y1975)	0.0000	0.0001
2	g(y2019) vs. f(y1975*EFF)	0.0030	0.0003
3	g(y2019) vs. f(y1975*TECH)	0.3290	0.0544
4	g(y2019) vs. f(y1975*KACC)	0.0030	0.0004
5	g(y2019) vs. f(y1975*HACC)	0.1890	0.0220
6	g(y2019) vs. f(y1975*EFF*TECH)	0.1880	0.0544
7	g(y2019) vs. f(y1975*EFF*KACC)	0.0030	0.0009
8	g(y2019) vs. f(y1975*EFF*HACC)	0.1000	0.0544
9	g(y2019) vs. f(y1975*TECH*KACC)	0.0030	0.0030
10	g(y2019) vs. f(y1975*TECH*HACC)	0.0480	0.0224
11	g(y2019) vs. f(y1975*KACC*HACC)	0.0000	0.0001
12	g(y2019) vs. f(y1975*EFF*TECH*KACC)	0.0010	0.0012
13	g(y2019) vs. f(y1975*EFF*TECH*HACC)	0.0090	0.0016
14	g(y2019) vs. f(y1975*EFF*KACC*HACC)	0.0090	0.0030
15	g(y2019) vs. f(y1975*TECH*KACC*HACC)	0.9360	0.9354

Notes: The functions g(.) and f(.) are (kernel) distribution functions. The Kolmogorov-Smirnov and the Goldman and Kaplan (2018) tests are used with 1000 bootstrap replications and the Silverman (1986) adaptive rule-of-thumb bandwidth.

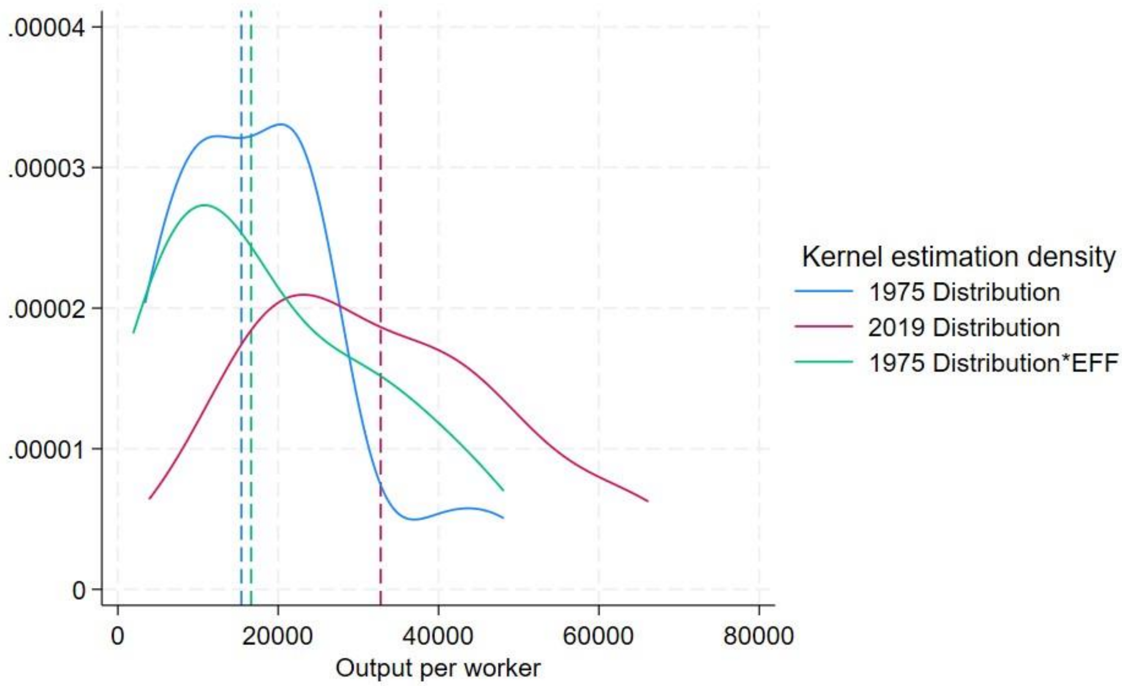
Appendix B: Analysis of the distribution of output per worker in Latin and Central American countries: 1975-2019

Figure B.1: Output per worker distribution in Latin and Central America countries



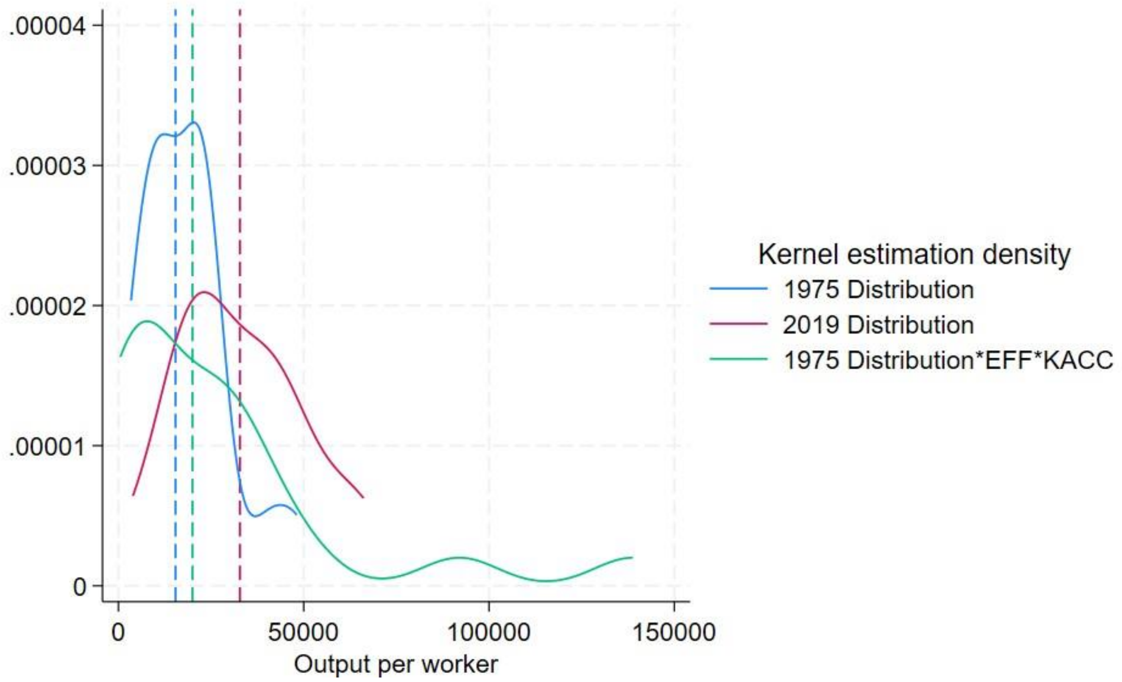
Note: The dotted vertical lines represent the median of each distribution.

Figure B.2: Effect of Efficiency Change in Latin and Central America countries



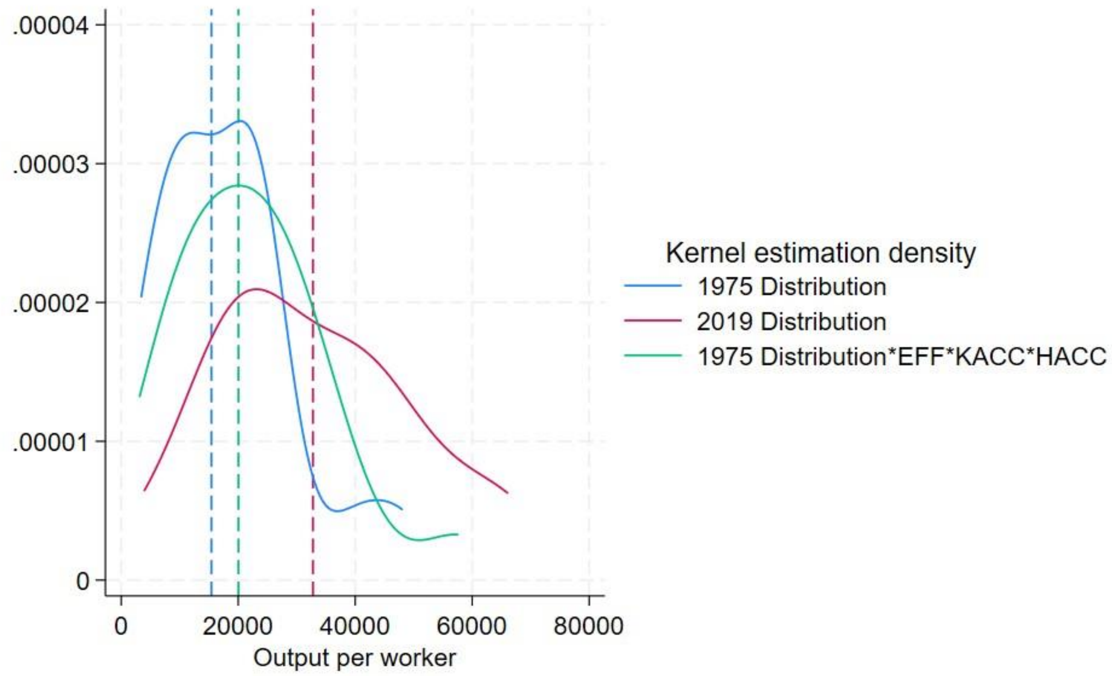
Note: The dotted vertical lines represent the median of each distribution.

