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RESEARCH PAPER

The Impact of Technological Innovation on Labor Market: Evidence from Low- and Middle-Income Countries

Zakaria El Menyari[a, *], Idriss El Abbassi[b]

a. Faculty of Law, Economics, and Social Sciences, University Mohammed V, Rabat, Morocco.

b. Department of Economics, Faculty of Law, Economics, and Social Sciences, University Mohammed V, Rabat, Morocco.

* Corresponding author, E-mail: zakaria_elmenyari@um5.ac.ma

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Abstract

With all the technological advancements over the world, a great interest is on its effect on jobs. Technological change takes away or creates more jobs for human? This debate has been going on for a long time and still ongoing in different countries. The limited studies on the topic in low and middle incomes countries gives us the opportunity to study a subject that have not yet been sufficiently addressed, specially that technology is changing work in these countries day by day as it was demonstrated in the covid19 pandemic. To be more objective in presenting the research finding we used a literature review based on the meta-analysis method. We tried to synthesize and summarize the results of 19 studies by using a quantitative method that allowed us to report 531 estimations. Three reference models were distinguished: Derived labor demand model (DDM) developed by Van Reenen (1997), skill share model (SSM) created by Machin and van Reenen (1998) and the most recent: innovation decomposition model (IDM) used by Harisson et al. (2014). The review found that the effect of technology varies depending on the type of innovation, for process innovation work can be more efficient and less time-consuming for skilled workers although unskilled workers are more likely to be replaced by automated processes. For product innovation the effect is positive on total employment, we may consequently state the validity of Skill biased technological change hypotheses (SBTC) for low- and middle-income countries. However, the presence of publication bias and heterogeneity limits the generalizability of these results.

Keywords: Employment, Meta-Analysis, Process Innovation, Product Innovation, Technology.

JEL Classification: E24, O31, O32, O33.

1. Introduction

The development of technologies all over the world creates considerable uncertainty. Automation, artificial intelligence and robotics has reshaped the workplace and the challenges in labor markets are growing. In one hand it brings the promise of higher productivity and efficiency (job creation effect). In the other hand it raises questions about the way it is replacing some jobs and changing the nature of others (job destruction effect).

Technology is defined by OCDE (1996) as "the state of knowledge concerning the means of transforming resources into products" or as "the machines and equipment developed through the application of scientific knowledge". Since the first time that Jacob Bigelow used in 1829 the term technology in his work "Element of Technology". Several authors have written on the subject. Technology resulting from advanced research and development activities was introduced by the new theory of economic growth as a main engine of economic growth (Romer, 1986; Aghion and Howitt, 1992). The production of a new technology involves two types of processes: invention and innovation. The first involves the formulation of scientific theories or processes while the second is the direct application of this knowledge for a useful purpose whether it be a process innovation (procedure innovation) by introducing new ways or product innovation by making changes to the existing product or introducing new one. Addressing the technology in its different aspects can help us understand its effect on jobs, skills and the nature of work itself.

According to our research, theoretical and empirical studies relating to the impact of technological innovation on employment in developed countries can be classified by reference to three hypotheses: Skill-based technological change (SBTC) hypothesis (Katz and Murphy, 1992; Bound and Johnson, 1992; Machin et al., 1998; Autor et al., 1998; Falk and Seim, 1999; Barteland et al., 2007; Gera, 2001; Gregory et al., 2001; Pivaand et al., 2005); Capital-skill complementarity hypothesis (CSC) (Berman and al., 1994; Golden and KATZ, 1998) and recently the routine-based technological change hypothesis (Autor et al., 2003; Acemoglu and Autor, 2011; Bessen, 2015; Graetz and Michaels, 2018; Frey and Osborne, 2017; Hemous and Morten, 2018; Agion et al., 2019; Acemoglu and Restrepo, 2020).

While the majority of studies analyzing the effect of technological innovation on employment have much been researched in developed countries our work focuses on analyzing this subject in countries classified by the World Bank as low and middle-income countries that have not been sufficiently studied. It was inspired from the empirical sample studied by Ugur and Mitra (2017) that we have extended to 19 studies in order to capture a more complete picture. Based on meta-analysis method to combine the results of multiple studies to provide a quantified and reproducible synthesis.

The remainder of this paper is organized as follows: Section II introduces the theoretical analysis, Section III presents the methodology Section IV present the findings and discusses the results, and the last section concludes and offers recommendations for future research and practice.

2. Theoretical Analysis

Apart of understanding the relation between technological innovation and employment, the theoretical analysis in this section is devoted to present a synthesis of the various reflections and articles that have covered the topic. Certainly, the subject has interested many authors that we cannot quote all especially in developed countries. However, we chose to focus our reflection on developing countries that presents a context not sufficiently studied, the thing that could give more value to our article. More explicitly, the objective of this section is to present an evaluation of the empirical models used to analyze the relation between technological innovation and employment in developing countries.

One of the most recent systematic revues published by Kerestin et al. (2022) shows that the availability of data allowed the author to expand the study to 127 contributions published between 1988-2021.This study has gone beyond the traditional analysis based on SBTC hypothesis commonly used in developing countries to deepen the analysis using additional factors in particular: Robotization digitalization or Information and Communication Technology. According to their work the replacement effects of new technologies on employment is based on the use of robots, this moved the debate currently to the effect of technological change on jobs that are sensitive to automation and lead to the identification of routine or non-routine jobs. Likewise, we have found that the most recent and comprehensive analyses from 2010 to 2022 are those of the developed countries because they have rich databases such as (PIAAC[1], International Federation of Robotics (IFR), EU Labor Force Survey (LFS) ...) that analyze the technology in its various aspects with more details, thing that have allowed them to increase the analysis from one level to another.

