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R&D and Employment Relation: Differences in Low and High-Skilled Employment in Developing Economies

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Abstract

This paper attempts to investigate the effect of technology on employment based on skill groups in developing countries using data from 23 countries between 1990 and 2019. We use the macroeconomic framework to split employment in developing countries into high-skilled and low-skilled and examine how these two groups are affected by progress in technology. Pedroni's (1999, 2004) and Kao's (1999) cointegration methods reveal the statistically significant relationship among variables in the long run. Coefficients estimated in cointegration highlight that technology is among the factors that increase unemployment in developing countries. In addition, our baseline models document that inflation and real interest rates have a positive impact on unemployment. Finally, both high-skilled and low-skilled employment in developing countries are negatively affected by technology, and the negative impact is greater on low-skill employment.

Keywords: *Technology, R&D, Unemployment, Skill, Pedroni Cointegration*

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1. Introduction

Studies on the direction and strength of the relationship between technology and unemployment lead to incompatible results. While some economists assert that technological developments trigger factors like mechanization and innovation to replace labor and increase unemployment, others claim that unemployment decreases with technological progress since technology causes new business opportunities and enlarge business in new sectors and industries. The examination of economic events under different conditions or the establishment of theories under different assumptions is effective in the formation of opposing views. Variables like productivity and wage, category of the workforce under investigation, metric to measure technology, type of unemployment as well as regional and country-wise differences directly affect the outcome of the analysis.

In practice, the main factor to spark innovation is the Research and Development (R&D) expenditure as the main driving force of technological progress. Large firms are capable of allocating considerable budgets to R&D and enabling product innovation. On the other hand, process innovation necessitates investment into machinery, methods, and procedures including managerial tactics to produce higher quality items less costly with properly designed automation. Once the technology in terms of product or process innovation is achieved it will be spread to different markets.

The progress in technology has a significant impact on the economy of many countries and the ramifications of technology have perplexing effects on labor markets. There are many factors to be considered in such a technology shock, ranging from the supply and demand in the labor markets to the heterogeneity of the workers' productivity. Many models have been established so far to account for subsets of all such factors. This complication makes it very difficult if not impossible to analyze the situation in a theoretical framework managing all the details governing the impact of technology on unemployment. That is why we preferred the empirical methodology of analysis. Indeed, conditions governing the empirical study can be pervasive, but all such conditions are taken into consideration per se in any typical empirical study.

According to skill-biased technological change discourse, the correlation between wage inequality and economic growth is positive. Endogenous production of technological knowledge which fuels economic growth favors skilled labor. This means that unskilled labor is supposed to suffer from such growth and is penalized (Acemoglu, 1998). The main institution to support the basic rights of unskilled labor is the labor union but, in many industries, the union is oligopolistic if it exists. Indeed, the wage of unskilled labor is rigid and as the wage in addition to fringe benefits of skilled labor progress, the unskilled does not take advantage. The benefits of growth to unskilled and skilled labor are asymmetric and the bargaining power of the unskilled labor stays reluctant as skilled labor enjoys better working conditions including even home offices as well as higher premium paid to skill. Firms willing to compete with advanced technology even in domestic markets cannot simply do this by importing hi-tech machinery and equipment since the labor administering them has to be employed. Technology replaces human labor with high automation (Frey & Osborne, 2017), affects the workforce directly or indirectly by changing the structure, content, and quality of tasks (Autor, 2010; OECD, 2018), and can make income inequality even more tragic by increasing the skill premium (Acemoglu, 2003; Acemoglu & Autor, 2011).

Literature on the relationship between technology[1] and employment is old and highly controversial. Many studies argue that technological progress is a threat to employment while others state that technological unemployment is counterbalanced by the benefits associated with technology. Many authors emphasize that the increase in productivity brought by new machines negatively affects employment since it destroys jobs, while opponent views point out that the advantages of technology affect employment positively with an internal compensation mechanism. Ricardo (1966/1817) argues that machines developed with technological advances increase net income and thus gross savings and accumulation also rise. In addition, Say (1971/1836) says that machines cannot be produced without people whose jobs are occupied by machines.

The theoretical literature deals with the developments in process and product innovation. While the operation, method, or tool changes provided by technological developments in the economy are considered process innovations, innovations that give a new product to the market, increase the product variety or change the structure of an existing product are defined as product innovation. Therefore, economists assess possible discharges that may arise due to product or process innovation over the existence of the compensation mechanism introduced by Marx (1976/1867) and discuss whether there is a balancing system, in other words, whether negative effects on employment can be offset by technological achievements. Part of the work claims that the negative effects of technology on employment can be fully counterbalanced by the compensation mechanism. On the contrary, opponents argue that the mechanism cannot work perfectly, and technology always leads to job losses and increases unemployment. While Say (1971/1836) states that the employment problems arising from process innovations create new job opportunities in the capital markets, and therefore there is balance,

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[1] We adopt the broadest definition of technology as "anything to increase the efficiency of a product or process that results in an increase in output, without an increase in input" in this paper. That is the invention or improvement of a product or process used to produce more with the same or less input. In this regard, technology shock transfers any such technology to an economy. In the following sections, we also construct the linkage between R&D and technology, explaining why we use this variable at the macro level. R&D activities directly affect the firm's market share and knowledge stock by leading the creation, adoption, and application of new technologies at all stages of the production processes (Freeman & Soete, 1987).

Hicks (1975/1939) claims process innovation is not able to positively influence employment in the capital markets. Marx (1976/1867) indicates that the increase in unemployment because of mechanization is much more than the increase in the number of new jobs; thanks to technology. On a side note, Freeman et al. (1982) argue that the machines cannot be part of any compensation mechanism since they already replace older machines.

In addition to process innovation, product innovation is also a remarkable issue in the literature. While Say (1971/1836) points out that new products developed in the business world give rise to new fields and new job opportunities, studies such as Marx (1976/1867), which mostly criticize the compensation mechanism, accept the positive effect of product innovations on employment. Freeman and Soete (1987), Pianta (2000), and Edquist et al. (2001) find that product-oriented technological advances affect employment positively by introducing new products or making changes in product form. On the other hand, Dosi (1982) acknowledges that product innovation contributes positively to employment, but the effect depends on the product type and industry, and it is influenced by different periods and institutional structures. Additionally, the author notes that the situation in which the product innovation comes with the process innovation is considerable and emphasizes that the total effect should also be evaluated. Arrighetti and Vivarelli (1999) indicate that new firms which have emerged from developing new products offer more jobs than others.

