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Income inequality: A pursuit race between education and technology

Ansar KERKENI

Department of Economics, Faculty of Economics and Management of Sfax, Tunisia

kerkeni.ansar@gmail.com

Sirine MNIF

Department of Economics, Faculty of Economics and Management of Sfax, Tunisia

mnifsirine@hotmail.fr

Resumen

La suposición subyacente es que la adopción de nuevas tecnologías requiere un alto nivel de capital humano, que a menudo es poco frecuente al comienzo del proceso de difusión de tecnología. Esta escasez conduce a un aumento de los salarios de los trabajadores calificados a expensas de los salarios de los trabajadores no calificados, que se mantienen estables o disminuyen. Esto lleva a un aumento en la desigualdad de ingresos. Pero estas desigualdades también pueden disminuir con el aumento repentino en la oferta de calificaciones. Entonces, por un lado, tenemos un «efecto tecnológico» y, por otro lado, un «efecto educativo». De este modo, obtenemos una evolución cíclica de las desigualdades. Varios estudios lo han demostrado para el caso de países desarrollados. En este trabajo, tratamos de verificar el efecto de las nuevas tecnologías y el efecto de la educación en la desigualdad de ingresos para una muestra de 52 países en desarrollo. Nuestro estudio empírico se basa en la estimación de un modelo econométrico con datos de panel.

Abstract

The adoption of new technologies requires a high level of human capital which is scarce at the start of technological diffusion. This scarcity leads to an increase in the wages of skilled workers at the expense of the wages of unskilled workers, which remain stable or decline. This causes an increase in income inequalities. But these inequalities can also decrease with the sudden rise in the supply of qualifications. So, on the one hand, we have a « technology effect » and on the other hand an « education effect ». We thus obtain a cyclical evolution of inequalities. This is well proven in the context of developed countries. In this work, we try to verify the effect of new technologies and the effect of education on income inequality for a sample of 52 developing countries. Our empirical study is based on Econometric Model with panel data estimation.

Key words: Apiculture, honey, production, exports

Keywords: Technological changes, Education, Inequalities.

JEL classification: C23 - D31 - D63 - J31 - O33.

Introduction

The introduction of technology has historically led to a massive rise in unemployment. Analyses such as those of Aghion and Howitt (1992, 1994) argue that the diffusion of technology leads to unemployment of re-allocation between sectors whose jobs are destroyed and those where there is job creation. In an economy where competition forces companies to innovate, innovation leads to the perpetual renewal of goods produced and an increased job turnover. This is called “creative destruction”.

Technical progress seems to be the most plausible explanation for the increase in pay and employment gaps at the expense of less skilled workers. One of the arguments put forward in support of this thesis is that skilled workers are best able to implement new technologies within a company.

Schumpeter (1961) shows how innovations explain cyclical movements in growth. The expansion phase is fueled by profits made by innovators, followed by the appearance of new producers. As a result, when the market is saturated, the product will be commoditized, productivity gains will be exhausted and competition will increase. Falling profits lead to recession or depression.

This paper is organized as follows: In the first section we present the review of the literature, and in the second section, we turn to empirical analysis where we will test the effect of new technologies and the effect of education on income inequality using the econometric model with panel data estimation.

1. Literature review

The debate on the determinants of inequality at national level has been the result of many economic developments. This observation was proposed by Kuznets (1955) via his U-reversed curve. The starting point of this model is that every region has a poorly paid agricultural workforce, but what is transitioning to higher wages is the industrial sector. The more the region develops, the more the wage of the first worker who moves to the industrial sector increases, which increases inequality. After a certain period of time, the number of workers who will move to the industrial sector increases and wages in turn increase, which will result in a decrease in inequality. In this way, then, inequality takes the form of a U-reversed curve.

Since the 1980s, social inequalities have risen dramatically in several countries, including Western countries. Wages of skilled workers have increased more than wages of unskilled workers. After the 1960s and 1970s, when wages stabilised in the United States, we saw an explosion in incomes in the 1980s. Katz and Murphy (1992) find that the wages of individuals with higher education increased by 10% between 1971 and 1987, whereas, the wages of workers from secondary education suffered a parallel decline of 20%. Thus, Kruger (1993) argues that these considerable variations in the distribution of wages in the US economy are mainly due to the installation of new technologies. Greenwood and Yorukoglu (1997) confirm this vision.