Understanding the relation between technological change and employment is the mean to verify the capability of this technology to transform a given set of inputs into outputs (Ruttan, 1959) destroy or create jobs to extent that it makes

[1]. Survey of Adults Skills

production processes more efficient and enabling firms to produce the same goods with less labor and capital.

Articles on less and middle-income economies dealing with this subject are based on three references models: ‘Derived Labor Demand model’ (DDM) proposed by Van Reenen (1997), ‘the skill structure model’(SSM) developed by Machin and Van Reenen (1998) and extended by Acemoglu (1998) and finally ‘the innovation decomposition model’s (IDM) presented by Harrison et al. (2014).

2.1 Derived Demand Model

The stochastic representation of Van Reenen (1997) is reproduced below. The starting point comes from a CES production function:

$$Y = A\left[(A_L L)^{(\sigma-1)/\sigma} + (A_k K)^{\sigma/(\sigma-1)}\right]^{\sigma(\sigma-1)} \tag{1}$$

where **Y** is production, **L** is employment, and **K** is capital. **A** is a parameter that embodies technology, neutral in the sense of Hicks; $A_L$is a parameter that reflects the increase in the labor factor, neutral in the sense of Harrord; while $A_k$represents technical change, neutral in the sense of Solow. Van Reenen (1997) assumes perfect competition for his model.

Indeed, Van Reenen (1997) replaces the unobservable technology term A_L and $A_k$with a measure of innovation so that the stochastic form of the demand function becomes:

$$l_{it} = \alpha Inno_{it} + \beta w_{it} + \gamma k_{it} + \tau_t + \mu_{it} \tag{4}$$

where ***i*** is the company, ***t*** the period, μ_{it} is an error term.

In order to deal with the endogineity problems the users of this model bring lags or instrumental variables to derive the innovative aspect of the firm; it therefore requires long series of data to give us several conclusions.

2.2 The Skill Structure Model (SSM)

By qualification, the theoretical model developed by Machin and Van Reenen (1998) to understand the impact of technological progress on the labor market were established on the basis of the hypothesis of skill-biased technological change (SBTC) that was the object of the majority of studies in developed countries in the 1990s. Among the models used to check the validity of this hypothesis, the model of Machin and Van Reenen (1998) stands out.

$$\begin{aligned} \Delta SHARE_{ijt} = {} & \alpha_j \Delta \log(K_{ijt}) + \beta_j \Delta \log(Y_{ijt}) \\ & + \gamma_j \Delta \log(R\&D/Y)_{ijt} + \eta_{jt} D_{jt} + u_{ijt} \end{aligned} \tag{3}$$

where Δ***SHARE*** denotes the part of skilled employees in the wage bill for an industry ***i*** in a country ***j*** at a time ***t***. The ratio of R&D expenses to production measures technological change. In Equation (5), capital is assumed to be a quasi-fixed. Consequently, the evolution of the demand for skilled workers depends on spending on research and development. In addition, the skill-sharing model by Machin and Van Renen (1998) also allows substitution between the labor and capital factors for the two types of employment (skilled and unskilled).

Following the same logic, Acemoglu (1998) developed a theoretical model based on the work of Aghion and Howitt (1992). The specificity of Acemoglu's work lies on the fact that technology is endogenous, expressed as a function of relative price and as a function of the ratio H/L of skilled labor compared to unskilled labor $\frac{A_h}{A_l} = f(p, H/L)$. As shown, the analysis of Acemoglu can be summarized in the graphic below:

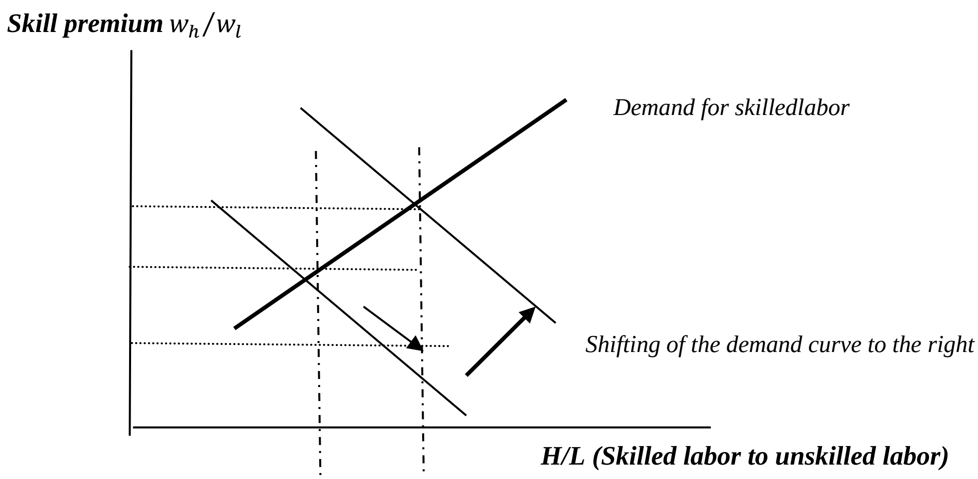


Figure 1. Technological Change and Demand for Skilled Labor
Source: Acemoglu (1998).

Therefore, it looks clear that the SBTC hypothesis is based on the assumption that technological progress augments the labor productivity of skilled workers by more than it does that of unskilled workers, thereby shifting to the right the labor demand curve for skilled workers further than that of unskilled workers.

The key insight Acemuglu’s framework is that, since technology is endogenous, it predicts for skilled workers an increase in the skill premium[1], when SBTC induces an acceleration in the demand for skilled relative to unskilled

[1]. The wage of skilled relative to unskilled workers.

workers, and a decrease in the skill premium when there is an acceleration in the supply of skilled relative to unskilled workers.

Note that SSM framework suppose that the substitutability between technology and skilled workers is less than that between technology and unskilled workers, therefore SSM framework can provide us a meaningful result when the data used relates to the type of activities that could be automated.