All these technological unemployment issues are a matter of great concern not only for developed countries but also for developing economies. And these concerns are not new to the economics literature. The primary source of current interest is based on the employment effects of the Industrial Revolution. In fact, this is an answer to why developing countries have not attracted enough attention to technological unemployment until today. Although the empirical literature on the technology-employment relationship is rich for developed countries, especially at the micro-level (Pianta, 2006; Vivarelli, 2014; Calvino & Virgillito, 2018; Dosi et al., 2021), studies addressing the issue for developing countries are limited. The fact that the machines that raise the concerns of technological unemployment were first produced in developed countries and that the developing geographies are mostly technology importers, caused the economics literature to neglect the developing economies. And the majority of the existing literature for developing countries reports the positive employment impact of product innovations in developing economies, either at the firm or sectoral level (Yang & Huang, 2005; Yang & Lin, 2008; Benavente & Lauterbach, 2008; Meriküll 2010; Crespi & Tascir, 2011; Laguna & Bianchi, 2020).

In addition, technological development is an essential factor that is responsible for the variations observed in the labor force, affecting the demand qualitatively as well as quantitatively. Because labor type, tasks of the occupations, and skill requirements vary and are affected by many different dynamics. Also, technology cannot be thought of independently from human skills, technological advances may tend to favor some skills more while rendering some skills worthless or unnecessary. Therefore, today, skills-focused technological change hypotheses are in vogue. This approach, which is called skill-biased technological change (SBTC) in literature, has attracted more attention since the end of the 20th century, especially with the developments in information and communications technologies (ICT). The main theme of the hypothesis is that new technologies require qualified employment with sufficient skills to be effective and efficient. New computers and, more generally, the technological revolution change the wage structure and on the other hand require the existing labor force to acquire new knowledge and acquire skills (Acemoglu, 2002). Because every new technology requires an adaptation process, and skill both facilitates and accelerates this process.

The situation is similar when we look at the issue not only from the perspective of “new computers” but also from the perspective of R&D expenditures. R&D activities directly affect the firm's market share and knowledge stock by leading the creation, adoption, and application of new technologies at all stages of the production processes (Freeman & Soete, 1987). Therefore, R&D can increase the demand for high-skilled workers, especially in high-tech countries (Autor & Dorn, 2013; Eeckhout et al., 2014). Moreover, R&D investments in sectors with highly specialized high-skilled workforces can encourage higher-skilled or skilled workers to work in R&D activities or related ancillary areas. On the other hand, R&D expenditures may adversely affect the demand for labor in areas where there is a high density of jobs that are prone to automation since those who work in these jobs are mostly unskilled for new jobs (Autor & Dorn, 2013; Mazzolari & Ragusa, 2013).

Whether the methodological approach is based on the skill of the labor (Acemoglu, 1998) or the task-oriented content of the occupations (Autor et al., 2006), it is a common belief that while technological innovations increase the demand for more educated and qualified in the labor market, the demand for the uneducated or less educated decreases or does not increase as much as the former (Goldin and Katz, 1998). In line with this common belief, empirical evidence is presented that technology is mostly skill-biased in developing economies as well as in developed countries (Görg & Strobl, 2002; Edwards, 2004; Tether et al. 2005; Vivarelli, 2014).

Although automation occurs later in developing countries than in developed countries, developing economies experience "premature deindustrialization" (Rodrik, 2016), because they are already indirectly affected by emerging technologies, and this could lead to technology inflicting deeper wounds on employment in the developing world (Frey & Rahbari, 2016). In studies such as the World Bank (2016), Egana-delSol (2019), and Soto (2020) it is noted that due to the current stages of developing countries, most of the workers are employed in sectors with high automation risks such as agriculture and manufacturing. Therefore, the risk of losing a job due to automation in these economies is higher than such risk in advanced countries. However, high automation risk does not mean that the rate of transition to automation or the speed of being affected by machines is equally high.

Although many jobs can be automated technically and theoretically in developing countries, the transition to automation is not as fast as in developed countries due to factors such as low wages and slower technology adoption, and thus employment is not yet affected to the same extent. Manyika et al. (2017) predict that in the coming decades, automation rates in developed countries such as Japan and the United Kingdom will be higher than in emerging economies such as India and Russia. Acemoglu and Restrepo (2018) draw attention to a similar issue and state that despite the increase in wages in developing countries in recent years, average wages remain far from developed economies. In countries with high wage levels, sensitivity to automation is also high due to rising costs. However, despite the increase in wages in developing economies over time, the fact that they are still far from the level of developed countries brings about the existence of cheap labor resources and therefore does not make automation economically attractive in many developing countries. Frey (2020) argues that the cost advantage of cheap labor against technology in developing economies will end soon. Besides, he states that although many studies focus on developed countries, the main problem will be experienced in developing countries due to early deindustrialization. In emerging economies such as China, Mexico, and Brazil, where labor costs are relatively low, labor may lose its comparative advantage, as the use of robots will be less costly in the coming decades (Rüßmann et al., 2015). The efficiency of benefiting from the employment opportunities opened by technology is lower in developing economies. Because even basic education indicators such as literacy rates in developing economies are lagging behind developed countries, and therefore, there is a lack of skills to complement new technologies. Most new jobs will require significantly higher skill levels, causing developing countries to lag in taking advantage of new technologies (Soto, 2020).

In this study, Research and Development (R&D) expenditures are used as a macro-level technology proxy because R&D activities include comprehensive and qualified studies carried out to increase the knowledge stock of human capital and the use of the obtained information to design new products and applications (Baş & Canöz, 2020). R&D is the determinant of technological innovations because "for the majority of industrial production systems, research and development come first. Research often serves as the foundation for innovations that lead to new goods and procedures. These innovations typically follow a path from laboratory concept to full-scale production and market introduction. Any innovation starts with an invention. In fact, one definition of innovation is the application of an invention to a sizable market need. Therefore, research is where inventions are born" (McLeod & Holstein, 2022). In addition, the outputs indicating that there is a positive relationship between R&D and innovation and patent applications (Feldman, 2013; Baş & Canöz, 2020) show that R&D is a strong technology proxy. Studies that directly deal with the relationship between R&D and/or patent applications and unemployment at the macro level mostly cover developed countries and do not include the technology-employment relationship based on different skill groups.

For instance, Feldman (2013) uses the macro data of 21 industrial countries from 1985 to 2009 and shows that one standard deviation increase in the number of patents increases unemployment by 2.3% to 3.0%. Matuzeviciute et al. (2017) use both R&D and triadic patent families' data from 25 European countries as technology proxy and find that both technological variables do not have a significant effect on unemployment at the macroeconomic level. Baş and Canöz (2020) examine the unemployment effect of R&D expenditures covering 15 OECD countries for the period of 1996-2017. Although no cointegration is found between R&D expenditures and unemployment in the preliminary results of the study, the authors explore the presence of hidden cointegration between R&D and unemployment shocks in the second stage of the analysis. Lydeka and Karaliute (2021) follow two previous similar studies, Feldman (2013) and Matuzeviciute et al. (2017), using data from 28 European Union countries and find that although there is significant evidence that R&D reduces unemployment in two of the six models, the coefficients are insignificant in all models including triadic patent families. As stated, these macro-level studies focus on advanced economies and do not detail empirical analyzes of skill groups. Therefore, this article aimed to fill an important gap in the literature regarding developing countries.