Figure B.3: Effect of Capital Deepening in Latin And Central America countries



Note: The dotted vertical lines represent the median of each distribution.

Figure B.4: Effect of Human Capital Accumulation in Latin And Central America countries



Note: The dotted vertical lines represent the median of each distribution.

Table B.1: Latin and Central America: Modality tests (*p values*)

	Distribution	H0: One mode H1: More than one mode
1	f(y2019)	0.6110
2	f(y1975)	0.2990
3	f(y1975*EFF)	0.8100
4	f(y1975*TECH)	0.8060
5	f(y1975*KACC)	0.7640
6	f(y1975*HACC)	0.3230
7	f(y1975*EFF*TECH)	0.9100
8	f(y1975*EFF*KACC)	0.2870
9	f(y1975*EFF*HACC)	0.1210
10	f(y1975*TECH*HACC)	0.8780
11	f(y1975*TECH*KACC)	0.2580
12	f(y1975*KACC*HACC)	0.0320
13	f(y1975*EFF*TECH*KACC)	0.3290
14	f(y1975*EFF*TECH*HACC)	0.8600
15	f(y1975*EFF*KACC*HACC)	0.2560
16	f(y1975*TECH*KACC*HACC)	0.1800

Notes: the bootstrapped Silverman (1981) test for multimodality is used as described in Izenman and Sommer (1988), with 1000 bootstrap replications.

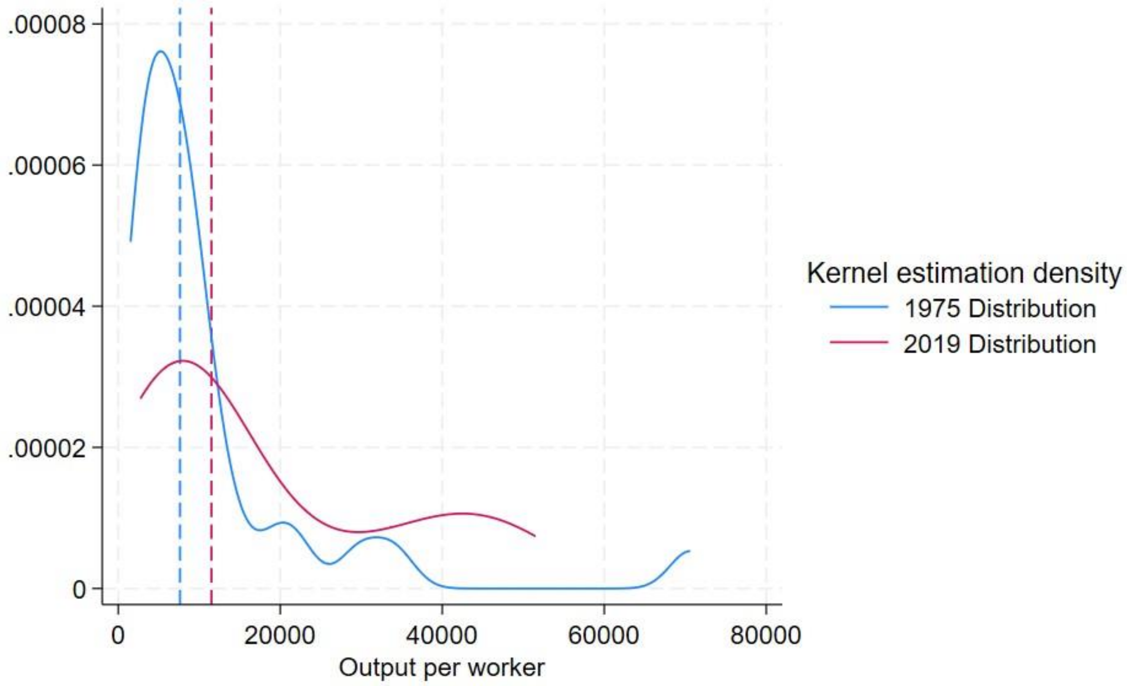
Table B.2: Latin and Central American Distribution hypothesis tests (*p values*)

	H0: Distributions are equal H1: Distributions are not equal	KS *p value*	GK *p value*
1	g(y2019) vs. f(y1975)	0.0680	0.0149
2	g(y2019) vs. f(y1975*EFF)	0.5380	0.2079
3	g(y2019) vs. f(y1975*TECH)	0.0680	0.0149
4	g(y2019) vs. f(y1975*KACC)	0.8080	0.8195
5	g(y2019) vs. f(y1975*HACC)	1.0000	0.9758
6	g(y2019) vs. f(y1975*EFF*TECH)	0.0030	0.0006
7	g(y2019) vs. f(y1975*EFF*KACC)	0.0030	0.0006
8	g(y2019) vs. f(y1975*EFF*HACC)	0.1530	0.1338
9	g(y2019) vs. f(y1975*TECH*KACC)	0.0000	0.0001
10	g(y2019) vs. f(y1975*TECH*HACC)	0.8080	0.4328
11	g(y2019) vs. f(y1975*KACC*HACC)	0.3060	0.0917
12	g(y2019) vs. f(y1975*EFF*TECH*KACC)	0.0000	0.0001
13	g(y2019) vs. f(y1975*EFF*TECH*HACC)	0.3060	0.0917
14	g(y2019) vs. f(y1975*EFF*KACC*HACC)	0.3050	0.0917
15	g(y2019) vs. f(y1975*TECH*KACC*HACC)	0.0680	0.0149

Notes: The functions g(.) and f(.) are (kernel) distribution functions. The Kolmogorov-Smirnov and the Goldman and Kaplan (2018) tests are used with 1000 bootstrap replications and the Silverman (1986) adaptive rule-of-thumb bandwidth.

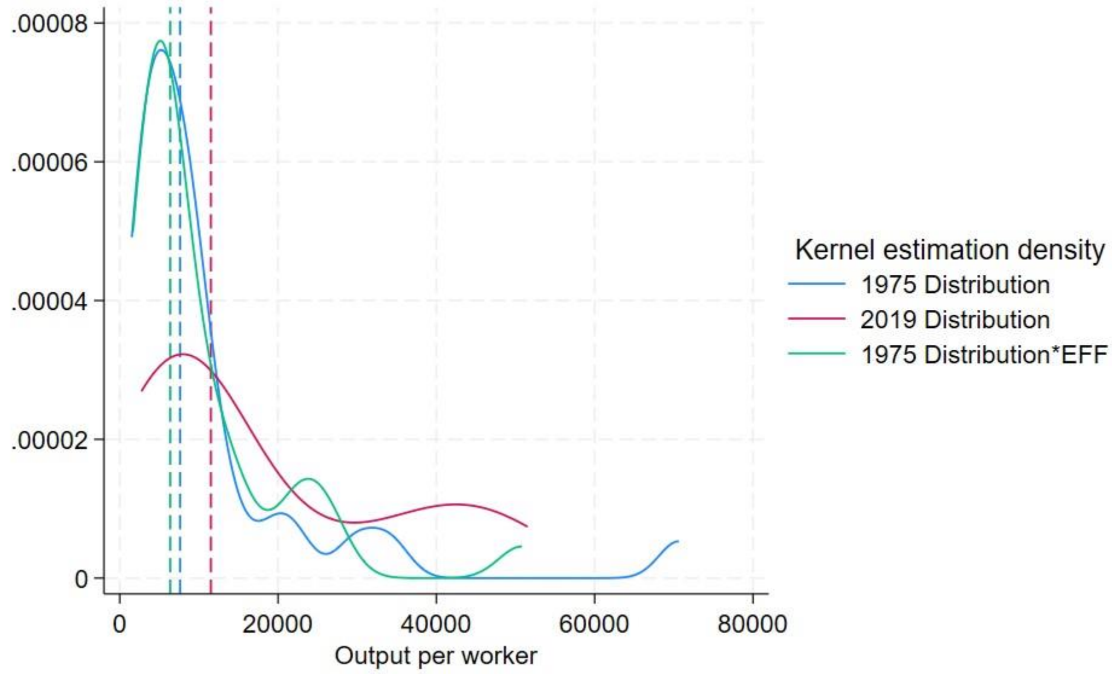
Appendix C: Analysis of the distribution of output per worker in African countries: 1975-2019