2.3 The Innovation Decomposition Model (IDM)

A third type of model is the one of Harrison et al. (2014), it is often used to interpret survey data established in accordance with the Enterprise Survey, it is also a model that distinguishes between product innovation and process innovation, it was the subject of several studies dealing with the relationship between technological innovation and employment. For Harrison et al. (2014) the employment growth rate is expressed in terms of the production growth rate of the new and old product. The stochastic equation is:

$$l_i - y_{1i} = \alpha_0 + \alpha_1 d_i + \beta y_{2i} + u_i \qquad (4)$$

where ***l*** is the growth rate of employment, y_{1i} and $y_{2i}$are the growth rates of sales of new and old products with u_i an error term that refers to unobserved random disturbances. Therefore, the Harrison et al. (2014) distinguishes between process innovation measured by a dummy variable and product innovation measured by the sales growth rate of a new product.

Studies that use IDM often use data from the Community Innovation Survey (CIS). These surveys are regularly conducted by statistical offices to assess the innovativeness of firms and regions. Typically, the surveys allow distinguishing between process and product innovation and, in some cases, organizational innovation. Process innovation is measured by survey questions asking firms to report whether they implemented a new improved production method that was empirically transformed into a dummy variable. The same, product innovation is evaluated based on a question asking firms whether they recently introduced a new product, then it is calculated by variation of sales.

We can deduct from this that the frontiers between product innovation and process innovation will not be always clear, as consequence including both types in the same model can involve ambiguities when interpreting results. The same, the introduction of a product innovation may coincide with input changing requirements as seen in the quantity and type of labor. This is why labor-saving technological change does not necessarily lead to layoffs, those employees that are no longer required to produce find other useful tasks within the firm.

The difference between Derived Labor Demand Model (DDM) and innovation Decomposition Model (IDM) is the omission of wages in the latter. Wages disappear in IDM because labor demand is determined by production growth rate of the new and old product and considered wages as given. In addition, the Skill Structure Model (SSM) suppose that the rate of substitution between inputs (capital and labor) depending on the type of skills is not constant. It seems that the innovation decomposition model (IDM) suffers from inherent limitations, the variable y_{1i} includes some employment implications that needs further information to be separated: the possible increase in demand for old product, the compensation effect of a decrease in the old product price due to process innovation and the reduction of old product demand.

In summary, it is challenging to verify the validity of SBTC hypothesis for low- and middle-income countries and whether or not technological change is labor replacing. We pointed out from our researches that the lack of data is the main factor that limits the analysis. The use of simple undeveloped variables such as sales of new product, R&D expenditure or dummy variable to capture the innovative character of a firm do not take into account automation and technical criteria and does not make it possible to deepen the analysis on others aspects and have indeed precise results, moreover some measures does not reflect the nature of tasks executed by employees such as diplomas/qualification or number of workers/hours. As results the analyses in developing countries are limited to SBTC hypothesis and the effect of technological innovation is likely heterogeneous across industries and occupations.

3. Data and Methodology

The aim of this section is to present the methodology adopted. It presents the models and methods adopted and explain the steps followed. In our work in order to have an effective understanding of the existing links between technological innovation and employment.

In so far, as there is an important study dealing with our subject, we chose to use meta-analysis method to have a better integration of empirical results, it takes into consideration moderating factors and provide a quantified and reproducible synthesis of the existing literature.

Our study was inspired from the empirical sample studied by Ugur and Mitra (2017) that we have extended to 19 studies published between 1976 and 2020 followed by PRISMA 2020 guidelines from several research platforms such as: JSTOR, Proquest, ScienceDirect, EconLit and SSRN, Springer, Web of Science.

The goal is to extend the period to capture a more complete picture of the effects of technological innovation in low- and middle-income countries for each model examined. The research was performed using terms that appeared either in the title, abstract, or list of keywords of studies that provides empirical relationship between labor combined with technology or innovation.

We first codified these studies and achieved 530 effect sizes[1]by a set of common moderating factors[2]such as: type of publication, estimation method, type of job, type of innovation, type of model, sector and country/region covered by the study (Table A1 in the appendix). Second, we used funnel plots to show the degree of heterogeneity and selection bias. It is the simplest and most commonly used method to detect publication selection bias (Sutton et al., 2000a). Third we adopted the approach recommended by Stanley and Doucouliagos (2012) (Figure A1 in the appendix) in order to confirm the absence of asymmetry deduced from the funnel plots and identify the existence and the nature of the relationship between technological innovation and employment, it is based on conducting a bivariate estimation using PET/FAT tests (Precision-effect testing/Funnel-asymmetry testing) calculated according to the following expression:

$$t_i = \alpha + \beta\left(\frac{1}{SE_{CCP_i}}\right) + \vartheta_i \tag{5}$$

In the light of the results provided by the PET/FAT tests, we proceeded to a PEESE estimate (The precision-effect estimate with standard error) to produce economic conclusions. The PEESE estimate takes into account the selection bias and the non-linearity of the relationship between effect sizes (According to the Figure A1 in the appendix for investigating and correcting bias).

Finally, we tried to determine the sources of the heterogeneity, identified by using a multiple meta-regression (MMR) in which we integrate the moderating factors (see the appendix for more technical details). It is based on the following reformulation:

$$\mathrm{t_i} = \delta_0 + \delta_1 (1 \big/ \mathrm{SE\_CCP_i}) + \sum_{2}^{k} \delta_k\, (\mathrm{Z_{ki}}/\mathrm{SE\_CCP_i}) + \epsilon_i \tag{6}$$

where $1/\mathrm{SE\_CCP_i}$ is the precision, $\mathrm{Z_{ki}}$ is a vector of moderating factors.

