Impact of technological interdependencies on employment by BCFE method: Evidence from GVC participation of developing countries

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Abstract. Technology has a profound impact on the job market, creating both opportunities and challenges for workers, companies and economies. Its effect on employment has been discussed extensively for developed countries while it has not been widely examined in developing countries. This paper provides an examination of the interplay between technology and employment in developing countries through their participation in global value chain in a sample of 33 developing countries over the period 2010-2020. The Dynamic panel bootstrap-corrected fixed effects estimation showed positive and relevant impact of Backward GVC participation and ICT imports on employment, while the effect of forward participation was not significant.

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1. Introduction

In recent decades, the world has witnessed an ever-increasing movement of physical, financial and human capital. This mobility was facilitated by technological advances, artificial intelligence as well as the rise of global value chains (GVC). These developments have changed the nature of world trade and have modulated the notion of production, income generation and competitiveness. Nowadays, the production process is located in different countries according to their comparative advantage and their ability to attract businesses, as a consequence this economic integration amplifies the interdependence of countries. Participation in international markets has become, therefore, complex and developing economies are exposed to strong competitive pressures and structural changes that need to be analyzed in light of countries' participation in GVC to estimate the likely impact on the economy. The rise of GVC has led to profound changes in the paradigms of international trade and economic development [39] and policymakers increasingly recognize that the economic opportunities arising from participating in GVC go beyond the traditional notion of increased exports, but they can also include technology transfer and job creation. Indeed, technology innovation is no longer stuck within the boundaries of a company or industry, but it is generally propagated through the international productive structure of GVC and the effect on employment dynamics can also be seen in distant economies as well as those where the effort of its initial creation has been stimulated due to technological interdependence.

In this context, researchers are interested in studying the effects of participation in GVC on the job market through technology. This relation has been extensively discussed for developed

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countries unlike developing countries. The interest of the article to examine the interplay between technology and employment through GVC participation in developing countries is justified by its significant contribution to the existing articles, it can be summarized in three points, first it will enrich the theoretical contribution through examining countries that are not studied so far, second it will determine the effect of technological interdependency on the employment of 33 developing countries over the period 2010-2020. Third, this article will be the first to estimate by the dynamic panel bootstrap-corrected fixed-effects (BCFE) technique the relation between technology and employment in developing countries. The main result shows a relevant impact of backward GVC participation on employment confirming the positive impact of technological interdependency in overall employment in developing countries.

The rest of the paper is organized as follow. Section 2 discusses literature review for developing countries and highlights the aimed conceptual contribution of the paper. Section 3.1 illustrates the empirical specification used and the methodology based on the dynamic panel bootstrap-corrected fixed-effects, the data employed and preliminary evidence. Subsection 3.2 presents the econometric setting and the results obtained in the baseline specification. Finally, section 4 concludes the paper.

2. Literature review: Cases of developing countries

New technologies enables and induces changes in the way goods and services are produced and distributed, with consequences on employment, work and skills needs. The economic integration enabled by the GVC generates the transfer of these new technologies all over the world and creates concerns about their impact on national employment. Based on an original concept by Hummels et al. [21], the GVC was defined by International organizations [45, 32] as the collection of activities carried out by businesses to bring a product or service from its conception to its final use by the final consumer. Many academic studies have focused on the integration of GVCs, starting with the work of Feenstra and Hanson [17] examining relocation indicators in interaction with changing labor demand.

In the case of developed countries, a substantial effort has been devoted to the distinction between skilled and unskilled labour [18], while more recently the focus has been on the concept of "tasks performed in each occupation" to comply with the routine-biased technological change hypothesis (RBTC) [28, 4]. Furthermore, economists struggle to dissect the properties of value chains by distinguishing between headquarters and factory economies [40, 18]. For example, Germany is considered a headquarter economy in Europe, even called a center of gravity which has a set of factories in other countries in the world, these factories connect to the headquarters and integrate into the value chain by specializing in a specific production component. In this context, a country can position itself in two major stages, backward, by importing and processing foreign intermediate goods that will later be used to produce and export its own goods; or forward, when a country exports its intermediate goods to its foreign trading partners, which incorporate them into their own exports [3].