Given the development of the phenomenon of inequality from the 1980s onwards between different countries and even within the same country, several studies have attempted to explain the different factors of the emergence of this inequality which threatens the well-being of individuals. It should be noted that the rise in inequality has been accompanied by the development of new technologies since the 1970s. Indeed, this observation triggered a new literature linking inequality and technological change. The proliferation of new technologies confirms, then, the challenge of the ever-positive role of these technologies in economic growth in such a way that it is now possible to talk about their negative role in wealth distribution. Extensive literature confirms the hypothesis that technologies are a factor in increasing inequality (Aghion and Howitt, 1998; Galor and Moav, 2000). Technology is thus biased in favour of skills.

Johnson (1997) complements the thesis of biased technological change in favour of the skilled workforce with several forms of innovation and differentiates three types of technological change: intensive, extensive or neutral. Intensive technological change biased in favour of the skilled workforce is a technological change that makes skilled workers more productive such as the diffusion of computers. An extensive technological change biased in favour of the skilled workforce characterizes the positions that have replaced unskilled workers with skilled workers. Technological change is neutral in skilled labour if it increases the productivity of skilled workers as well as unskilled workers in the same proportions.

In the context of the Lisbon Agenda and Europa 2020, innovation has been seen as the key to creating the wealth of the European economy. Similarly, the United States has put policies in place to encourage the process of innovation. They consider, in particular, that investment in the innovation process is essential in the sense that it maintains a competitive advantage, an increase in productivity and the creation of jobs. Van Reenen (1996); Faggio, Salvanes and Reenan (2007); Echeverri-Carroll and Ayala (2009) suggest that individuals in companies and innovative professions receive higher wages than those who are not.

Tinbergen (1969) shows that Inequality is the Outcome of a race between education and technology. When Technological advance Vaults ahead of educational change, Inequality generally Rises. By the same token, when increases in educational Attainment speed up, economic Inequality often declines. Piketty (2013) in turn explains the increase in inequalities. Even if this theory does not allow the explanation of everything, it nevertheless contains important elements to justify certain historical evolutions. The theory is based essentially on two hypotheses: the first states that the salary of a given employee is equal to his marginal productivity. The second assumes that this productivity depends on the qualification and the state of supply and demand for qualifications in the company in question.

In addition, work on the link between technological change and inequality within a country is still very cautious (Lee, 2011). However, the majority of studies in the United States ignore the distribution of skills and confirm that in the bosom of an innovative company, those who earn more are those who are the most qualified (Echeverri-Carroll and Ayala 2009). Florida (2005) finds a significant wage gap between those who occupy a

“creative class” position and those who do not. According to him, this implies a higher overall inequality.

Thus, research to investigate the link between innovation and inequalities has tended to focus on the theory of technological change biased in favour of skills and its implications on different groups of workers. Lemieux (2008) confirms that technological change favours the division of the labour market into “highly skilled” and other “low skilled” jobs.

The empirical studies which refer mainly to the American economy support the thesis of technological bias. Berman, Bound and Griliches (1994) carried out their studies on 450 industrial sectors, finding that the increase in skilled labour is positively correlated with R&D spending. These results were subsequently confirmed by Doms, Dunne and Troke (1997). These authors show a positive correlation between new technologies and qualifications, In other words, establishments using new technologies are characterized by a greater share of skilled labour.

Duguet and Greenan (1997), taking a sample of 4954 French companies from 1991 to 1996, show the existence of a technological bias that favours the most skilled workforce. In Canada, Gera, Gu and Lin (2001) using a panel of 26 industries over the period 1981-1994 show that indicators of technological level (the stock of patents, the age of capital stock) are positively correlated with the degree of intensity of skill use. This study confirms the result of Betts (1997) which states that technical progress was unfavourable for unskilled labour in most sectors of Canadian industry over the period 1962-87.

In their research on the effects of innovation on inequality in European and American regions, Lee and Rodríguez-Pose (2012) found that innovation necessarily leads to inequality in European regions, but this is not the case for American cities. Indeed, the influence of technological change on inequality in American cities is limited and linked to sectors of activity. A relevant explanation lies in the fact that in the United States individuals with a low level can enter the labour market, while this is not the case for Europe; these individuals have less chance of finding a job (Kaplanis, 2010).