Figure C.1: Output per worker distribution in African countries



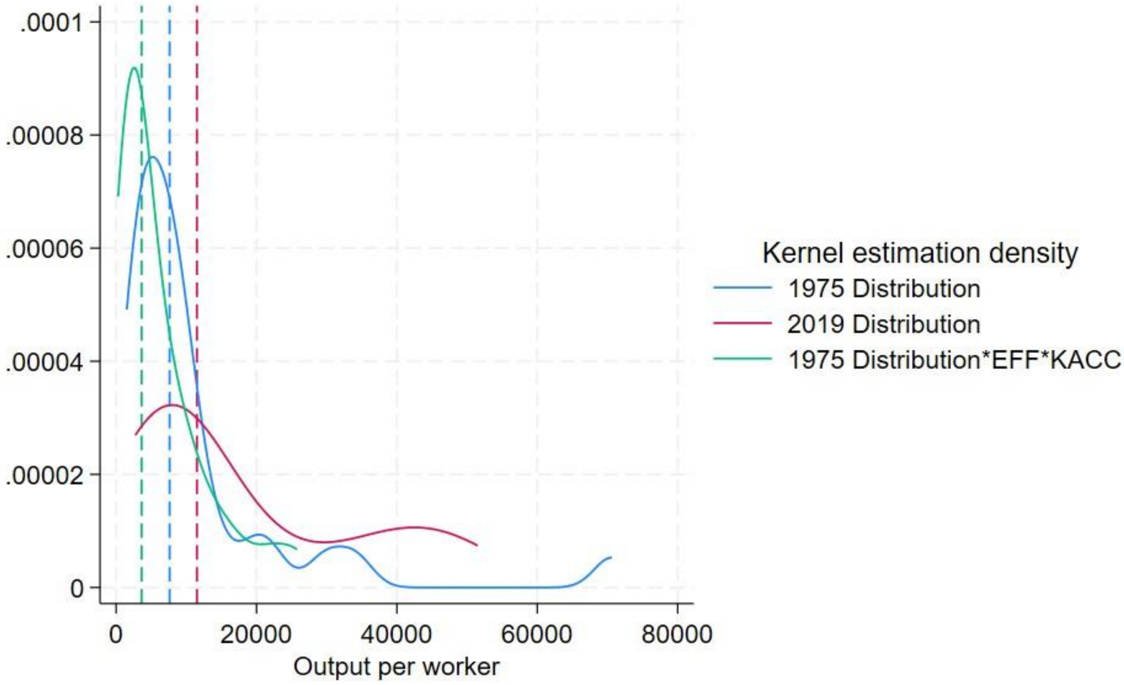
Note: The dotted vertical lines represent the median of each distribution.

Figure C.2: Effect of Efficiency Change in African countries



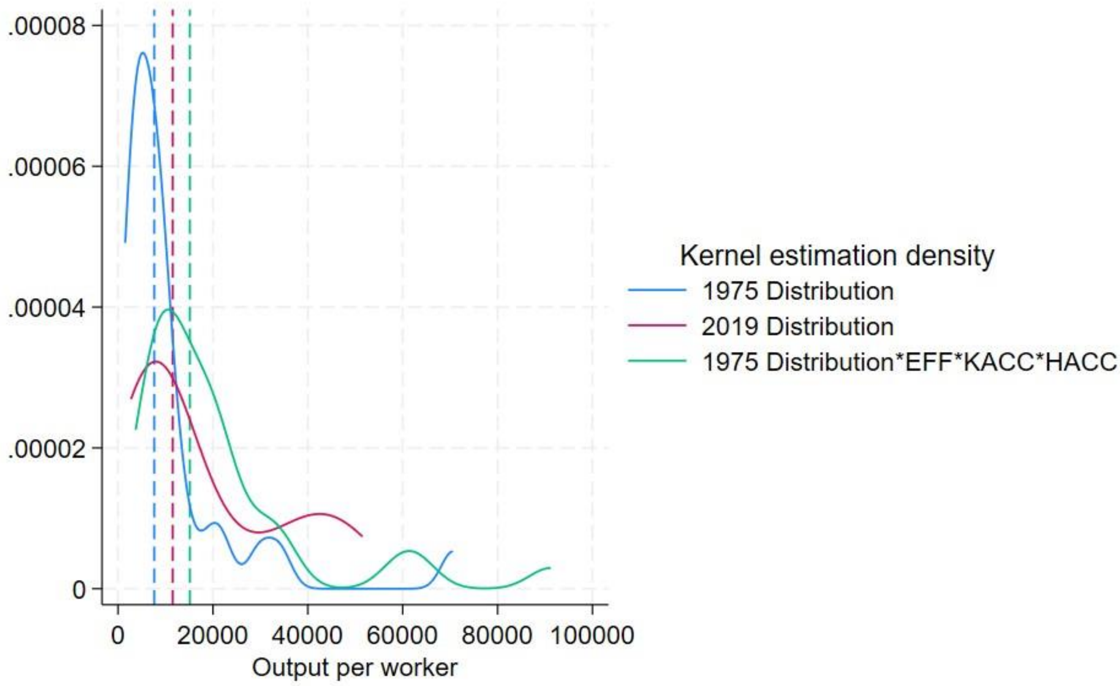
Note: The dotted vertical lines represent the median of each distribution.

Figure C.3: Effect of Capital Deepening in African countries



Note: The dotted vertical lines represent the median of each distribution.

Figure C.4: Effect of Human Capital Accumulation in African countries



Note: The dotted vertical lines represent the median of each distribution.

Table C.1: Africa: Modality tests (*p values*)

	Distribution	H0: One mode H1: More than one mode
1	f(y2019)	0.0520
2	f(y1975)	0.0210
3	f(y1975*EFF)	0.0710
4	f(y1975*TECH)	0.1650
5	f(y1975*KACC)	0.2980
6	f(y1975*HACC)	0.7540
7	f(y1975*EFF*TECH)	0.0100
8	f(y1975*EFF*KACC)	0.6240
9	f(y1975*EFF*HACC)	0.6820
10	f(y1975*TECH*HACC)	0.0140
11	f(y1975*TECH*KACC)	0.7890
12	f(y1975*KACC*HACC)	0.3840
13	f(y1975*EFF*TECH*KACC)	0.0230
14	f(y1975*EFF*TECH*HACC)	0.0080
15	f(y1975*EFF*KACC*HACC)	0.4080
16	f(y1975*TECH*KACC*HACC)	0.6430

Notes: The bootstrapped Silverman (1981) test for multimodality is used as described in Izenman and Sommer (1988), with 1000 bootstrap replications.

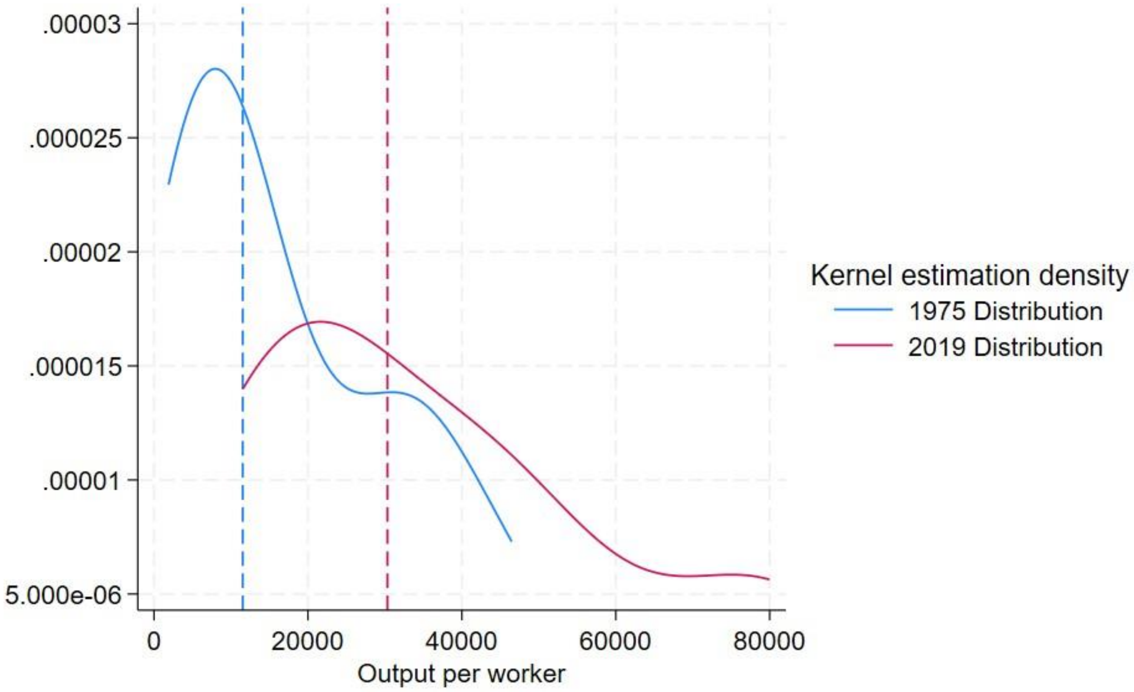
Table C.2: Africa: Distribution hypothesis tests (*p values*)