Unemployment is a social and individual reality that has persisted since the beginning of the use of labor as a factor of production, especially in the 20th century. Today, the most relevant and compelling issue for states and politicians is the development of policies supporting employment and the prevention of economic crises. To this end, scientific research is transformed into technology, and emerging products are presented for the service of human beings. As a result, technological progress leads to structural changes in existing jobs, causing some professions to be destroyed or replaced by new ones. When we look at the change that technology has made in the past, it is evident that the replacement of the labor force by machines evolved from unskilled labor to highly qualified labor.

A large literature, including a considerable amount of research, has not produced a definitive conclusion on the relationship between technology and unemployment. Our empirical research fills this gap by addressing the main related variables at the macro level. We go one step further to split the workforce into high-skilled and low-skilled since the impact of technology on these are somewhat different. We make use of data from developing countries to explore this relation empirically. The main objective of our paper is to figure out the relationship between technology and unemployment empirically.

2. Empirical Methodology

2.1. Equations to be estimated

We establish six models to examine the technology-unemployment relationship in developing countries. In all six models, RD_{it}, which represents the per capita R&D expenditure, is included as the main core explanatory variable. Natural logarithms of

GDP_{it} (per capita income), and CPI_{it} (inflation) are included in all models representing the macro variables that have been repeatedly proven to directly affect unemployment in both empirical and theoretical literature. In line with these considerations, the first baseline model is:

$$U_{it}=\beta_0+\alpha RD_{it}+\beta_1 GDP_{it}+\beta_2 CPI_{it}+e_{it} \quad \text{(Model 1.0)}$$

where U_{it} stands for unemployment rate in decimal fraction while, RD_{it}, GDP_{it}, and CPI_{it} are natural logarithms of per capita R&D expenditure, per capita GDP, and consumer price index respectively, for country *i (=1, …, 23)* and year *t (=1990, …, 2019)* and e_{it} is the error term. Different model combinations are evaluated in addition to the baseline model which include other macroeconomic variables such as PRD_{it} , INT_{it}, OPN_{it} and EXC_{it} where, PRD_{it} is natural logarithm of "productivity" that is calculated as "total output/total workers" , INT_{it} denotes real interest rate while OPN_{it} and EXC_{it} are indexes that are used to indicate "openness" and "real effective exchange rate". All variables are in natural logarithms, except for the dependent variable U_{it} and one of the explanatory variables, INT_{it}.

Since employment includes workers with different qualifications and characteristics, and each group of workers can be affected by technology differently, we estimate Model 2.0 and Model 3.0 for high-skilled and low-skilled labor. That is, the LHS of Model 1.0 to Model 1.5 are replaced by HSE_{it} and LSE_{it} in these sets of equations, respectively.

$$HSE_{it}=\beta_0+\alpha RD_{it}+\beta_1 GDP_{it}+\beta_2 CPI_{it}+e_{it} \quad \text{(Model 2.0)}$$

$$LSE_{it}=\beta_0+\alpha RD_{it}+\beta_1 GDP_{it}+\beta_2 CPI_{it}+e_{it} \quad \text{(Model 3.0)}$$

It is worth remembering that in this study, the parameter α is used as the coefficient of RD_{it} in all models, and the β is used for the intercept and coefficients of other explanatory variables.

2.2. Panel cointegration approach

Cointegration is one of the most employed approaches to investigate the long run relationship in panel data. We performed Kao's cointegration (Kao, 1999) test on homogeneous panels in addition to Pedroni (1999). Both tests work under the independence assumption between cross-sections. In addition, we estimated the cointegrated $I(1)$ series by Panel Dynamic OLS (PDOLS) and Fully Modified OLS (FMOLS) methods, both of which are preferred to be on grouped means (Pedroni, 2001a). These estimators cause less scale distortions than within-group estimators and in parallel, if the cointegration vectors exhibit a heterogeneous structure, these estimators provide more accurate estimates. When describing the grouped-mean PDOLS estimator, a cointegrated panel system is considered as $y_{it} = \alpha_i + \beta_i x_{it} + u_{it}$, where x_{it} and y_{it} are integrated processes of $I(1)$. $x_{it} = x_{it-1} + \varepsilon_{it}$ and $y_{it} = y_{it-1} + \upsilon_{it}$ where both are cointegrated with slopes β_i which might or might not be homogenous among i . This model can be extended to panel data and applied a DOLS estimation on each country in the referred equation as $y_{it} = \alpha_i + \beta_i x_{it} \sum_{j=-p_i}^{p_i} \gamma_{ik} \Delta x_{it-k} + u_{it}^*$, where i=1, 2, 3, . . . , N is the cross-sectional dimension, country, t=1, 2, 3, . . . , T is the time period, p_i is the number of lags and leads, β_i is the coefficient of slope and x_{it} is the explanatory variable. From this regression, the group-mean panel DOLS estimator can be formed as $\hat{\beta}_{G-PDOLS}^* = \left[\frac{1}{N}\sum_{i=1}^{N}(\sum_{t=1}^{T} z_{it} z_{it}')^{-1}(\sum_{t=1}^{T} z_{it}\tilde{y}_{it})\right]$, where $\tilde{y}_{it} = y_{it} - \bar{y}_i$ and z_{it} is the regressors' vector; $z_{it} = (x_{it} - \bar{x}_i, \Delta x_{it-K}, \dots, \Delta x_{it+K})$. Then the grouped-mean PDOLS estimator is simplified by $\hat{\beta}_{G-PDOLS}^* = \frac{1}{N}\sum_{i=1}^{N} \hat{\beta}_{DOLS,i}^*$, where $\hat{\beta}_{DOLS,i}^*$ is the standard DOLS estimator, employed to the i^{th} panel member. The test statistic for the standard DOLS estimator is $t_{\hat{\beta}_{DOLS,i}^*} = (\hat{\beta}_{DOLS,i}^* - \beta_0)[\hat{\sigma}_i^{-2}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2]^{\frac{1}{2}}$ where, $\hat{\sigma}_i^2$ is the long run variance of the residuals u_{it}^* that is computed using Bartlett kernel estimator by Newey and West (1987). The related t-statistic for the grouped-mean PDOLS estimator can be computed as $t_{\hat{\beta}_{G-PDOLS}^*} = N^{-0.5}\sum_{i=1}^{N} t_{\hat{\beta}_{DOLS,i}^*}$.