In developing countries, although estimates of the effects of technical progress on wages or employment are limited, several studies conclude that the diffusion of technology has a positive and significant effect on the demand for skilled labour. Studies of Berman and Machin (2000) show an increase in demand for skilled labour during the 1980s in developing countries. In their study of 32 countries during the years 1980-1991, Conte and Vivarelli (2007) analyse the effects of the import of technologies produced by developed countries on the structure of development in developing and least developed countries. Their results indicate that the import of technology is helping to increase the skilled workforce and reduce the number of unskilled employees.

Esposito and Stehrer (2008) tested the technology bias hypothesis for the Czech Republic, Hungary and Poland during the years 1995-2003. These authors deduced that technological change is biased towards skills in Hungary and Poland, but this is not

obvious for the Czech Republic. The possible explanation of Esposito and Stehrer is the economic backwardness of the country.

Finally, in his study using Tunisian data, Saafi (2013) shows that technological diffusion has resulted in the increase in demand for skilled labour and the decrease in demand for unskilled labour. This enabled him to confirm the hypothesis of technological bias for Tunisian industry.

We have therefore tried to clarify the concept of technological bias in favour of skills and the models of technological bias. In the rest of this paper, we will empirically highlight the link between technological change and income inequality. We will seek a clear answer to this question: What is the nature of the relationship between income inequalities on the one hand and technology and education on the other?

2. Empirical Study

In this section we will try to present an empirical study based on the Panel's data technique in order to verify the impact of technological change on inequality, especially for a range of developing countries.

2.1. The model and DATA

In this empirical analysis, we estimate inequality by skill, population density, income, innovation, and unemployment. The model is inspired by the work of Lee and Rodríguez-Pose (2013) who studied the link between innovation and inequality and presented a comparative study between different European regions and American cities.

To test the link between innovation and inequality, we adopt a model that estimates the level of inequality in a given country based not only on skills and innovations, but also other control variables influencing inter-individual inequality such as income per capita, population density and unemployment rate. The model is written as follows:

$$Gini_{it} = \alpha + \beta_1 innovation_{it} + \beta_2 population\ density_{it} + \beta_3 income_{it} + \beta_4 skills_{it} + \beta_5 unemployment\ rate + v_i + \epsilon_{it}$$

Where "t" refers to the years and "i" refers to the countries in our sample. Inequality refers to income inequality between individuals within the same country. It is measured by the Gini index. Innovation is the measure of innovation by country calculated by the number of patents filed by residents. Population is the density of the population in a given country. It includes all residents regardless of legal status or citizenship, with the exception of refugees who are not permanently settled in the receiving country. They are generally part of the population of their country of origin. Income indicates the average income per capita measured by GDP per capita. Skills are a measure of human capital measured by the rate of the skilled population. It is represented by the number of skilled workers who have received a university education. Unemployment tells us about the unemployment rate in a given country. It

refers to the share of the labour force that is unemployed but available for and seeking employment. Time error is represented by v_i and ε_{it} is the global error term.

Several studies have used the number of patents as a proxy for innovation measurement. We include, for example, Chen and Puttitanun (2005), Furman, Porter and Stern (2002), Mancusi (2004) and Lee and Rodríguez-Pose (2012). Another measure of innovation that appears in the literature is R&D spending. According to Lee and Rodríguez-Pose (2012), the number of patents is the most suitable measure for innovation, since it is considered as an “output” of innovation, while R&D spending is considered as an “input” of innovation.

Our contribution is based on statistical data from several different data sources. The Gini Index is collected from the World Institute for Development Economics Research (WIDER, 2014). Data on the number of patents filed by residents are collected from WDI (2015). Population density data are collected from WDI (2015). Income data are from Pen World Table (PWT) version 9.0 (Feenstra, Inklaar and Timmer, 2015). Skills data are collected from World Development Indicators (WDI 2015). Finally, the unemployment rate has been drawn from WDI (2015).

Our study is based on a panel of 52 developing countries from 1986 to 2015. Since the database for the Gini coefficient contains several missing data, we were forced to work with five-year data (the 5-year average). We obtained six periods: 1986-1990, 1991-1995, 1996-2000, 2001-2005, 2006-2010, 2011-2015. The countries in our sample are Armenia, Azerbaijan, Bangladesh, Belarus, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominican Republic, Ecuador, Egypt, Ethiopia, Georgia, Guatemala, Honduras, Hong Kong, India, Indonesia, Iran, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyzstan Republic, Madagascar, Malawi, Malaysia, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Nicaragua, Nigeria, Pakistan, Panama, Paraguay, Peru, Philippine, Romania, Serbia, Tajikistan, Thailand, Tunisia, Turkey, Uganda, Ukraine, Uzbekistan, Vietnam, Zambia. So we got 311 observations. So all the variables are in logarithm.