We estimate MMR with five estimators (fixed effect estimates, fixed effects estimates with bootstrapped standard errors, hierarchical method estimation with random slopes and intercepts, hierarchical method estimation with random

[1]. Measures the strength of the relationship between two variables.
[2]. The variables susceptible to be associated with the results of the study.

slopes/intercepts and bootstrapped standard errors, weighted fixed effects estimates using 1/N as weights), the interpretation of results is based on the estimation that provides the lowest AIC and BIC values between OLS, fixed effects, and hierarchical model estimations.

4. Result and Discussion

Starting with the codification of the empirical studies included in our sample we dressed a table (see Table A1 in the appendix) where estimates are reported by length of study and classified by: type of innovation, type of employment (skilled or unskilled) and by type of models (SSM, DDM and IDM) described above. It displays the median value of the effect size measured by the partial correlation coefficient (PCC).

Our sample have nine (n=9) studies supporting Derived Labor Demand Models (Conte and Vivarelli, 2011; Lundin and Fredirik, 2007; Mitra, 2019; Mitra and Jha, 2015; Oberaj and Iftikhar, 1981; Otsuka et al., 1994; Raju, 1976; Saafi, 2014; Merikull, 2010), and nine (n=9) studies using Innovation Decomposition Model (Benavente and Lauterbach, 2008; Cirera and Sabetti, 2019; Crespi et al., 2019; Medase and Wyriwich, 2021; Okum et al., 2019; Avenyo et al., 2019; Sithole and Buchana, 2020; Aboal et al., 2015; Elejalde, 2015) but only one study used Skill Share Model (Almeida, 2010). The latter clearly shows that technological change is biased toward skills by showing that a lower skilled worker tends to be replaced by higher skilled workers in East Asia.

Note that although the majority of these studies used Ordinary Least Squares (OLS) and instrumental variables IV as estimation method and survey data collected by local institution or World Bank (CIS); The majority of contribution focused on the manufacturing sector, while few of them examined the agricultural one (n=3). In this regard, it looks clear that it is not possible to use dynamic panel because technology is not presented by variable with large temporal structure of data for developing countries.

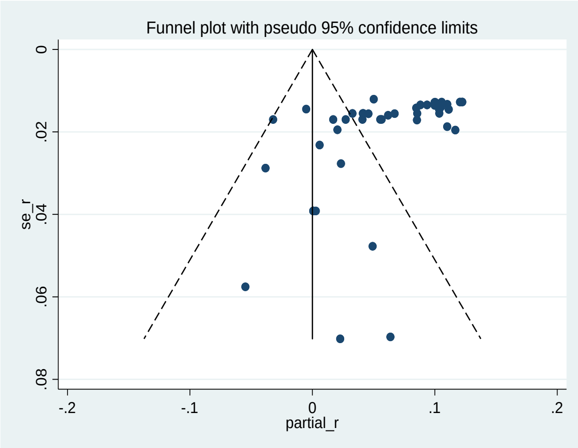
Studies based on (DDM) and (IDM) use as measure of innovation: variable dummy, trade value, R&D expenditure or total factor productivity.

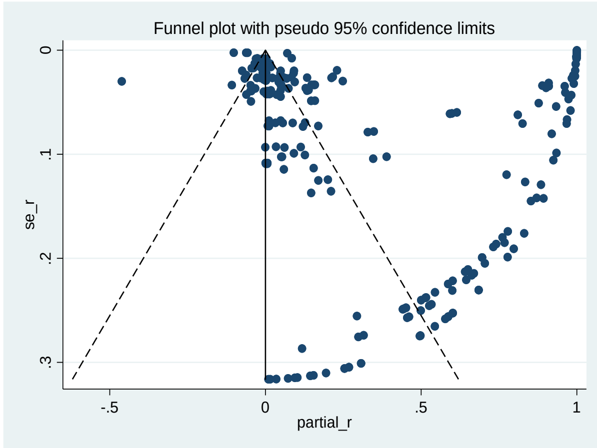
Despite the fact that the nine studies were based on the most recent model IDM they have covered old periods. The most recent period is 2015 studied by Cirera and Sabetti (2019). The lack of recent data only allows the analysis based on SBTC hypothesis in developing countries instead of RBTC hypothesis that needs recent and supplement data.

Statistically, concerning the effect size value, it varies between 0.98 (Mitra, 2019) and -0.017 (Lundin and Fredirik, 2007) while the median t-value exceeds "2" in six studies. At this step we can reach no conclusion as to the relation between technological innovation and employment, which led us to use funnel graphs[1] (Figure 2) to look for possible biases in the selection of publications and identify the presence of heterogeneity.

Therefore, we divided our sample into four groups according to the type of innovation (process/product) and to the qualification of the job (skilled/unskilled). Again, we applied this distribution to studies based only on innovation distribution model (IDM) as they make up the share of the most recent studies in our sample (Table A2 in the appendix).

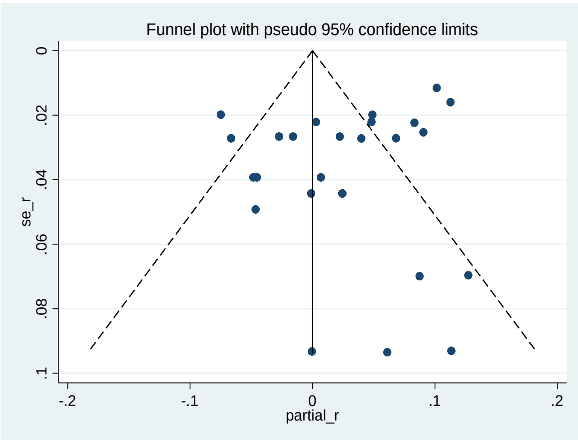
[1]. Funnel plots proposed the first time by Light and Pillemen (1984).