Since the main purpose of this study is to explain unemployment, the dependent variable y_{it} represents U_{it}. Besides, U_{it} and explanatory variables are cointegrated with slopes β_i, which may or may not be homogeneous across countries i. It should be noted that HSE_{it} and LSE_{it} are also used as dependent variables with the same regressors in different specifications.

As discussed before, grouped-mean PDOLS results are reported with the grouped-mean FMOLS results to demonstrate the consistency of empirical findings. Like grouped PDOLS, Pedroni (2001b) recommends an estimator which takes the average of all individual units' FMOLS estimates. The grouped FMOLS estimator can be simplified as $\hat{\beta}_{G-FMOLS}^* = \frac{1}{N}\sum_{i=1}^{N} \hat{\beta}_{FMOLS,i}^*$ where, $\hat{\beta}_{FMOLS,i}^*$ is the standard FMOLS estimator for country i. The test statistic for the standard FMOLS estimator is computed as $t_{\hat{\beta}_{FMOLS,i}^*} = (\hat{\beta}_{FMOLS,i}^* - \beta_0)\left(\hat{\Omega}_{11i}^{-1}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2\right)^{\frac{1}{2}}$. The t-statistic for the grouped FMOLS is similarly calculated as $t_{\hat{\beta}_{G-FMOLS}^*} = N^{-0.5}\sum_{i=1}^{N} t_{\hat{\beta}_{FMOLS,i}^*}$.

As a result, following cointegration tests, PDOLS and FMOLS methods are particularly proper choices to estimate the long run relationship. Due to the non-stationary regressors, it is well known that the OLS estimators are asymptotically biased despite their super consistency; PDOLS and FMOLS methods, on the other hand, generate unbiased estimators asymptotically. Another advantage of these approaches is that they allow the accumulation of long run information in the panel while letting short run dynamics and fixed effects to be heterogeneous among different members of the panel (Pedroni, 2001a).

2.3. Data

The main purpose of this paper is to analyze the relationship between technology and unemployment at macro level using data of developing countries. The list of countries covered for this purpose in line with the MSCI Market Classification Framework (MSCI, 2020)[2] is reported in Table 1. Indeed, this is the MSCI list of emerging market economies, and therefore, includes Korea, one of the leading Asian economies, and Greece, deep-rooted member of the European Union, as well as countries such as Argentina and Egypt, which have recently struggled with economic crises. At this point, although the number of developing countries is much larger, 23 developing countries, including Turkey, are included due to data availability and accuracy. Table 1 displays these countries as well as their abbreviations.

Table 1. List of selected developing countries

ID	Country Name	Abbreviation	ID	Country Name	Abbreviation
1	Argentina	ARG	13	Korea, Rep.	KOR
2	Brazil	BRA	14	Malaysia	MYS
3	Bulgaria	BGR	15	Mexico	MEX
4	China	CHN	16	Pakistan	PAK
5	Colombia	COL	17	Poland	POL
6	Cyprus	CYP	18	Romania	ROU
7	Czechia	CZE	19	Russia	RUS
8	Egypt, Arab Rep.	EGY	20	Slovakia	SVK
9	Greece	GRC	21	South Africa	ZAF
10	Hungary	HUN	22	Thailand	THA
11	Iceland	ISL	23	Turkey	TUR
12	India	IND			

Note: 23 countries included in the MSCI Emerging Markets Indexes are used. The EM list is updated periodically by the MSCI Inc., so the classes of countries may change. In this study, countries that were in the EM group for a period between 1990 and 2019 and had sufficient data for empirical analysis were included.

The variables in Table 2 are the indicators used in the study to explain the technology-employment relationship. All data on unemployment and employment are retrieved from the database of the International Labor Organization (ILO). According to the classification made by the ILO, employees are divided into four categories based on their skill groups. The ILO defines 3 and 4 of these categories as “high-skilled”, 2 as “medium-skilled” and 1 as “low-skilled”. In this paper, skill classes are divided into two and 3-4 are grouped as “high-skilled”. On the other hand, 1-2 are considered as “low-skilled” which is the combination of low and medium skills.

The variable *RD* denotes per capita research and development expenditures, and its unit is real USD. The GDP per capita indicator is expressed with the *GDP* and shows

[2] The MSCI market classification, developed for international investors to compare countries in terms of investment opportunities according to their current economic conditions, is frequently used in academic studies. It is considered as a common global classification standard and the structure accurately reflects the current state of economies. Please refer to https://www.msci.com/our-solutions/indexes/market-classification for further technical and conceptual details.

real per capita income of the countries in constant USD. *CPI* is the consumer price index with base year 2010. Productivity (*PRD*), on the other hand, stands for output per worker, again in real USD. These four variables, including *RD*, which is used as a technology variable, are identified as core regressors.

On the other hand, real interest rate (*INT*) and real effective exchange rate (*EXC*) are used in different specifications as other explanatory variables. Real interest rate is in percentage but used as decimal fraction in estimation. The real effective exchange rate is treated as an index and the base year is 2010. Openness (*OPN*) as a variable is a statistic that expresses the ratio of the sum of the export and import activities of the countries to total income. We converted this to an index by assuming 2010 as base year.

Table 2. List of the variables

Variable Type	Description and Units of Variables	Symbol	Source
Dependent Variables	Unemployment rate (% of total labour force)	*U*	ILO (2020)
	High-skilled employment rate (% of total labour force)	*HSE*	ILO (2019), Authors' calculations
	Low-skilled employment rate (% of total labour force)	*LSE*	ILO (2019), Authors' calculations
Core Explanatory Variables	R&D Expenditure per capita (Constant 2010 USD)	*RD*	OECD (2018), Authors' calculations
	GDP per capita (Constant 2010 USD)	*GDP*	World Bank (2020)
	Consumer price index (2010 = 100)	*CPI*	World Bank (2020)
	Productivity (Output per worker, constant 2010 USD)	*PRD*	ILO (2020), Authors' calculations
Other Explanatory Variables	Real effective exchange rate index (2010 = 100)	*EXC*	World Bank (2020)
	Real interest rate (%)	*INT*	World Bank (2020)
	Openness index (Trade: % of GDP, 2010 = 100)	*OPN*	World Bank (2020), Authors' calculations

Note: The dependent variables namely U, HSE and LSE were calculated as percentage of the total labor force but used decimal fractions in the analyses. RD was obtained as a percentage of total GDP and calculated as R&D per capita based on constant 2010 USD.

Figure 1 shows the average of the changes in R&D expenditure and per capita income as well as the percentage point changes in the average unemployment, high-skilled, and low-skilled employment rates between 1990-2019. As the chart highlights, most of the increase in unemployment rates in developing countries is from LSE. This is because the weight of unskilled workers in developing countries is almost three times that of skilled workers. The change in HSE is always positive except for the 1998 and 2008-2011 periods in developing countries. One can conclude that the 2008 global financial crisis negatively affected high-skilled employment in these countries.