Despite considerable improvements, the collection of Gini coefficient data still has several problems. Indeed, not all Gini coefficients are based on identical units of estimation. For example, some are expenditure-based, some are income-based, and some are consumption-based. To try to overcome this problem, we chose our sample on the basis of the Gini coefficient having the same units of estimation.

2.2. Results

a) Descriptive analyses

Table 1 provides descriptive statistics of the different variables that describe inequality. It includes the means of each variable, the standard deviations, the minimums, the maximums and the medians of each.

Table 1: Descriptive Statistics

Variables	means	Standard deviations	min	max	medians	observations
<i>Dependent Variable</i>						
Inequality	3.371	1.136	2.225	7.178	3.683	310
<i>Independent Variables</i>						
Innovation	2.982	2.219	1.122	6.767	3.109	310
Population density	4.141	1.342	1.712	8.122	4.301	310
Income	8.331	1.904	2.235	10.707	8.753	310
skills	2.210	1.491	-0.802	4.641	2.754	310
Unemployment rate	1.338	1.070	-1.049	4.228	1.533	310

b) The correlation matrix and the VIF test

The estimation of multiple regression models requires the absence of multi-collinearity between variables. A multi-collinearity problem occurs when two independent variables are strongly correlated. The term multi-collinearity means the existence of a perfect or exact linear relationship between some (or all) explanatory variables of a given regression model.

In order to determine whether there are correlations between the different variables in our study and to ensure that the variables used are adequate, in other words, so that our model is reliable, the explanatory variables must be independent to avoid the risk of multi-co linearity.

To verify the presence or absence of multi-co linearity between the independent variables, we calculated Pearson correlation coefficients between the determining explanatory variables, the control variables, as well as the VIF coefficients "Variance Inflation Factor", which are presented in Table 2. Analysis of the matrix below confirms the absence of a co linearity problem. Indeed, all Pearson correlation coefficients between independent variables are less than 0.6, the limit from which the phenomenon of co linearity becomes more pronounced (Mkadmi and Halioui 2016).

Although the correlation coefficients are not high, we calculate the VIF to test the absence of multi-co linearity in our estimates. In addition, based on Table 2, we noted that all of our explanatory variables have a VIF value of less than 10, as suggested by Gujarati (1995). These results have led us to conclude that we do not have a serious problem of multi-co linearity.

Table 2: The correlation matrix and the VIF coefficient

	<i>Innovation</i>	<i>Population</i>	<i>Income</i>	<i>Skills</i>	<i>Unemployment</i>	<i>VIF</i>
<i>Innovation</i>	1.0000					1.22
<i>Population</i>	0.1546	1.0000				1.14
<i>Income</i>	0.2341	0.3136	1.0000			1.47
<i>Skills</i>	0.3854	0.0788	0.4435	1.0000		1.46
<i>Unemployment</i>	0.1109	0.1109	0.3716	0.3487	1.0000	1.22

c) Estimation method

We should first check whether the process specification is homogeneous or heterogeneous. This amounts to testing the equality of the coefficients of our model in the individual dimension. We use the Fisher test to do this. We consider the following hypothesis:

$$H_0: \beta_i = \beta, \alpha_i = \alpha; \text{ for } i \in [1; N]$$

$$H_1: \beta_i \neq \beta, \alpha_i \neq \alpha; \text{ for } i \in [1; N]$$

If the probability of this test is less than Fisher's critical value, we will accept the null hypothesis of absence of heterogeneity of individuals. On the other hand, if the probability of this test is greater than Fisher's critical value, we will reject the null hypothesis and accept the hypothesis of existence of heterogeneity of individuals. In our case the probability of the test is 1.66 which is higher than that of Fisher (0.060). We conclude, therefore, that there is heterogeneity of individuals and the MCO estimator is not convergent. In this case, we must use either the fixed effect model or the random effect model.