By analyzing the studies carried out on this subject so far, two approaches are followed: the first approach is based on the collection of survey data for a specific firm or product. However, it does not represent the broader role of production networks and technological interdependencies in the overall of creating added value. The second approach is based on trade in value added generated during the GVCs integration and relies on the Inter-Country Input-Output Tables (ICIOT) (TIVA, WIOD, EORA etc.) that has recently become a powerful tool for analysing and diagnosing technological interdependencies. Recent studies used this approach such as Johnson and Noguera [22], Wang, Wei and Zhu [44], Koopman, Wang and Wei [25], Nagengast and Stehrer [31], Borin and Mancini [5], Miroudot and Ye [30] and Meng et al. [29]. These studies examine the idea of "trade in value-added" to better understand the interactions between global value-chain participation, employment, and technology.

Regarding developing countries, the literature review shows that the researchers' analysis are focused on three regions, mainly the countries of Asia, Western Europe and to a lesser extent on Africa [34, 8, 1, 2, 15, 36]. Value chain linkages remains a key factor in assessing the impact of technology on employment, for example, Constantinescu et al. [10] found that the backward participation in a GVC has a positive and robust effect on national productivity comparing to forward participation. They argue that labour-rich developing countries tend to have a relatively high level of backward GVC participation as they specialize mainly in labour-intensive activities. The countries of East and South-East Asia are a remarkable example of countries with an abundant low-wage workforce and highest upstream integration. Working on Inter-country input-output table for 112 sectors in India, Veermani and Dhir [43] demonstrated in recent contribution that greater backward participation leads to higher employment by using the GMM method on linear regression.

In a similar way, Cieslik et al. [9] applied the Herfindahl-Hirschman index to detect the position of a country in the GVC between 2000 and 2012. The post-socialist countries in central and Western Europe progressively integrated GVC technology-intensive in electronics and transportation equipment sectors. They conclude that some countries as Poland, Hungary, Lithuania and Estonia are all located in the backward segment and they recorded high employment rates. Likewise, Grodzicki and Geodecki [19] explained following a "centre-periphery index" that the participation of the Central and Western Europe countries to GVC has been accelerated in the high-tech sectors, mainly justified by their continued dependence on foreign capital and technology. They also argue that these countries have seen an increase in labor demand, which is characterized by low wage and complementing Europe's main economies in terms of labor division.

In a sample of 46 countries Lewandowski et al. [27] find that between 2000 and 2017 the job content of tasks in a given profession varied systematically across countries. Employment in low-income countries is more routine than in developed countries, these are the main provider of non-routine and skilled employment in the world. This finding was justified by the low use of technology in low- and middle-income countries. The authors used routine task intensity (RTI) as an indicator, calculated from OECD PIAAC survey and the World Bank Skills Survey (STEP). The same results were shared by Das and Hilgenstock (2018) across 85 developing countries. However, Lewandowsk's opinion conflicts with the idea that occupations are the same in all countries (Such as studies referring to the O*NET database), in the sense that it suffer from optimistic bias that overestimates the content of non-routine work. Moreover, the theory suggests that tasks are endogenously assigned by employers according to supply and demand and also according to available technology.

In addition, among the few studies about the African countries we note the one of Hjort and Poulsen (2019) who found that the introduction of broadband internet via submarine cables connecting the countries from sub-Saharan Africa to European countries had a positive impact on employment in its different categories (skilled and unskilled). Hjort and Poulsen [20], confirms that since the introduction of the Internet several companies have been relocated to African countries (in the ICT sector and the automotive sector etc.) The empirical reformulation of [20] is based on an equation similar to that of Van Reenen [42] models commonly used in this type of research. As consequence, the deployment of new technologies can reduce the price of goods and services, encourage product innovation which allows the labour market to be more attractive and absorb more workers.

The main concern of developing countries is employment. Therefore, they will be forced to use technologies creating job when integrating the value chain. Globally, these technologies allows upstream position in the GVC, hence there can be no convergence between developed and developing economies.

As a result, researchers consider technological progress, digitalization and artificial intelligence as a factor of development by leading developing economies to promote employment strategies.