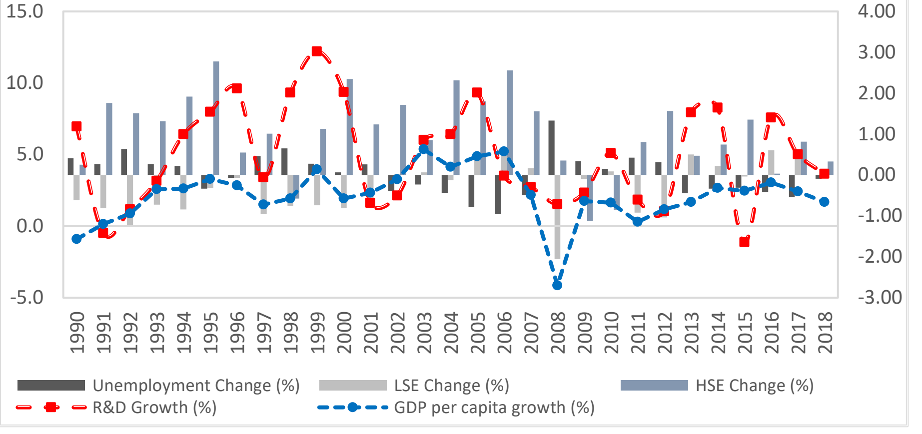

Figure 1. Average per capita R&D, per capita GDP, unemployment, high-skilled employment, and low-skilled employment changes in developing countries.

Note: In this figure, percentage changes in per capita GDP and per capita R&D are shown on the primary axis (left), while the percentage point changes in (un)employment are located on the secondary axis (right). Source: Authors' calculations.

On the other hand, the change in the LSE ratio in developing countries was negative until 2004, and after this date, the direction and trend of the relationship are more fluctuating. While interpreting the graph, it should be kept in mind that the analysis covers developing countries with different profiles. Because although the share of high-skilled employment in the total labor force has increased significantly in some countries, the share of low-skilled workers in total employment is still higher. In addition, while the change in average R&D expenditures of developing countries over the years is always positive, except for 1991 and 2015, it is not possible to talk about a constant "increase" or "decrease" acceleration for change. Interestingly, the change in average unemployment rates followed the change in average R&D expenditures with a 1-2 year' lag until the 2008 crisis. However, this pattern deteriorated after 2008. The graph alone cannot prove the long-run relationship between the two variables, but it may contain important clues about the direction of the relationship. An important detail is that the average increase in unemployment rates in developing countries was the highest in 2008.

3. Empirical results

As it is widely known, accurate, consistent, and unbiased estimators in panel time series are based on stationarity. Any data set, including time series, must be tested for stationarity first. The stationarity of the series in panel data means that the mean, variance, and covariance of the series remain constant over time. Changes in these values over time cause high t and R^2 values causing spurious regressions, which means there is no relationship between the variables but the estimated models report as if there is. Therefore, classical estimation methods like OLS are invalid when panel data series are non-stationary. On the other hand, for the $I(1)$ series, which are not stationary at levels but at first differences, the proposed estimation methods, such as Pedroni PDOLS and FMOLS are extremely useful since they also eliminate endogeneity and serial correlation problems. Although there are many methods to test for stationarity of series in the literature, including first and second-generation unit root tests, we prefer the LLC, IPS, and Fisher-Type ADF tests with the Null Hypothesis "each series contain unit root" against the alternative hypothesis of "at least one of the cross-sections is stationary".

Table 3 presents the unit root test statistics of the variables at both levels and the first differences without and with trend, respectively.

Table 3. Panel unit root tests results

Variables	IPS				LLC			
	w/o trend		w/ trend		w/o trend		w/ trend	
	Level	First difference	Level	First difference	Level	First difference	Level	First difference
U_t	-3.801	-13.850	-4.009	-11.231	-3.081	-13.492	-2.701	-11.342
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.001]***	[0.000]***	[0.004]**	[0.000]***
HSE_t	0.934	-16.064	-0.830	-14.486	-1.690	-16.090	-1.314	-14.824
	[0.825]	[0.000]***	[0.203]	[0.000]***	[0.046]*	[0.000]***	[0.094]	[0.000]***
LSE_t	-1.340	-14.947	0.020	-13.369	-2.692	-15.399	-0.323	-14.077
	[0.090]	[0.000]***	[0.508]	[0.000]***	[0.004]**	[0.000]***	[0.373]	[0.000]***
RD_t	0.830	-12.732	-0.710	-12.027	-3.861	-7.363	4.384	-4.241
	[0.797]	[0.000]***	[0.239]	[0.000]***	[0.000]***	[0.000]***	[1.000]*	[0.000]***
GDP_t	3.199	-12.912	-3.690	-8.824	-2.132	-11.995	-3.042	-7.235
	[0.999]	[0.000]***	[0.000]***	[0.000]***	[0.017]*	[0.000]***	[0.001]**	[0.000]***
CPI_t	-10.738	-13.359	-5.996	-10.092	-7.060	-13.853	-0.573	-7.829
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.283]	[0.000]***
PRD_t	1.958	-17.683	0.388	-16.358	-1.398	-15.641	-0.294	-14.426
	[0.975]	[0.000]***	[0.651]	[0.000]***	[0.081]	[0.000]***	[0.384]	[0.000]***
INT_t	-7.124	-25.278	-8.245	-24.508	-4.228	-24.497	-4.912	-17.264
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
OPN_t	0.270	-19.357	-0.902	-17.358	-5.216	-21.245	-1.384	-17.278
	[0.606]	[0.000]***	[0.184]	[0.000]***	[0.000]***	[0.000]***	[0.083]	[0.000]***
EXC_t	-1.910	-16.571	-1.382	-17.997	-3.395	-15.991	-1.845	-15.633
	[0.028]*	[0.000]***	[0.083]	[0.000]***	[0.000]***	[0.000]***	[0.033]*	[0.000]***

Note: Schwarz Information Criterion (SIC) is used to fix optimal lag length. Newey-West bandwidth selection with Bartlett kernel is applied for the LLC test. All variables are in natural logs, excluding U_t, HSE_t, LSE_t, and INT_t. p-values are reported in brackets. *Rejection of the null hypothesis of nonstationarity at 0.05 level, **Rejection of the null hypothesis of nonstationarity at 0.01 level, ***Rejection of the null hypothesis of nonstationarity at 0.001 level. Source: Authors' calculations.

One of the ten variables according to the LLC test, six of the ten variables according to the IPS test, and four of the ten variables according to the ADF-Fisher type test are not stationary at levels because the null hypothesis of "each series contain unit root" cannot be rejected even at 5% significance level. On the other hand, the series is $I(1)$ for all three test types. Results with the trend are similar in this regard. All in all, all series are $I(1)$ according to three unit-root tests performed both with and without trend.