	H0: Distributions are equal H1: Distributions are not equal	KS *p value*	GK *p value*
1	g(y2019) vs. f(y1975)	0.0000	0.0002
2	g(y2019) vs. f(y1975*EFF)	0.0350	0.0062
3	g(y2019) vs. f(y1975*TECH)	0.0001	0.0011
4	g(y2019) vs. f(y1975*KACC)	0.0070	0.0043
5	g(y2019) vs. f(y1975*HACC)	0.0000	0.0001
6	g(y2019) vs. f(y1975*EFF*TECH)	0.0010	0.0011
7	g(y2019) vs. f(y1975*EFF*KACC)	0.0350	0.0022
8	g(y2019) vs. f(y1975*EFF*HACC)	0.0000	0.0001
9	g(y2019) vs. f(y1975*TECH*KACC)	0.0000	0.0001
10	g(y2019) vs. f(y1975*TECH*HACC)	0.0000	0.0001
11	g(y2019) vs. f(y1975*KACC*HACC)	0.0000	0.0001
12	g(y2019) vs. f(y1975*EFF*TECH*KACC)	0.0000	0.0001
13	g(y2019) vs. f(y1975*EFF*TECH*HACC)	0.0000	0.0001
14	g(y2019) vs. f(y1975*EFF*KACC*HACC)	0.0000	0.0002
15	g(y2019) vs. f(y1975*TECH*KACC*HACC)	0.0710	0.0161

Notes: The functions g(.) and f(.) are (kernel) distribution functions. The Kolmogorov-Smirnov and the Goldman and Kaplan (2018) tests are used with 1000 bootstrap replications and the Silverman (1986) adaptive rule-of-thumb bandwidth.

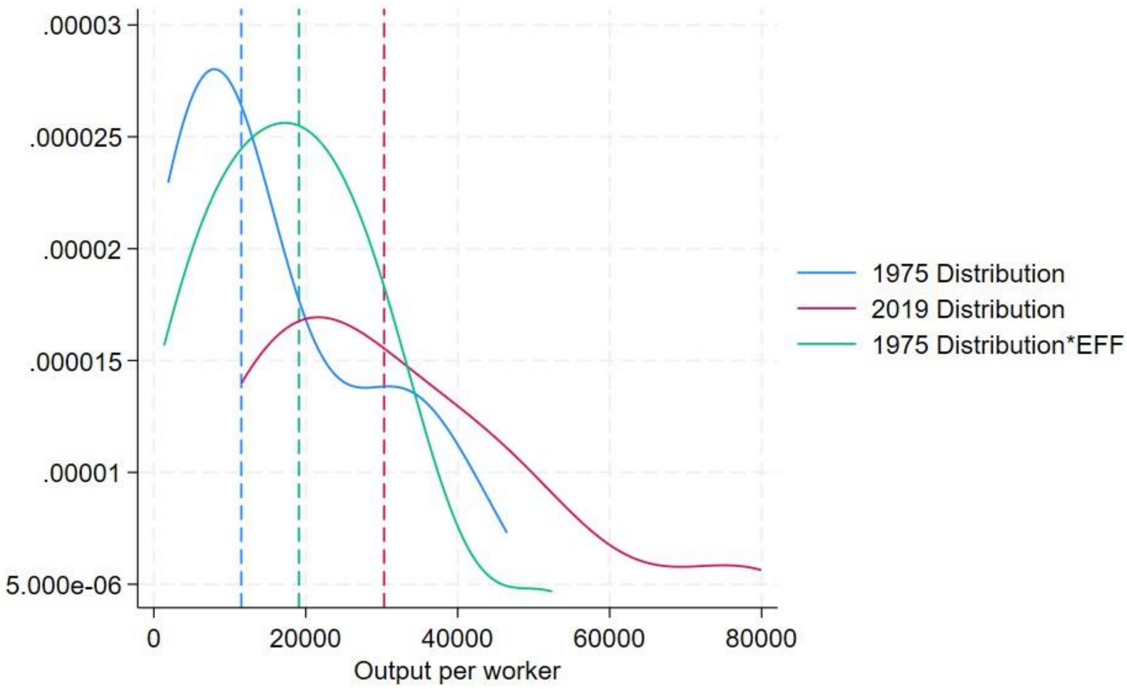
Appendix D: Analysis of the distribution of output per worker in Asian countries: 1975-2019

Figure D.1: Output per worker distribution in Asian countries



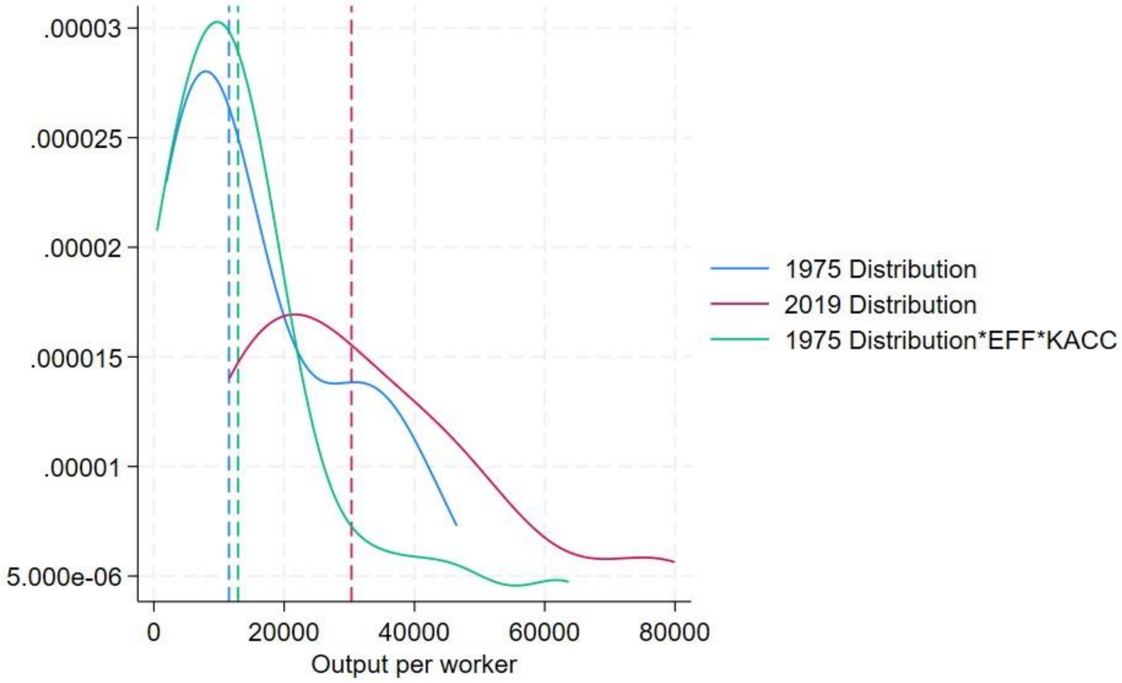
Note: The dotted vertical lines represent the median of each distribution.