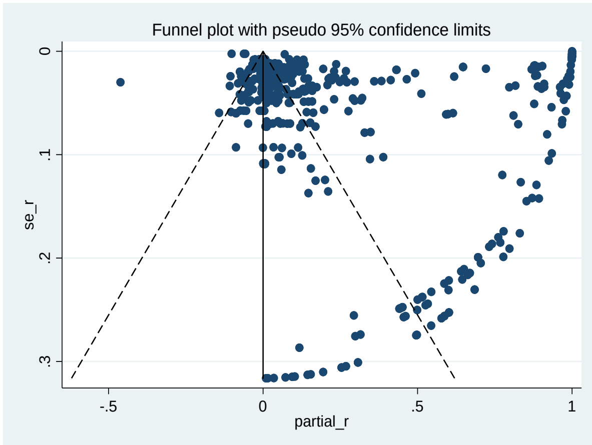




A. Process innovation and skilled-labor demand Residual variation due to heterogeneity 72.46%

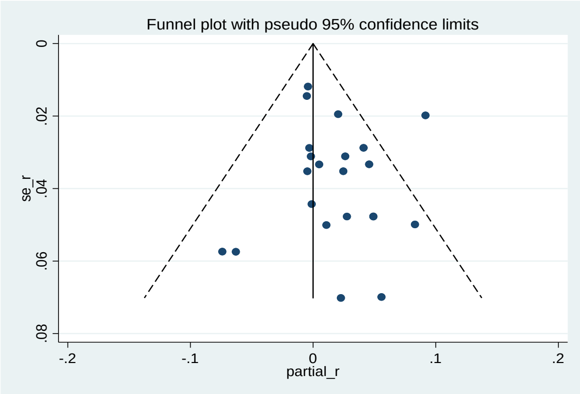
B. Process innovation and mixed-skill labor demand (Skilled, Unskilled) Residual variation due to heterogeneity: 97.16%



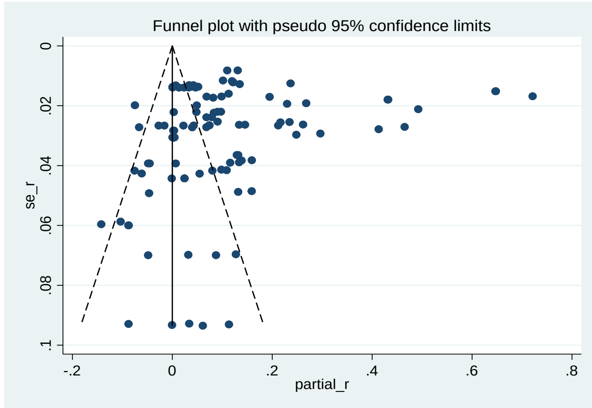


C. Product innovation and mixed-skill labor demand Residual variation due to heterogeneity 99.78%

D. Full sample (all innovation and skill types) Residual variation due to heterogeneity 99.78%



E. Process innovation and skilled-labor demand Residual variation due to heterogeneity: 32.37% (Innovation decomposition model)



F. Product innovation and mixed-skill labor demand Residual variation due to heterogeneity: 98.26% (Innovation decomposition model)

Figure 2. Compiled of Table 1

Note: Funnel plots of technology adoption and employment Residual variation due to heterogeneity is obtained from random-effect meta-regression proposed by Harbord and Higgins (2008), who suggest that residual variation above 75% reflects high levels of heterogeneity.

However, we cannot generalize at this level the economic conclusions related to the impact of technological innovation on employment. In order to take into consideration, the publication selection bias we will move on to the second phase of our approach, which consists of applying the PET/FAT tests *(Precision-effect testing/Funnel-asymmetry testing)* and estimating the bivariate PEESE *(The precision-effect estimate with standard error)*, model that takes into account the relation of the nonlinear effect size calculated by the partial correlation coefficient and their standard errors.

Table 2. Test FAT/PET/PEESE

	Process/Skilled, FE1, B/Strap	**Process/Unskilled, FE B/Strap**	**Product, Mixed FE, B/Strap**	**Full sample FE**	**Process/Skilled, OLS, B/Strap**	**Product/Mixed OLS, B/Strap**	**Full sample B/Strap**
Dependent variable: *t-value*	PET/FAT	PEESE					
Precision PCC	0.11 (0.012)***	0.18 (0.27)	0.94 (0.38)***	1.31 (0.151)***	0.076 (0.018)***	0.995 (0.005)***	0.998 (0.0018)***
Constant (Bias)	-2.61 (0.711)***	-0.62 (1.06)	-2.07 (1.31)	-3.86 (0.516)***			
Standard Error of PCC					-515 (273.22)*	-52.3 (24.47)***	-70.16 (98.73)
Number of observations	63	48	306	504	63	306	504
Number of studies	7	7	16	19	7	16	19
AIC	277.87	128.61	1323.065	1705.10	285.07	2959.79	5758.12
BIC	282.16	130.48	1330.512	1709.37	289.36	2967.24	5766.67

Source: Compiled by the authors.