To find out which of the two models we will use the fixed effect or random effect; we use the Hausman test (1978). We consider the following body of hypothesis:

$$H_0: E(a_i/X_i) = 0: \text{ random effect.}$$

$$H_1: E(a_i/X_i) \neq 0: \text{ fixed effect.}$$

Hausman statistics are distributed according to a law of $\chi^2(r)$ with degrees of freedom, r being the number of explanatory variables. If the probability of this test is lower than 5% we reject the null hypothesis and favour the adoption of individual fixed effects and the use of the within estimator. On the other hand, if the probability of this test is higher than 5% we accept the null hypothesis and prefer the adoption of random individual effects and the use of the MCG estimator. The Hausman test results show a probability of less than 5% ($\chi^2 = 0.0044$), so the fixed individual effect model is the most appropriate.

The results of estimates show that apart from the coefficient of the variable indicating the unemployment rate, all the other variables are significant. Table 3 shows the results of our fixed effect estimation:

Table 3: Results of fixed effect estimation

<i>Estimation</i>	<i>Gini (ln)</i>
<i>Patent (ln)</i>	0.5001697 (0.064)*
<i>Population (ln)</i>	0.4025464 (0.000)***
<i>Income (ln)</i>	0.2458714 (0.000)***
<i>Skills (ln)</i>	-0.1547527 (0.009)***
<i>Unemployment rate (ln)</i>	0.075405 (0.303)

Values in parentheses represent probabilities. *significant at the 10% threshold, ** significant at the 5% threshold and *** significant at the 1% threshold.

We will examine the influence of fundamental variables on income inequality: the level of innovation and skills. Not only should the estimated coefficients be consistent with those traditionally reported in the literature, but they should also be significant. Our main research question in this model is whether the level of innovation, represented by the number of patents filed, and the skills, represented by skilled labor, of a country can explain the inequality between individuals.

We found that innovation positively affects inequality. Indeed, the coefficient of the “patent” variable is positive and significant at the 10% threshold. In other words, the more the development of innovations increases, the more the level of inequality increases. Ricardo (1951) and Marx (1969) emphasized the effects of new technologies on the wages and incomes of different workers, based on the Industrial Revolution. They found that New Technologies increased the productivity of the most skilled and subsequently widened the wage gap and consequently income inequality (Murphy, Riddell, and Romer, 1998). Krueger (1993) shows that computer users receive a wage premium. On the other hand, they earn 10 to 15% more than non-users.

While, for our sample of countries, the results of our estimate show that skilled work negatively affects inequality, the coefficient of the “competence” variable is negative and largely significant. Several studies have highlighted the importance of distributing the skills of the population on inequality (Wheeler, 2005; Glaeser, Resseger and Tobio, 2009; Tselios, 2008; Rodríguez-Pose and Tselios, 2009a, 2009b). This is fundamental to any interpretation of inequality. For example, Glaeser, Resseger and Tobio (2009) suggest that inequality is determined on the basis of these three variables: the distribution of skills, the skill premium and the institutions that determine how labour market processes affect the structure of wages. We can therefore say that inequalities may decrease with the increase in the supply of skills.

We note that innovation and the distribution of skills have two contradictory effects on the evolution of inequality. One possible explanation for this is that the demand for skilled labour (technology effect) and the supply of skilled labour (education effect) have contradictory effects on inequality. In the face of changes in the various

labour markets, the distribution of income is increasingly unequal. The thesis advanced in the majority of studies (as Nickell and Bell, 1995; Katz and Autor, 1999) is that demand for skilled workers has increased faster than supply, resulting in a relative increase in wages for the most skilled compared to the least qualified. Tinbergen (1975) confirms this result. He stated that the relationship between growth and inequality is driven by the competition between technological development and education.

Using the new growth theory that comprises human capital and technological change, Eicher and Penalosa (2001) show that the relationship between growth and inequality is complex. This is due to the contrary effects of supply and demand. The effect of an increase in the supply of human capital is to reduce wages and inequality. They also show that the accumulation of human capital indirectly leads to more innovations that increase the demand for skilled workers to absorb new technologies.

Results of Eicher and Penalosa (2001) reflect the hypothesis of Tinbergen (1975): During the development process, relative wages depend on the intensity of demand for technology-based skills in relation to the supply of education-based skills. The use of advanced technologies reduces the substitution elasticity between skilled and unskilled work.