Figure D.2: Effect of Efficiency Change in Asian countries



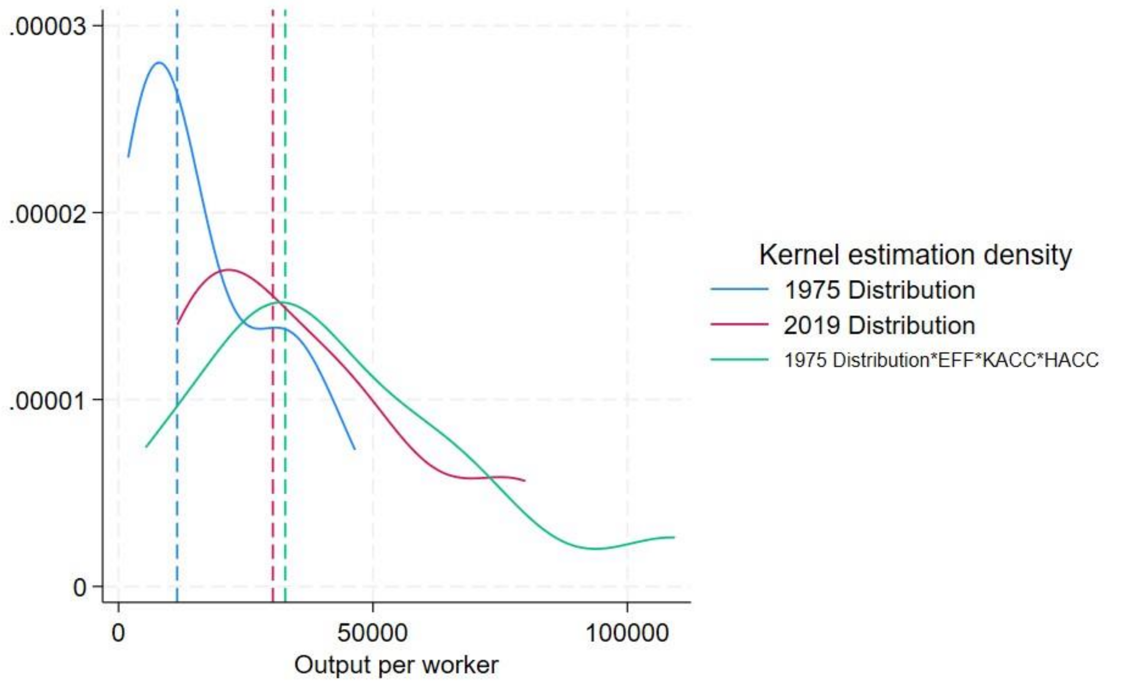
Note: The dotted vertical lines represent the median of each distribution.

Figure D.3: Effect of Capital Deepening in Asian countries



Note: The dotted vertical lines represent the median of each distribution.

Figure D.4: Effect of Human Capital Accumulation in Asian countries



Note: The dotted vertical lines represent the median of each distribution.

Table D.1: Asia: Modality tests (*p values*)

	Distribution	H0: One mode H1: More than one mode
1	f(y2019)	0.3660
2	f(y1975)	0.3170
3	f(y1975*EFF)	0.4300
4	f(y1975*TECH)	0.2500
5	f(y1975*KACC)	0.0550
6	f(y1975*HACC)	0.7540
7	f(y1975*EFF*TECH)	0.6910
8	f(y1975*EFF*KACC)	0.7160
9	f(y1975*EFF*HACC)	0.1170
10	f(y1975*TECH*HACC)	0.4970
11	f(y1975*TECH*KACC)	0.4110
12	f(y1975*KACC*HACC)	0.2190
13	f(y1975*EFF*TECH*KACC)	0.8070
14	f(y1975*EFF*TECH*HACC)	0.1360
15	f(y1975*EFF*KACC*HACC)	0.3450
16	f(y1975*TECH*KACC*HACC)	0.2430

Notes: The bootstrapped Silverman (1981) test for multimodality is used as described in Izenman and Sommer (1988), with 1000 bootstrap replications.

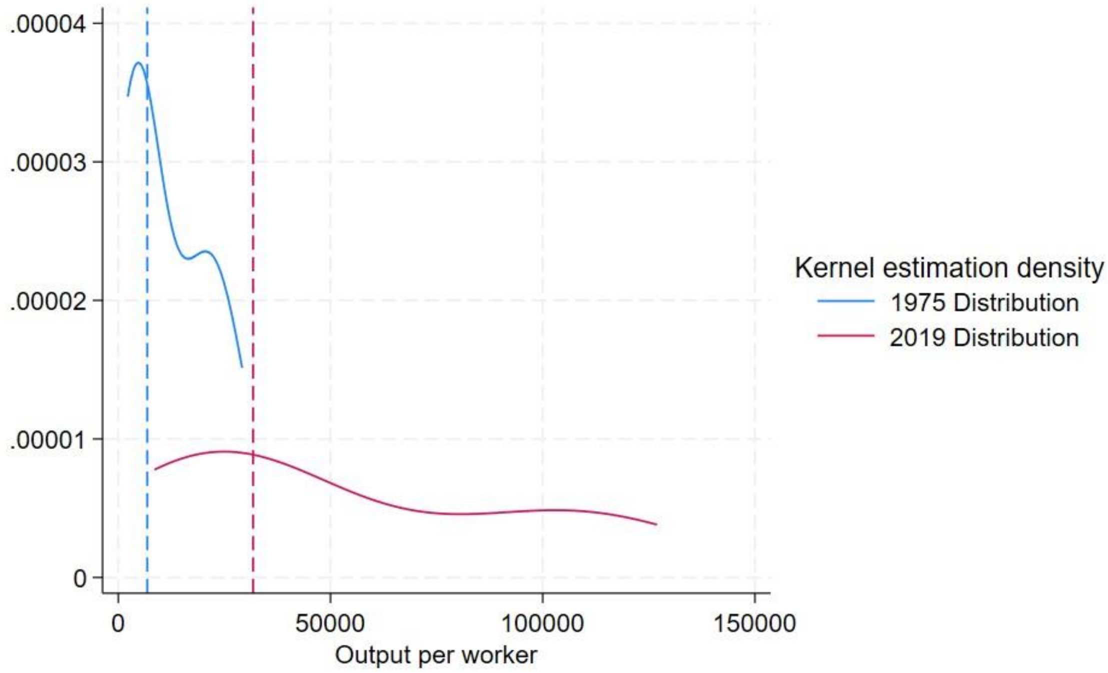
Table D.2: Asia Distribution hypothesis tests (*p values*)

	H0: Distributions are equal H1: Distributions are not equal	KS *p value*	GK *p value*
1	g(y2019) vs. f(y1975)	0.5360	0.2909
2	g(y2019) vs. f(y1975*EFF)	0.2560	0.1259
3	g(y2019) vs. f(y1975*TECH)	0.5360	0.2909
4	g(y2019) vs. f(y1975*KACC)	0.5320	0.2910
5	g(y2019) vs. f(y1975*HACC)	0.0000	0.0003
6	g(y2019) vs. f(y1975*EFF*TECH)	0.2560	0.1770
7	g(y2019) vs. f(y1975*EFF*KACC)	0.8690	0.6285
8	g(y2019) vs. f(y1975*EFF*HACC)	0.0010	0.0010
9	g(y2019) vs. f(y1975*TECH*KACC)	0.1000	0.0687
10	g(y2019) vs. f(y1975*TECH*HACC)	0.008	0.007
11	g(y2019) vs. f(y1975*KACC*HACC)	0.2560	0.1254
12	g(y2019) vs. f(y1975*EFF*TECH*KACC)	0.0310	0.0140
13	g(y2019) vs. f(y1975*EFF*TECH*HACC)	0.0310	0.0233
14	g(y2019) vs. f(y1975*EFF*KACC*HACC)	0.5360	0.2909
15	g(y2019) vs. f(y1975*TECH*KACC*HACC)	0.8690	0.6282

Notes: The functions g(.) and f(.) are (kernel) distribution functions. The Kolmogorov-Smirnov and the Goldman and Kaplan (2018) tests are used with 1000 bootstrap replications and the Silverman (1986) adaptive rule-of-thumb bandwidth.