Note: Estimator choice is based on minimum AIC and BIC values, as indicated in the methodology. ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Table 3. Multivariate Meta-Regression

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Precision of PCC	1.22 (0.19)***	1.22 (0.086)***	1.03(0.15)***	1.08 (0.15)***	1.28(0.06)***
Journal Article	4.21 (0.66)***	4.21 (0.36)***	2.61 (1.32)***	2.61 (1.32)***	3.63 (1.57)***
Farm Data	0.9 (1.17)	0.9 (0.24)	-0.05 (0.73)	-0.05 (0.73)	0.22 (0.96)
Product innovation	1.48 (0.49)***	1.48 (0.17)***	1.2(0.13)***	1.2 (1.39)***	1.16(0.14)***
Unskilled labor	-0.006 (0.52)	-0.006 (0.19)	0.23 (0.16)	0.23 (0.16)	0.29 (1.16)**
Middle-income country	2.57 (0.812)***	2.57 (0.34)***	1.22 (0.5)***	1.22 (0.5)***	1.42 (0.48)***
IV estimator	-0.48 (0.28)*	-0.48 (0.14)***	-0.42 (0.2)***	-0.43(0.2)***	-0.40 (0.2)***
Constant	-11.15(1.29)	-11.15 (0.64)	-7.91 (1.69)	-7.76 (1.72)	-9.84 (1.61)
Number of observation	504	504	504	504	504
Number of studies	19	19	19	19	19
AIC	2060.99	2062.993	1726.2	1726.2	1721.76
BIC	2090.87	2097.146	1768.892	1768.892	1764.45
VIF	1.31	1.31	1.31	1.31	1.31
Residual heterogeneity	98%	98%	98%	98%	98%

Source: Compiled by the authors

Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

[1]. According to Stanley and Doucouliagos (2014) the fixed effects estimator is the most technically appropriate in the context of meta-analysis because it gives unbiased results and it considers the size of the effect to be fixed and homogeneous in all studies in the sample.

In addition, to identify the sources of heterogeneity and the factors likely to vary the results, we conducted a multi meta-regression that includes several moderating factors in order to draw economic conclusions. To do this we were based on a hierarchical estimation, in particular, we conducted: estimation based on the method of ordinary least squares (OLS) taking into account a fixed-effects and hierarchical model that consider the dependence between studies. Table (3) displays the results of this estimation. The preferred estimate the one whose AIC and BIC criteria are the smallest (model 5). We note that the introduction of the moderating factors did not reduce the variation of the heterogeneity of the residuals since it displays a value of 98%, this value is not far from that recorded for the group (D) in the funnel graph, and hence confirms the level of heterogeneity recorded. Multicollinearity is irrelevant in the sense of VIF (variance inflation factor) it recorded 1.42, lower than the maximum value of 10 required in econometric work.

In addition, table 4 allow us to draw several conclusions, the first is that in general innovation impacts employment, with a broader level of impact when it comes to product innovation, it corroborates the results of bivariate estimation discussed earlier and confirmed by Cirera and Sabetti (2019) for 15000 firms in developing countries. Similarly, the impact of innovation on less qualified employment remains very low which goes with the results obtained in the work of Ugur and Mitra (2017) that confirms, among other things, the validity of the hypothesis of skilled-biased technological change in developing countries. This perspective also suggests that an increase in the supply of skills can lead to an acceleration in the demand for skills in low- and middle-income countries as suggested by (Acemoglu, 1998).

Another conclusion related to the multi meta-regression is that technology is not totally exogenous because of the simultaneity in the innovation and employment relation. This is explained by problems related to measurement errors and specification model as evidenced by the small coefficient of the effect size obtained from the instrumental variables estimates that takes into account endogeneity. It gives us also an attractive interpretation, since the shortage of qualified workers is able to drive new technologies may slow down its implementation, as the introduction of new technologies likely requires the availability of skill workers, in other words, technology is more skill-biased as a result of an exogenous increase in the supply of highly skilled labor and this was demonstrated by Acemoglu's framework in our literature.

Similarly, we do not have strong evidence that confirms the impact in the agricultural sector is greater than the industrial sector. This can be explained by the limited number of studies relating to this sector in our work.

The effect-size estimates related to middle income countries are relatively larger than those related to employment effect in lower income countries. However, journal articles tend to report larger effect-size estimates compared to working papers and reports. Considering the few studies on the agricultural sector, the impact is not statically significant which lead us to uncertain employment effect at that sector.

5. Conclusion

This study reviewed the main articles on the impact of technological innovation on employment in developing countries it provides an articulation between theoretical analysis and meta-analysis.

The vast majority of researches use three reference models. Derived labor demand model (DDM) developed by Van Reenen (1997) where technological progress is expressed by an innovation variable such as (R&D expenditure, stock of patent, hours worked, etc.), the skill share model (SSM) that differentiate skilled from unskilled workers created by Machin and Van Reenen (1998) and developed by Acemoglu (1998) to demonstrate the endogeniety of innovation and the most recent innovation decomposition model (IDM) that distinguished between process innovation and product innovation presented by Harisson et al. (2014).

We found that a considerably number of studies gives support to the positive effect of technological innovation on job creation. Innovation has diverse materializations in the organizational context several studies analyse its impact on employment according to the type of innovation: product innovation and process innovation and also according to the type of qualifications: skilled workers, unskilled workers. We verified the implications of these two types of innovation whether they have the same effect on the two types of qualifications or not. With the process innovation the implementation of a new or improved production method has a positive effect only on skilled workers it goes with the skill biased hypothesis While the creation of a new good or service or the introduction of an improved version of a previous product to the market has a positive effect on both skilled and unskilled workers.

Despite the fact that the effect of product innovation is larger than process innovation and can be qualified as the main source of job creation we can note generalize this result that should be taken under the reservation of the presence of high heterogeneity.

Our exercise points out some limitations related to the availability of data especially for the middle-income countries' context, the data bases need to be extended to more exhaustive surveys on technological innovation which is a first and foremost a necessity to increase efficiency of the study, moreover technological innovation may have different effects that needs to be measured including the aspects of displacement and compensation.

Under the routine-biased technological change literature the debate turns more around skill polarization instead of skill shares, focused in replacing routine tasks this hypothesis needs to be verified and developed in future studies for developing countries. The role and quality of institutions should be included in the relationship between employment and technological innovation in order to have a transversal vision about effect on employment in low and middle income

We noticed that the articles analyzing the relation between technological innovation and employment in developing countries are not in line with the current technological changes. None of the articles included the impact of the latest technological advances that have already changed the way we live and work and we can expect for example that artificial intelligence will be integrated further into assisting or even replacing people at work. The analysis cannot be sufficiently relevant with high added value if it remains based on limited data, studies need to be deepened and extended to the effect of these latest advances and be also interested with the potential effect of this continuous process of technological change.