We make use of Pedroni's panel cointegration test to confirm the existence of the long-run relationship after documenting that all panel series are $I(1)$ processes. Table 4 displays test results attributable to Pedroni and Kao. The test statistics suggest that the null of no cointegration is strongly rejected in all models except Model 1.5. Cointegration in Model 1.5 is not as statistically significant and powerful as in other models. In conclusion, even though selected series in different model variations themselves might be non-stationary, they move firmly together in the long run.

Table 4. Results of panel cointegration tests for unemployment

Test	Statistics		Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5
			RD, GDP, CPI	*RD, GDP, CPI, PRD*	*RD, GDP, CPI, PRD, INT*	*RD, GDP, CPI, PRD, OPN*	*RD, GDP, CPI, PRD, EXC*	*RD, GDP, CPI, PRD, OPN, EXC*
Pedroni	Panel	Panel PP	-0.390	-2.595**	-1.784*	-2.338**	-1.327^{+}	-0.764
		Panel ADF	-3.916***	-3.843***	-3.239***	-3.159**	-3.981***	-1.448^{+}
	Panel weighted	Panel PP	-0.786	-1.054	-1.376^{+}	-1.197	-0.598	0.055
		Panel ADF	-3.537***	-2.750**	-3.443***	-2.744**	-2.407**	-0.641
	Group	Group PP	0.229	-0.729	-0.872	-2.019*	-1.332	-1.875*
		Group ADF	-4.131***	-2.647**	-1.938*	-2.735**	-1.866*	-0.764
Kao		ADF	-4.802***	-4.343***	-4.170***	-4.630***	-4.508***	-4.668***

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. To detect the optimal lag length, the AIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the variables are in natural logs, excluding U_t and INT_t. $^{+}$Rejection of the null hypothesis of no cointegration at 0.10 level, *Rejection of the null hypothesis of no cointegration at 0.05 level, **Rejection of the null hypothesis of no cointegration at 0.01 level, ***Rejection of the null hypothesis of no cointegration at 0.001 level. Source: Authors' calculations.

The estimates of PDOLS and FMOLS methods for Model 1.0 to Model 1.5, are shared in Table 5. Since we focus on technology, we are primarily concerned with $\propto$ estimates, which is the coefficient of R&D. Positive α coefficients indicate that there is a positive relation between technology and unemployment in developing countries, which in turn means technology causes labor saving more than labor creating. Although the direction of α does not change in these different model estimates, its magnitude varies from model to model. When all six models are considered, the α coefficient varies between 0.02 and 0.05.

Table 5. PDOLS and FMOLS estimation results for the models of unemployment

Variables	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5
PDOLS						
RD_t	0.0304 (3.557)***	0.0351 (5.127)***	0.0204 (2.369)*	0.0443 (5.363)***	0.0207 (2.309)*	0.048 (4.102)***
GDP_t	-0.1703 (-8.713)***	-0.4456 (-17.321)***	-0.3224 (-7.312)***	-0.5116 (-12.574)***	-0.3586 (-10.166)***	-0.4734 (-7.168)***
CPI_t	0.0558 (3.265)**	0.0502 (4.532)***	0.0652 (4.513***	0.0569 (6.473)***	0.0905 (7.241)***	0.0377 (1.981)*
PRD_t		0.3389 (11.256)***	0.2202 (4.718)***	0.3897 (7.815)***	0.2082 (4.403)***	0.5331 (6.131)***
INT_t			0.1065 (3.019)**			
OPN_t				-0.0047 (-0.376)		-0.0372 (-1.752)+
EXC_t					0.0104 -0.625	0.0029 -0.134
FMOLS						
RD_t	0.0346 (6.246)***	0.0332 (8.699)***	0.0347 (9.798)***	0.0261 (7.110)***	0.03 (7.537) ***	0.0252 (7.894)***
GDP_t	-0.2053 (-15.327)***	-0.3449 (-21.997)***	-0.3381 (-22.152)***	-0.3794 (-23.979)***	-0.3641 (-24.949)***	-0.3763 (-24.880)***
CPI_t	0.0727 (13.835)***	0.0573 (11.324)***	0.0568 (11.618)***	0.0513 (12.486)***	0.0559 (11.651)***	0.0522 (13.969)***
PRD_t		0.2157 (11.541)***	0.2077 (11.707)***	0.2766 (15.267)***	0.2557 (13.766)***	0.2913 (17.757)***
INT_t			0.0256 (2.512)*			
OPN_t				0.0031 -0.655		-0.0022 (-0.471)
EXC_t					-0.0169 (-3.793)***	-0.012 (-2.508)*

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags, and fixed leads & lags results are also reported. Grouped estimation is used as a panel method for both estimators. As the dependent variable, decimal fraction of U_t is used. All independent variables are in natural logarithms and t-values are given in the parentheses. +Significance at 0.1 level, *Significance at 0.05 level, **Significance at 0.01 level, ***Significance at 0.001 level. Source: Authors' calculations.

In addition, when other control variables are examined, it is seen that GDP per capita is inversely related to unemployment. According to PDOLS results, GDP per capita coefficient, varies between -0.17 and -0.51. The effect of inflation on unemployment is parallel to the findings obtained in developed countries and the relationship between inflation and unemployment is positive. As expected, real interest rate is among the factors that increase unemployment. In Model 1.2 coefficient of INT_t is estimated as 0.107 with PDOLS and 0.026 with FMOLS. OPN_t, which is represented by the ratio of countries' export and import activities to total income, is negatively related to unemployment according to PDOLS results, but this coefficient is not satisfactorily significant. Only the coefficient of OPN_t estimated in Model 1.5 is negative and significant at 10%. Therefore, it is concluded that there is a positive but weak relationship between the openness levels of countries and employment. Finally, the coefficient of EXC_t is insignificant, according to PDOLS estimations.

After empirical reporting of the effect of technology on overall employment, the analyses are extended to two different skill groups. Firstly, in Table 6, the cointegration results of the variables in the four models established for the high employment group are displayed. According to almost all Pedroni's cointegration test statistics in all models, the null hypothesis of no cointegration is rejected, so it is concluded that the series in the model have a significant relationship with each other in the long run. All Kao cointegration results are also significant at a 5% significance level and support the Pedroni test results.