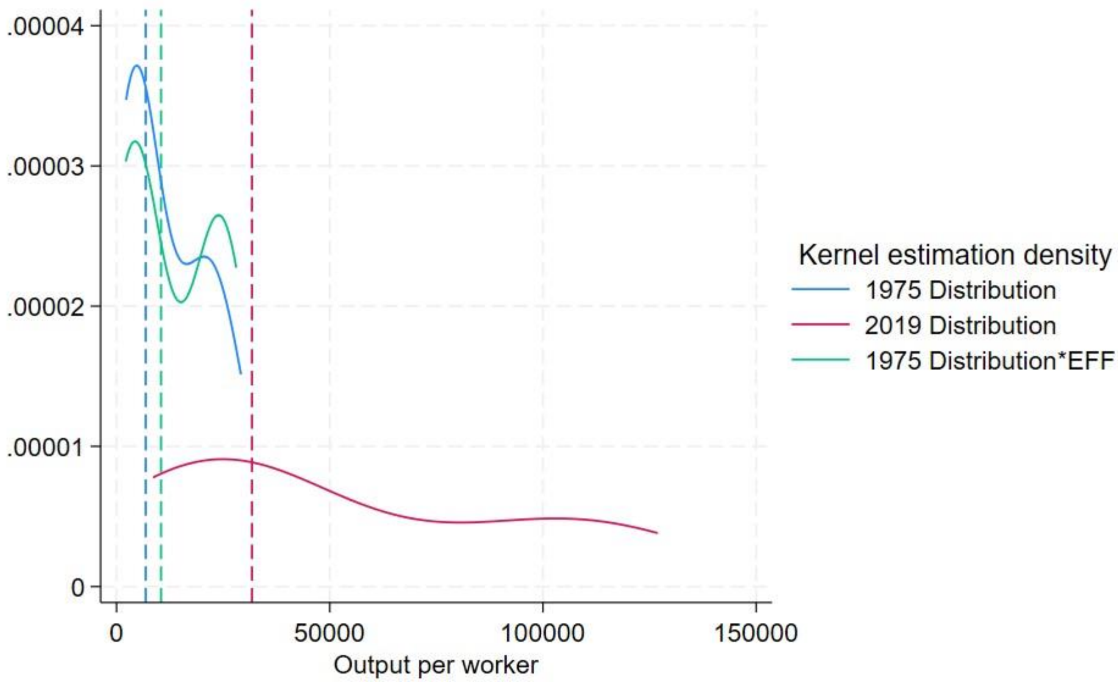
Appendix E: Analysis of the distribution of output per worker in East Asian countries: 1975-2019

Figure E.1: Output per worker distribution in East Asian countries



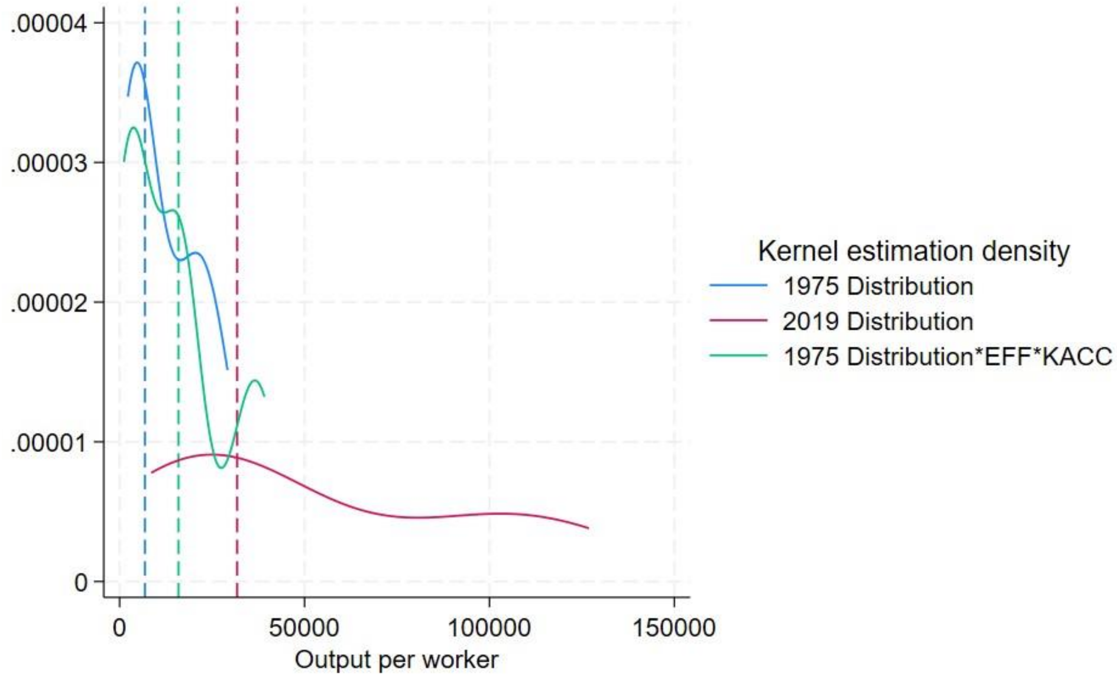
Note: The dotted vertical lines represent the median of each distribution.

Figure E.2: Effect of Efficiency Change in East Asia countries



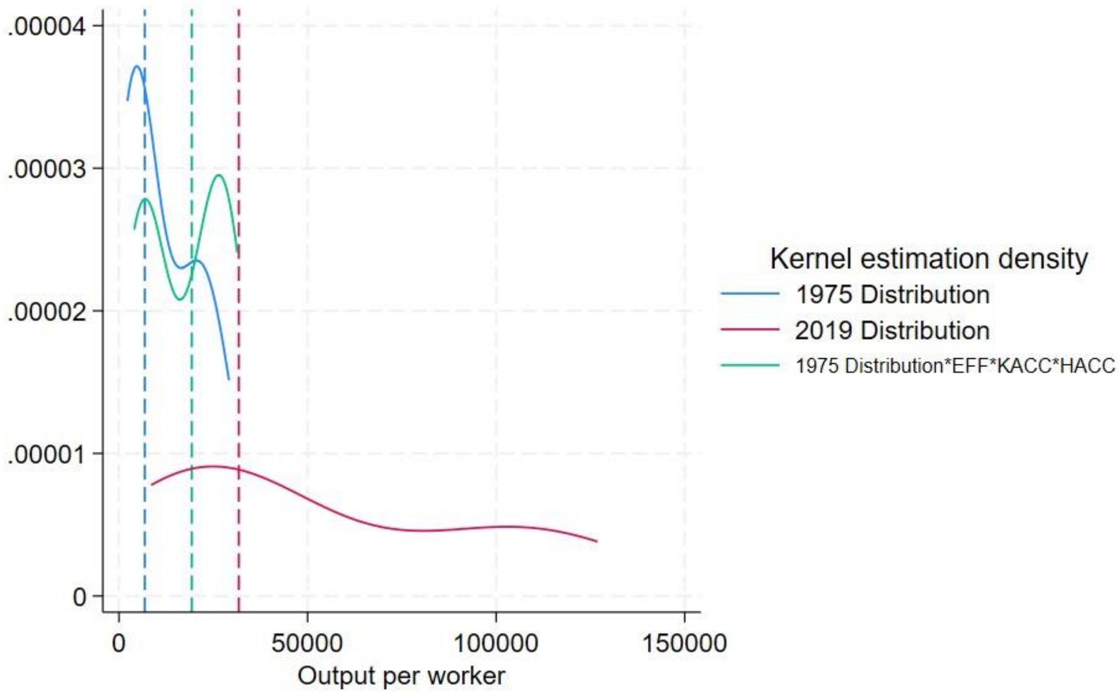
Note: The dotted vertical lines represent the median of each distribution.

Figure E.3: Effect of Capital Deepening in East Asia countries



Note: The dotted vertical lines represent the median of each distribution.

Figure E.4: Effect of Human Capital Accumulation in East Asia countries



Note: The dotted vertical lines represent the median of each distribution.

Table E.1: East Asia: Modality tests (*p values*)

	Distribution	H0: One mode H1: More than one mode
1	f(y2019)	0.2370
2	f(y1975)	0.2570
3	f(y1975*EFF)	0.0740
4	f(y1975*TECH)	0.4400
5	f(y1975*KACC)	0.4680
6	f(y1975*HACC)	0.2160
7	f(y1975*EFF*TECH)	0.2180
8	f(y1975*EFF*KACC)	0.2990
9	f(y1975*EFF*HACC)	0.3430
10	f(y1975*TECH*HACC)	0.1150
11	f(y1975*TECH*KACC)	0.1820
12	f(y1975*KACC*HACC)	0.1360
13	f(y1975*EFF*TECH*KACC)	0.1730
14	f(y1975*EFF*TECH*HACC)	0.1920
15	f(y1975*EFF*KACC*HACC)	0.0480
16	f(y1975*TECH*KACC*HACC)	0.4290

Notes: The bootstrapped Silverman (1981) test for multimodality is used as described in Izenman and Sommer (1988), with 1000 bootstrap replications.