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Appendix

Table A1. Collected of the Empirical Studies

Study	Data Period	Reported estimates	Country	Data	Estimation Method	Model	Type of Technological Innovation	Skill Type	Sector	Median PCC	Median t-value
Almeida (2010)	2003-2005	29	East Asia	Survey Data	OLS	SSM	Process	Skilled	Manufacturing	0.1003	7.3684
Benavente and Lauterbach (2008)	1998-2001	4	Chili	Survey Data	OLS, IV	IDM	Product	Mixed	Manufacturing	0.0243	0.5497
Cirera and Sabetti (2019)	2013-2015	39	Developing Country	World Bank Enterprise Survey	OLS, IV	IDM	Process/Product	Skilled Unskilled	Manufacturing	0.0204	1.1
Conte and Vivarelli (2011)	1980-1991	9	Developing Country	Survey Data	GMM	DDM	Process	Mixed	Manufacturing	0.0408	2.407
Crespi et al. (2019)	1995-2009	52	Argentina, Chili	Survey Data	OLS, IV	IDM	Product	Mixed	Manufacturing non-Manufacturing	0.04902	1.170
Lundin and Fredirik (2007)	1998-2004	8	China	Survey Data	OLS, IV, FE	DDM	Process	Mixed	Manufacturing	-0.01746	-2.1663
Mitra (2019)	1998-2010	44	India	Survey Data	OLS, FE, RE	DDM	Process/Product	Mixed	Manufacturing	0.9872	36.4499
Mitra and Jha (2015)	1998-2010	33	India	Survey Data	OLS, FE, RE	DDM	Process/Product	Mixed	Manufacturing	0.1698	1.61157
Oberaj and Iftikhar (1981)	1977	8	India	Survey Data	OLS	DDM	Process/Product	Mixed	Agricole	0.0503	1.4933
Otsuka et al. (1994)	1966-1990	13	Philippines	Survey Data	Maximum Likelihood Method	DDM	Process/Product	Mixed	Agricole	0.0095	0.1306
Raju (1976)	1968-1971	72	India	Survey Data	OLS	DDM	Process/Product	Mixed	Agricole	0.5386	2.1769
Saafi (2014)	1997-2006	13	Tunisia	Survey Data	GMM, FE	DDM	Process/Product	Mixed	Manufacturing	0.0013	0.0173
Medase and Wyrwich (2021)	2005-2010	14	Nigeria	Survey Data	OLS, Quantile Regression	IDM	Process/Product	Mixed	Manufacturing and services	0.0925	2.230
Okumu et al. (2019)	2011-2015	22	Africa (27 Country)	Survey Data	OLS, IV	IDM	Process/Product	Mixed	Manufacturing	0.022	1.6138
Avenyo et al. (2019)	2013	9	Africa Sub Saharian: DRC (Democratic Republic of Congo), Ghana, Tanzania, Uganda, Zambia	Survey Data	Model Dose-Response and IV	IDM	Process/Product	Mixed	Manufacturing	0.0009	0.0320
Sithole and Buchana (2020)	2010-2012	37	South Africa	Survey Data	OLS, IV	IDM	Process/Product	Mixed	Manufacturing	0.003	0.099
Meriküll (2010)	2001-2006	12	Estonia	Survey Data	GMM, OLS	DDM	Process/Product	Mixed	Manufacturing	0.022	1.853
Aboal et al. (2015)	1998-2009	28	Urguay	Survey Data	OLS, IV	IDM	Process/Product	Mixed	Manufacturing	0.139	2.989
Elejalde (2015)	1998-2001	45	Argentina	Survey Data	OLS, IV	IDM	Process/Product	Mixed	Manufacturing	0.0735	1.665

Source: Research finding, followed by PRISMA 2020 guidelines.

Table A2. Test FAT/PET/PEESE (Innovation Decomposition Model only)

	Process/Skilled, FE, B/Strap	Process/Unskilled, FE B/Strap	Product, Mixed FE, B/Strap	Process/ Skilled, OLS, B/Strap	Product/Mixed OLS, B/Strap
Dependent variable: t-value		PET/FAT		PEESE	
Precision du PCC	0.024 (0.566)***	-0.075 (0.317)	1.5 (0.109)***	0.020 (0.293)***	0.121 (0.048)***
Constant (Biais)	-0.171 (13.34)	-0.046 (1.16)	-5.17 (0.394)***	-23.6 (22.801)	
Standard Error of PCC					-364.96 (288.2)
Number of observation	22	41	121	22	121
Number of studies	5	7	10	5	7
AIC	75.09	138.736	392.454	73.426	832.171
BIC	77.28	142.163	395.249	75.6	837.763

Source: Compiled by the authors**.**

Note: Estimator choice is based on minimum AIC and BIC values, as indicated in the methodology.

***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Meta-regression Tools

Formally, the calculation of the effect size in our study is based on the calculation of the partial correlation coefficient (PCC) given by:

$$PCC_i = t_i \Big/ \sqrt{t_i^2 + df_i} \text{and} PCC_i = t_i \Big/ \sqrt{t_i^2 + df_i}$$

where ***i*** represent reported estimates from the primary studies (the estimates resulting from the association of economic variables). $t_i$is the associated t-statistic, df_i the degree of freedom and SE_{PCC_i}represents the variance of the error associated with the partial correlation coefficient.