Table 6. Results of panel cointegration tests for high-skilled employment

Test	Statistics		Model 2.0	Model 2.1	Model 2.2	Model 2.3
			RD, GDP, CPI	*RD, GDP, CPI, PRD*	*RD, GDP, CPI, PRD, INT*	*RD, GDP, CPI, PRD, OPN*
Pedroni	Panel	Panel PP	-1.044	-2.126*	-1.354+	-2.338**
		Panel ADF	-2.068*	-2.491**	-2.015*	-4.264***
	Panel weighted	Panel PP	-3.111***	-3.682***	-2.303*	-4.102***
		Panel ADF	-4.044***	-4.972***	-3.268***	-4.823***
	Group	Group PP	-1.606+	-3.131***	-2.263*	-3.904***
		Group ADF	-2.559**	-2.812**	-2.099*	-3.516***
Kao		ADF	-1.688*	-1.925*	-2.195*	-2.204*

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the variables are in natural logs, excluding HSE_t and INT_t. +Rejection of the null hypothesis of no cointegration at 0.1 level, *Rejection of the null hypothesis of no cointegration at 0.05 level, **Rejection of the null hypothesis of no cointegration at 0.01 level, ***Rejection of the null hypothesis of no cointegration at 0.001 level. Source: Authors' calculations.

After proving that the series are cointegrated, the coefficients of the variables in the models are estimated with PDOLS and FMOLS methods and reported in Table 7. It is striking to note that the effect of technology on high-skilled and low-skilled employment is strongly differentiated in developing countries. According to PDOLS estimates, the RD_t coefficient β ranges between -0.0084 and -0.0042 in developing countries, and all coefficients are statistically significant. Technology negatively affects high-skilled employment in developing countries. However, it should be emphasized that the impact of R&D on high-skilled employment in developing countries is exceedingly small compared to other coefficients. Although there are many important reasons for this, one such reason is that the use of technology in developing countries is based on imported high-tech products as well as R&D investments. However, R&D stock is an important indicator in developing countries in terms of both the quality of technology and the ability of technology usage. As a result, the demand for skilled employment in developing countries cannot turn into employment to compensate for job losses.

GDP per capita is among the factors that increase high-skilled employment, as expected. It should be noted that the GDP per capita coefficient for high-skilled employment varies between 0.072 and 0.086 in developing countries. Inflation, another important control variable, moves in the same direction as high-skilled employment. The demand for high-skilled workers, which increases with the use of technology in these countries, increases the average wage of high-skilled workers, causing inflation.

Table 7. PDOLS estimation results for high-skilled employment

Variables	Model 2.0	Model 2.1	Model 2.2	Model 2.3
RD_t	-0.0042 (-2.520)*	-0.0049 (-1.926)$^{+}$	-0.0084 (-2.622)**	-0.0073 (-2.682)**
GDP_t	0.0716 (15.150)***	0.0815 (6.445)***	0.0857 (4.660)***	0.0663 (4.899)***
CPI_t	0.0058 (5.335)***	0.0057 (5.232)***	0.0083 (4.399)***	0.0065 (4.990)***
PRD_t		-0.0137 (-1.120)	-0.0071 (-0.442)	-0.0350 (-2.822)**
INT_t			0.0282 (1.663)	
OPN_t				0.0163 (3.964)***

Note: For the PDOLS estimator, the AIC is used to determine the leads & lags. The pooled weighted estimation is used as the panel method for the PDOLS estimator. All independent variables are in natural logarithms excluding INT_t. Besides, t-values are given in the parentheses. As the dependent variable, decimal fraction of HSE_t are used. +Significance at 0.1 level, *Significance at 0.05 level, **Significance at 0.01 level, ***Significance at 0.001 level. Source: Authors' calculations.

Although the coefficient of PRD_t is estimated as negative for high-skilled employment according to the PDOLS results, it is insignificant in two of the three models. There is a potential for high-skilled employment to be compensated by the increase in income in developing countries as a result of the increase in productivity with the effect of technology shocks. In the last two control variables, real interest rate and openness, the results show that the first has no significant effect on high-skilled employment, while the second is more significant at 1% level and has a positive effect on high-skilled employment.

Table 8 shows the cointegration test results of models established for low-skilled employment in developing countries. Strong cointegration is reported among series in three specifications but not for Model 3.0. In Model 3.0, while one of the six Pedroni cointegration test statistics is significant at 5% and two at 10%, the results are not as strong as in other models because the other three test statistics are insignificant. In addition, the Kao test statistic is significant even at 1% level in all models. As a result, there is a statistically significant cointegration between the series in the models established for low-skilled employment in developing countries.

Table 8. Results of panel cointegration tests for low-skilled employment

Test	Statistics		Model 3.0 *RD, GDP, CPI*	Model 3.1 *RD, GDP, CPI, PRD*	Model 3.2 *RD, GDP, CPI, PRD, INT*	Model 3.3 *RD, GDP, CPI, PRD, OPN*
Pedroni	Panel	Panel PP	-0.203	-1.664*	-0.732	-2.144*
	Panel	Panel ADF	-2.037*	-3.886***	-2.717**	-4.179***
	Panel weighted	Panel PP	-0.683	-2.968**	-1.833*	-3.886***
	Panel weighted	Panel ADF	-1.537+	-4.858***	-2.911**	-5.311***
	Group	Group PP	0.963	-1.049	0.260	-2.170*
	Group	Group ADF	-1.341+	-2.091*	-1.160	-2.791**
Kao		ADF	-3.143***	-2.998***	-2.809**	-3.503***

Note: Pedroni panel-data cointegration test results are reported both with and without a trend. In order to detect the optimal lag length, the SIC is used. In panel PP and ADF results, both unweighted and weighted statistics are reported. All the variables are in natural logs, excluding LSE_t and INT_t. +Rejection of the null hypothesis of no cointegration at 0.1 level, *Rejection of the null hypothesis of no cointegration at 0.05 level, **Rejection of the null hypothesis of no cointegration at 0.01 level, ***Rejection of the null hypothesis of no cointegration at 0.001 level. Source: Authors' calculations.

Having detected the powerful cointegration in the panel series, PDOLS results are presented in Table 9. Technology adversely affects low-skilled employment in developing countries since α estimates are negative ranging between -0.028 and -0.018. These results lead the study to an important finding. The effect of technology on employment in developing countries is 3.5 to 4.5 times higher for low-skilled workers than for high-skilled workers. In developing countries, manpower still has a comparative advantage in terms of wages against technology in many areas, and therefore technology spreads slowly in developing countries and low skilled workers at jobs prone to automation are affected more slowly. On the other hand, this negative effect seems to be less compensated; that is, it cannot be fully compensated by other channels for low-skilled employment in developing countries.