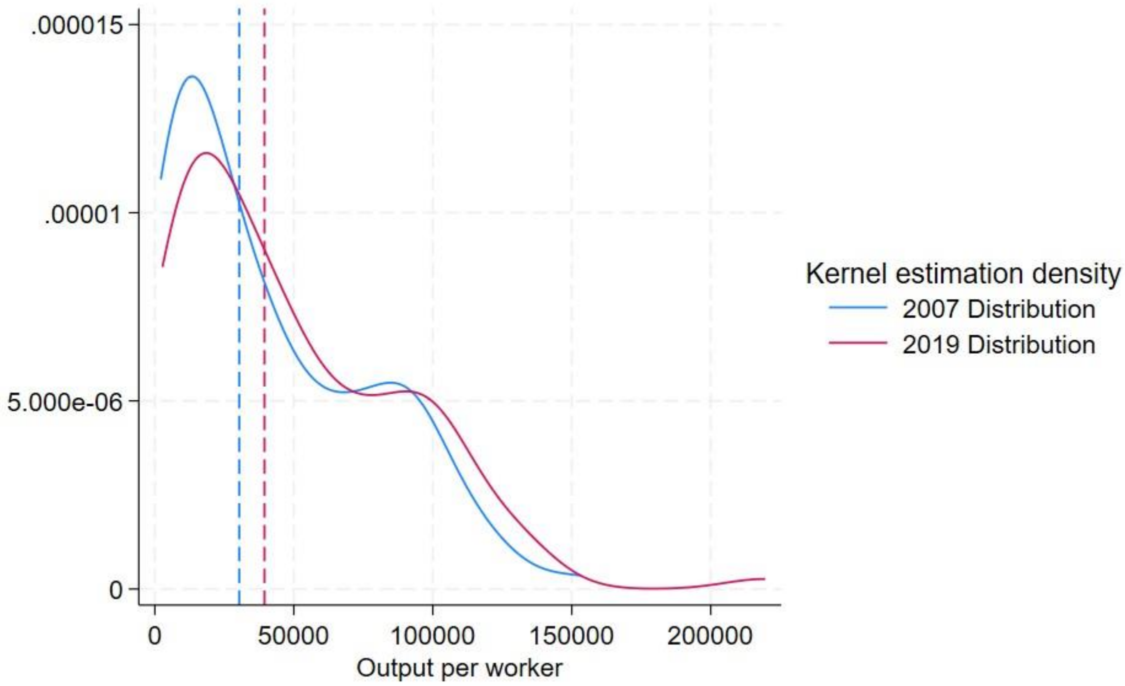
Table E.2: East Asia: Distribution hypothesis tests (*p values*)

	H0: Distributions are equal H1: Distributions are not equal	KS *p value*	GK *p value*
1	g(y2019) vs. f(y1975)	0.0010	0.0056
2	g(y2019) vs. f(y1975*EFF)	0.0000	0.0001
3	g(y2019) vs. f(y1975*TECH)	0.7300	0.6121
4	g(y2019) vs. f(y1975*KACC)	0.0010	0.0006
5	g(y2019) vs. f(y1975*HACC)	0.0340	0.0181
6	g(y2019) vs. f(y1975*EFF*TECH)	0.3520	0.2086
7	g(y2019) vs. f(y1975*EFF*KACC)	0.0060	0.0043
8	g(y2019) vs. f(y1975*EFF*HACC)	0.0010	0.0006
9	g(y2019) vs. f(y1975*TECH*KACC)	0.3520	0.2086
10	g(y2019) vs. f(y1975*TECH*HACC)	0.7300	0.7307
11	g(y2019) vs. f(y1975*KACC*HACC)	0.0000	0.0005
12	g(y2019) vs. f(y1975*EFF*TECH*KACC)	0.1260	0.0684
13	g(y2019) vs. f(y1975*EFF*TECH*HACC)	0.7310	0.4976
14	g(y2019) vs. f(y1975*EFF*KACC*HACC)	0.0000	0.0005
15	g(y2019) vs. f(y1975*TECH*KACC*HACC)	0.9890	0.8801

Notes: The functions g(.) and f(.) are (kernel) distribution functions. The Kolmogorov-Smirnov and the Goldman and Kaplan (2018) tests are used with 1000 bootstrap replications and the Silverman (1986) adaptive rule-of-thumb bandwidth.

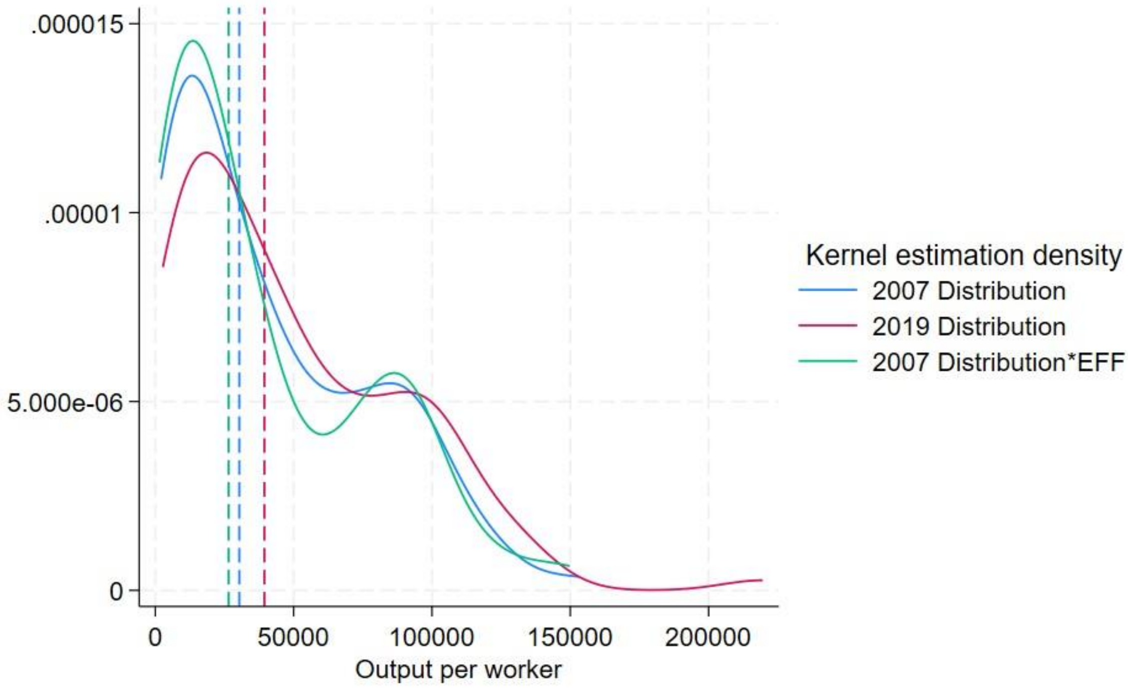
Appendix F. Analysis of the world distribution of output per worker, 2007-2019

Figure F.1: Output per worker distribution



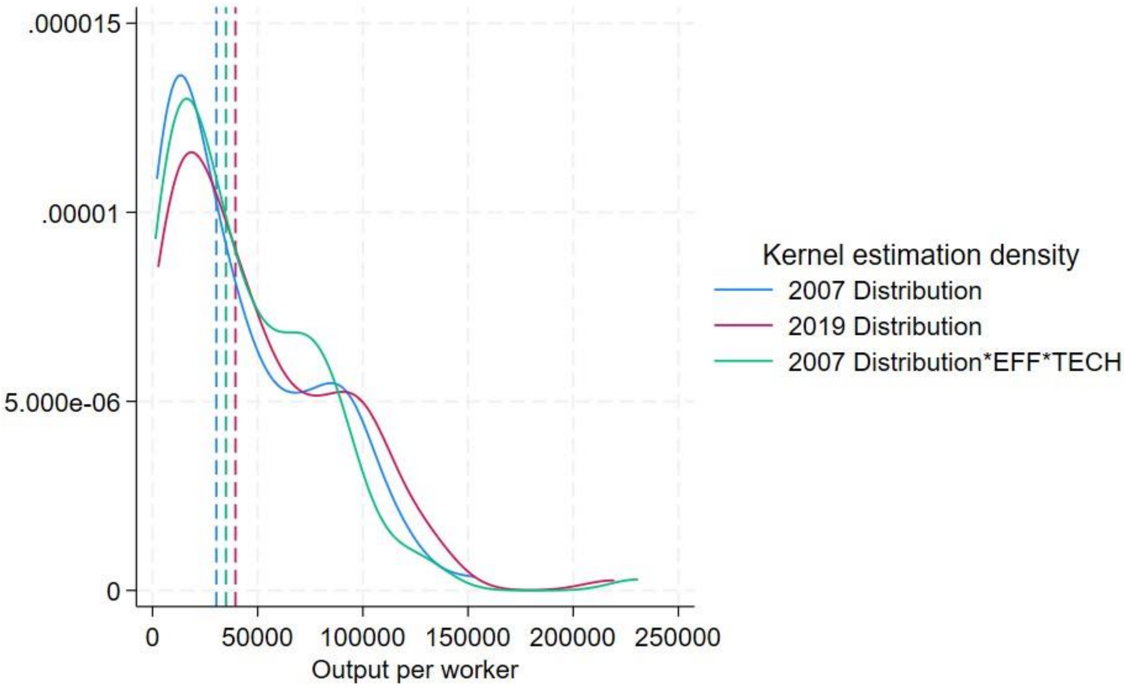
Note: The dotted vertical lines represent the median of each distribution.