Caselli (1999); Galor and Tsiddon (1997); Galor and Moav (2000); Maoz and Moav (2000); Maoz and Moav (2004) and Fang, Huang and Wang (2008) have found that technical progress is not always an adoption of innovations that increases skill yields. There have been alternations between innovations favourable to skilled work and innovations favourable to unskilled work. They address the question of the cyclical development of the qualification premium. They call for the technology externality between groups of workers with different qualifications in the same country to produce a cyclical model of long-term wage premium. Inequalities can increase or decrease with the surge in the supply of skilled labour. Maoz and Moav (2000) also present an alternative explanation, based on the complementarity between capital and skills and the accumulation of endogenous physical and human capital. They explain how the proportion of educated workers can increase monotonously while the education premium can increase, decrease or show a cyclical change, depending on the initial distribution of wealth in the economy.

These results set us up, in particular within the framework of the theory of a continuation race between education and technology, presented earlier, to explain the rise of inequalities. We can deduce that inequality is the result of the competition between technology and education. Thus low-skilled workers had the advantage during the first decades of the 20th century, but they lost it with the technological revolution to skilled workers.

In addition to innovation and skilled labour, inequality is influenced by population density, income and unemployment rates. Our estimation results showed a positive and largely significant coefficient for population density. Wheeler (2004) finds that population density is positively associated with inequality. Korpi (2008) studies this relationship using a Swedish labour market. He finds that the larger the labour market, the greater the level of inequality. Considering the use of fixed-effect models, it should be noted that

population density has the same impact as the overall population size Korpi (2008). Similarly, the income coefficient has a positive and significant value, which is consistent with the results of Lee and Rodríguez-Pose (2013). Thus, it appears that the unemployment rate affects income inequality in developing countries. Its coefficient takes a positive but not significant sign. This result confirms the work of Lee and Rodríguez-Pose (2013) who found that the unemployment rate is not important enough in explaining inequalities in the different regions of Europe.

In the end, it appears that the main cause of the rise in pay inequalities is innovation, which confirms the thesis of technological bias in favour of skills, as the majority of empirical studies stipulate. However, more recent work has brought more content to the determinants of rising inequality. International trade, organisational change, institutional change and technological change are the main factors advanced in the economic literature. Recent work, however, shows the weakness of the direct effects of the first three factors and highlights the major role played by technological change dependent on the level and structure of human capital in the dynamics of inequalities. In fact, for Acemoglu (2002) these factors in themselves cannot be a cause of the dynamics of inequality, but become important when they interact with technological change; they contribute to amplifying the direct effect of technological change on income inequality.

It is important to note that Juhn, Murphy and Pierce (1993) showed that it was possible to attribute the increase in residual inequality, that is, inequality within homogeneous groups of workers in terms of their experience and education, to an increase in demand for more skilled workers. In this context, the key assumption is that among workers with the same observable characteristics (experience, education, etc.), those who earn more do so because of better unobserved skills such as quality of education, motivation or intrinsic ability. The thesis of Juhn, Murphy and Pierce (1993) is that a general increase in the relative demand for skilled workers explains both the increase in performance associated with the observed skills, and the increase in residual inequality associated with unobserved skills. It also helps to explain why inequality has grown in every area of distribution.

Conclusion

We have tried to validate empirically, under the control of other variables, the thesis of technological changes biased in favour of skills. We confirmed the hypothesis that innovation influences income inequalities for a sample of developing countries. Our results for developing countries corroborate the theoretical and empirical literature for developed countries. Indeed, we have observed that innovation linked to skilled human capital influences income inequalities.

In this work, we tried to verify the effect of new technologies and the effect of education on income inequalities for a sample of 52 developing countries. Despite the considerable improvements, the collection of Gini coefficient data still has several problems. Since the database for the Gini coefficient has several missing data, we were forced to work with five-year data (the 5-year average).

Furthermore, the adoption of new technologies leads to an increase in income inequalities. But these inequalities can also decrease with the sudden increase in the

supply of skills. So, on the one hand, we have a “technology effect” and on the other hand an “education effect”. We thus obtain a cyclical evolution of inequalities.

In the case of developing countries, if the import of technologies causes an increase in inequalities, we can control these inequalities through education and by increasing the supply of skilled labor. Thus, education is the key to this major social problem, which threatens especially the developing countries, which is inequality.

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