Table 9. PDOLS estimation results for low-skilled employment

Variables	Model 3.0	Model 3.1	Model 3.2	Model 3.3
RD_t	-0.0181 (-2.261)**	-0.0268 (-3.935)***	-0.0280 (-3.259)**	-0.0221 (-2.022)*
GDP_t	0.1074 (5.806)***	0.3758 (13.829)***	0.3483 (7.310)***	0.4004 (8.596)***
CPI_t	-0.0833 (-4.523)***	-0.0628 (-4.130)***	-0.0776 (-3.852)***	-0.0871 (-5.481)***
PRD_t		-0.3719 (-10.882)***	-0.3671 (-6.858)***	-0.3675 (-5.903)***
INT_t			-0.0976 (-1.649)	
OPN_t				0.0167 (1.126)

Note: For the PDOLS estimator, the SIC is used to determine the leads & lags and grouped estimation is used as the panel method. All independent variables are in natural logarithms Technology adversely affects low-skilled employment in developing countries since α estimates are negative ranging between -0.028 and -0.018. These results at 0.1 level, *Significance at 0.05 level, **Significance at 0.01 level, ***Significance at 0.001 level. Source: Authors' calculations.

For example, when the estimated coefficients of GDP per capita, which is among the core independent variables, are examined, it is seen that the values are higher than high-skilled employment. Therefore, the increase in GDP has more power to compensate for the losses in low-skilled employment, but since the loss of workers as a result of increased productivity due to technological and non-technological shocks is much higher in this group than in high-skilled, it can be concluded that the difference cannot be balanced by the increase in income only. Finally, when this situation is combined with the negative effect on high-skilled employment, it causes overall employment to be negatively affected by technology.

The coefficient of inflation is negative, unlike in high-skilled employment estimates. This conclusion is also plausible, as the reduction in low-skilled employment in developing countries causes low-skilled workers to earn lower wages, which in turn reverses the relationship between inflation and low-skilled employment. The coefficients of the real interest rate and openness variables are as expected, the first is negative and the second is positive. However, according to the PDOLS results, both variables are statistically insignificant.

4. Concluding Remarks

We investigated the effect of technology on the employment of two skill groups in developing countries using data from 23 developing countries from 1990 to 2019. The effects of technology on the current demand for low-skill or routine jobs in developing countries are more limited than in developed economies since technology adaptation takes more time in developing countries. In addition, the average wages of the current workforce in these countries are relatively low, which enables the workforce to maintain its comparative advantage over technology. Therefore, automation does not become attractive as early as in developed countries. On the other hand, if technology is ready to use in developing countries, the skill constraint in countries reveals that few employees or firms can benefit from it. However, this does not mean that the entire developing country pool cannot benefit from technological change. Asian countries such as China and India have switched from traditional methods to modern technologies, especially in the manufacturing sector, and have achieved significant gains.

We split employment in developing countries into high-skilled and low-skilled and examined how these two groups are affected by technology. In this direction, three different unit-root tests, the LLC, the IPS, and ADF-Fisher, proved that all variables used in different model variations are $I(1)$. We then show by both Pedroni (1999, 2004) and Kao (1999) cointegration methods that the series are $I(1)$ and there is a statistically significant relationship among variables in the long run. Then we estimated the coefficients of the variables by grouped mean PDOLS (Pedroni, 2001a) and grouped mean FMOLS (Pedroni, 2001b) methods. Based on the estimation results we conclude:

- Unemployment, R&D expenditures, and other control variables included in the study are cointegrated in the long-run in developing countries. The coefficients obtained with the PDOLS and FMOLS estimators show that technology is among the factors that increase unemployment in developing countries. Considering baseline models, inflation is among the factors that increase unemployment in developing countries. Among the other control variables, the interest rate coefficient was estimated as 0.1065, as reported by the PDOLS method, and 0.0256, based on the FMOLS. Subsequently, the real interest rate is among the factors that increase unemployment in developing countries. As estimated by the PDOLS method, trade openness seems to be among the factors reducing unemployment in developing countries, but its statistical significance is weak. Finally, the real exchange rate coefficient is positive in the models established for unemployment according to the PDOLS method, but it is not statistically significant.

- Secondly, the coefficients of the series in the four models in which both high-skilled and low-skilled employment are established are estimated by PDOLS (Pedroni, 2001a) and FMOLS (Pedroni, 2001b). The results show that both high-skilled and low-skilled employment in developing countries is negatively affected by technology. The technology coefficients estimated by PDOLS range from -0.0221 to -0.0181, indicating that the disruptive impact of technology on low-skilled employment in developing countries is 2.5 to 5.3 times greater than that estimated for high-skilled employment. On the other hand, in the models established for low-skilled employment, the coefficient of income varies between 0.1074 and 0.4004, while the productivity coefficient varies between -0.3719 and -0.3675. In the models estimated by FMOLS, the coefficients are in a narrower range, but the signs are parallel with PDOLS. In this respect, increase in income is an important compensation channel in developing countries, but the labor-saving effect from technical and nontechnical shocks cannot be fully compensated. When the inflation effects on high-skilled and low-skilled employment are controlled separately, it is seen that the direction of this effect is different for skill groups. Inflation and high-skilled employment move in the same direction, but low-skilled employment is negatively affected by inflation. There is no statistically significant effect on the interest rate for both groups. The effect of trade openness on both high-skilled and low-skilled employment is positive, but the coefficient calculated for low-skilled employment is not statistically significant.
- In developing countries, the effect of technology on employment is negative, but coefficients for both groups of countries are different. In the models established for unemployment, based on all β coefficients estimated, the range is 0.0204 to 0.0480 in developing countries.

As a result, the overall unemployment effect of technology in developing countries is in the direction of labor-saving. These findings can be deduced in line with the implications for the technology-unemployment relationship handled with job polarization and task-based approaches (Autor, 2010). In addition, empirical evidence that the comparative advantage of the workforce in terms of wages has diminished over time in developing countries (Frey, 2020), arguments that developing countries are not as fast and effective in technology adaptation as developed countries (Soto, 2020), and findings on developing countries to experience deindustrialization earlier (Rodrik, 2016) support our empirical findings. Furthermore, although it is seen that both skill groups are negatively affected by technology in developing countries, the negative effect on high-skill employment is relatively low. On the other hand, the increase in income channel is an effective compensation mechanism for high-skilled employment. Measures such as eliminating bottlenecks, restrictions, and inequalities in access to technology, providing affordable and reliable internet, and advanced digital payment systems are important. Supporting the participation of education systems in the digital world with the necessary equipment, IT-oriented workforce models and effective integration of online work platforms into labor markets will help the workforce become qualified for jobs that require higher skills. The direct and indirect effects of technology are inevitable and continuous. The cost advantage of labor in developing countries is not permanent and this advantage disappears as robots become cheaper. Thus, the destructiveness of the labor-saving effect may be more sudden and severe in developing countries. The implications of our findings should be followed by developing countries to manage their labor force. Apparently, low-skilled laborers are subject to more unemployment and, thus, lower wages. Strategies by policymakers would be followed to let these laborers acquire talent and qualifications.

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