Figure F.2: Effect of efficiency change



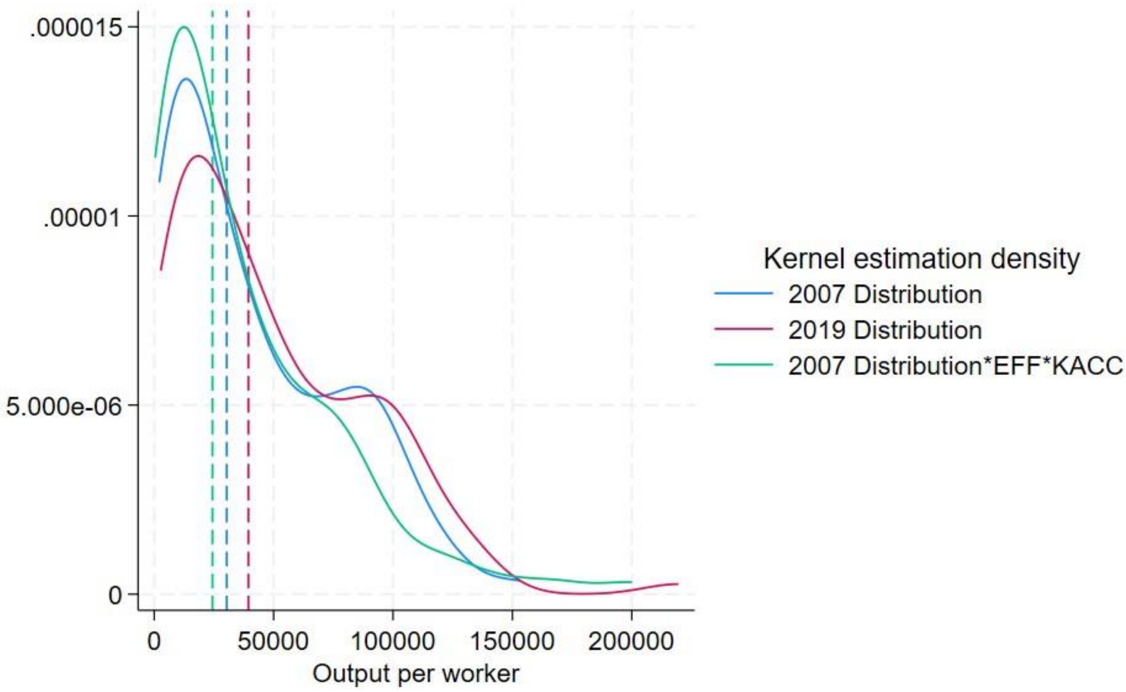
Note: The dotted vertical lines represent the median of each distribution.

Figure F.3: Effect of technology change and efficiency change



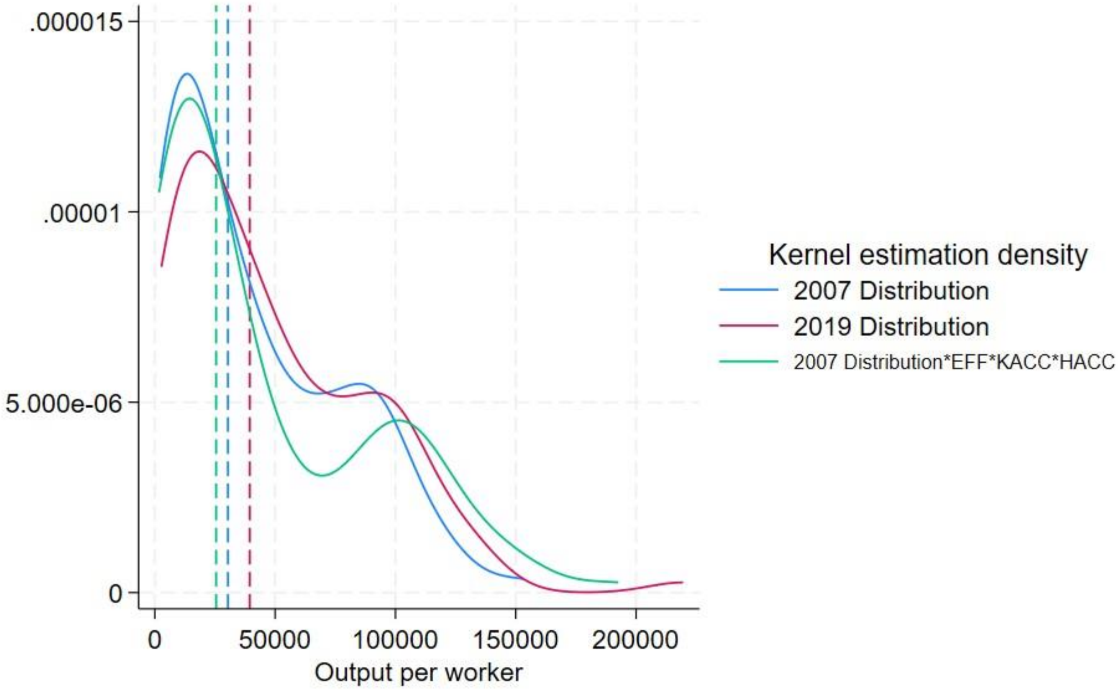
Note: The dotted vertical lines represent the median of each distribution.

Figure F.4: Effect of physical capital deepening and efficiency change



Note: The dotted vertical lines represent the median of each distribution.

Figure F.5: Effect of Human Capital Accumulation, Capital Deepening, and Efficiency Change



Note: The dotted vertical lines represent the median of each distribution.

Table F.1: Modality tests (*p values*)

	Distribution	H0: One mode H1: More than one mode
1	f(y2019)	0.0700
2	f(y2007)	0.2090
3	f(y2007*EFF)	0.0120
4	f(y2007*TECH)	0.0130
5	f(y2007*KACC)	0.2860
6	f(y2007*HACC)	0.0450
7	f(y2007*EFF*TECH)	0.0340
8	f(y2007*EFF*KACC)	0.7640
9	f(y2007*EFF*HACC)	0.4120
10	f(y2007*TECH*HACC)	0.0550
11	f(y2007*TECH*KACC)	0.0990
12	f(y2007*KACC*HACC)	0.0140
13	f(y2007*EFF*TECH*KACC)	0.3190
14	f(y2007*EFF*TECH*HACC)	0.2580
15	f(y2007*EFF*KACC*HACC)	0.0230
16	f(y2007*TECH*KACC*HACC)	0.0740

Notes: The bootstrapped Silverman (1981) test for multimodality is used as described in Izenman and Sommer (1988), with 1000 bootstrap replications.

Table F.2: Distribution hypothesis tests (*p values*)

	H0: Distributions are equal H1: Distributions are not equal	KS test P-Value	GK test P-Value
1	g(y2019) vs. f(y2007)	0.0390	0.0042
2	g(y2019) vs. f(y2007*EFF)	0.0120	0.0001
3	g(y2019) vs. f(y2007*TECH)	0.8600	0.3680
4	g(y2019) vs. f(y2007*KACC)	0.0120	0.0001
5	g(y2019) vs. f(y2007*HACC)	0.0220	0.0169
6	g(y2019) vs. f(y2007*EFF*TECH)	0.5490	0.7272
7	g(y2019) vs. f(y2007*EFF*KACC)	0.0390	0.0042
8	g(y2019) vs. f(y2007*EFF*HACC)	0.0390	0.0451
9	g(y2019) vs. f(y2007*TECH*KACC)	0.2720	0.4554
10	g(y2019) vs. f(y2007*TECH*HACC)	0.2720	0.0346
11	g(y2019) vs. f(y2007*KACC*HACC)	0.0220	0.0003
12	g(y2019) vs. f(y2007*EFF*TECH*KACC)	0.1120	0.1736
13	g(y2019) vs. f(y2007*EFF*TECH*HACC)	0.2720	0.0533
14	g(y2019) vs. f(y2007*EFF*KACC*HACC)	0.1120	0.0292
15	g(y2019) vs. f(y2007*TECH*KACC*HACC)	0.7170	0.8293

Notes: The functions g(.) and f(.) are (kernel) distribution functions. The Kolmogorov-Smirnov and the Goldman and Kaplan (2018) tests are used with 1000 bootstrap replications and the Silverman (1986) adaptive rule-of-thumb bandwidth.