Furthermore, the size of the effect in our study estimated by a meta-regression model proposed by (Egger et al. 1997, Card and Krueger, 1995; Ashenfelter et al., 1999; Gorg and Strobl, 2001):

$$PCC_i = \beta + \alpha SE_{PCC_i} + u_i \tag{1}$$

By definition this model is heteroscedastic, because the effect size has different standard errors, so to remedy this phenomenon, we adopted the weighted least squares estimator where the precision $\frac{1}{SE_{PCC_i}{}^2}$ is used as a weight. We then divide both sides of equation (1) by the standard error associated with the partial correlation coefficients SE_{CCP} which give:

$$t_i = \alpha + \beta \left(\frac{1}{SE_{PCC_i}} \right) + \vartheta_i \tag{2}$$

$t_i = PCC_i / SE_{CCP_i}$is the t-value of the partial correlation coefficient.

However, to deal with the non-linearity between the standard errors and the collected estimates Stanley and Doucouliagos (2014) provide a quadratic model if the PET test (precision test of the size effect) rejects the null hypothesis:

$$PCC_i = \gamma + \delta SE_{PCC_i}{}^2 + \omega_i \tag{3}$$

The weighting of model (3) gives:

$$t_i = \gamma \left(\frac{1}{SE_{CCP_i}} \right) + \delta SE_{PCC_i} + \theta_i \tag{4}$$

The estimation of the multivariate meta-regression model is based on the following reformulation:

$$\mathrm{t_i} = \delta_0 + \delta_1 (1 \Big/ \mathrm{SE\_PCC_i}) + \sum_{2}^{\mathrm{k}} \delta_{\mathrm{k}} \left(\mathrm{Z_{ki}} / \mathrm{SE\_PCC_i} \right) + \epsilon_{\mathrm{i}} \tag{5}$$

where $1/\mathrm{SE\_PCC_i}$ is the precision, $\mathrm{Z_{ki}}$ is a vector of moderating factors. The moderating factors are represented by dichotomous (binary) variables:

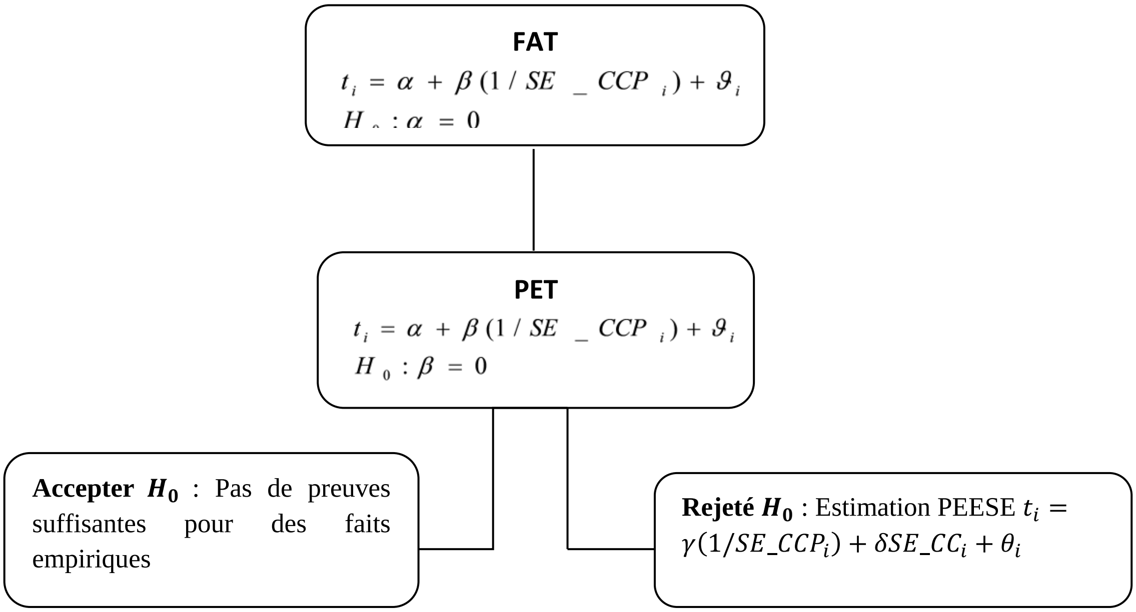

Figure A1. Schema for Investigating and Correcting Publication Bias
Source: Stanley and Doucouliagos (2012).

Journal Article: Variable that takes the value of 1 if the estimated effect size appears in a scientific journal; and the value of 0 if reported estimates are based on a thesis or report.
Farm Data: Variable that takes the value of 1 if the effect size concerns the agricultural sector and the value of 0 if it concerns the industrial sector.
Product Innovation: Variable that takes the value of 1 if the effect size relates to product innovation and the value of 0 if it relates to process innovation.
Unskilled labor: Variable that takes the value of 1 if the effect size relates to unskilled employment and the value of 0 if it relates to skilled employment.
Middle-income country: Variable that takes the value of 1 if the effect size concerns middle-income countries and the value of 0 if the country is in the rank of low-income countries.
IV estimator: Variable that takes the value of 1 if the estimated effect size relates to the instrumental variables' method and the value of 0 if it relates to another method (GMM, double least squares, etc.)

Heterogeneity

The heterogeneity is based on the procedure of Hunter and Smith (1990) based on a Chi-square statistic, such as Cochran'sQ_T, given by:

$$\chi^2_{k-1} = \frac{N}{(1 - r^2)^2} S_r^2$$

while $S_r^2 = \frac{\sum_{i=1}^{k} N_i (r_i - \bar{r})^2}{\sum_{i=1}^{k} N_i}$ is the observed variance calculated by the sum of the squared differences between each effect size and the estimated effect size in the population and weighted by the sample sizes of each study, it is compared to a Chi-square with k-1 degree of freedom, with k the number of studies. Furthermore, Harbord and Higgins (2008) suggest that a level of heterogeneity above 75% reflects high heterogeneity.

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