Finally, it should be noted that the effects of technology on employment under GVCs participation for developing countries has not been sufficiently studied and evaluated due to data availability issues and the quality of labor market statistics. In fact, some surveys such as PIAAC or STEP are not (yet) available for many several developing economies, such as Argentina, Brazil, Bangladesh, India, Morocco, Nigeria and South Africa. As a consequence, the available studies are not sufficient to quantify routine and non-routine tasks, or to test the job polarization hypothesis.

3. Empirical study

In light of the literature discussed in the previous section, our methodology include all the flow resulting from the production process captured by the backward and forward participation in inter-country output input table of the TIVA database, it helps to explore the interconnections and technological interdependencies between economies. This approach was developed by Leontief [26] and deepened by Pasinetti [35] their basic idea date back to the founding work of the French school of the physiocrats. Therefore, the analysis of industrial interdependencies reflects, among other things, the diffusion of technological innovation.

The measures of participation in GVC (backward and forward) adopted in this work are based on the contribution of Borin and Mancini [5] which is none other than the vertical specialization index proposed by Hummels et al. [21] separated into two stages, it takes into account the "double counting" of flows to assume implicitly that the technological flows are embedded in the intermediate inputs [3]. However, we are conducting an analysis at an aggregate level to suppose that the variation in employment in the countries is related not only to the properties of the country but also to its role in the productive structure in the global value chain.

3.1. Empirical specification and methodology

In this part of the paper we put up specification based on the fixed effect model, commonly relevant in literature review for developing countries [41] inspired from Cresti et al.[11]. In our specification, backward participation seek to reflect technological interdependencies.

The empirical specifications are given as follows:

$$E_{i,t} = \alpha \mathrm{E}_{i,t-1} + \beta_1 \mathrm{GVC}_{participation} + \beta_2 \mathrm{VA}_{i,t} + \beta_3 \mathrm{ICTimport}_{i,t-1} + \epsilon_i + \mu_{i,t} \tag{1}$$

Where $i = 1, \ldots, 33$ and $t = 2010, \ldots, 2020$.

List of countries in the sample: Argentina, Bangladesh, Belarus, Chile, Cameroon, Colombia, Egypt, Arab. Rep., Estonia, Croatia, Hungary, Indonesia, India, Jordan, Kazakhstan, Cambodia, Lao PDR, Latvia, Morocco, Mexico, Malaysia, Nigeria, Philippines, Poland, Romania, Senegal, Singapore, Slovak Republic, Slovenia, Thailand, Tunisia, Turkey, Vietnam, South Africa.

All variables are in logarithm. Lagged variables with one-period were introduced to take into account the period after which the technology has an effect on dynamics employment. The value of the dependent variable in the first difference $\Delta \log(E)_{t-1}$. Also, the main objective of value added $VA_{i,t}$ in our econometric specification is to take into account the role of demand according to the Keynesian approach. Value added is not lagged in our specification because it is supposed having an instant effect on employment and assumed always relevant to stimulate the lingering effect on employment [35].

Finally, ϵ_i denotes unobserved heterogeneity or the individual fixed effect and $\mu_{i,t}$ the term of unobserved and uncorrelated error or white noise between countries.

Variables	Description	Source
$GVC_{backward_t}$	The backward participation of countries in global value chains based on the conceptual framework defined by Borin and Mancini (2019), is the import content of exports	OECD TIVA
$GVC_{forward_t}$	Measures the share of national production that is supplied to the importing country for processing and reuse	OECD TIVA
ICT goods imports (% total goods imports)	This is the percentage of imports in new information and communication technology (ICT)	World Development Indicator Database (WDI)
Value Added (VA)	Value added generated by country i	OECD TIVA
$E_{i,t}$	Employment to population ratio, 15+, total (%) (modeled ILO estimate)	World Development Indicator Database (WDI)

Table 1: *Description of variables.*

The GVC participation, measures the extent to which an entity is participating in GVCs. It can be broken down into two additive terms, i.e. a "backward" component corresponding to import content of exports and a "forward" component, which measures the part of domestic production that is supplied to the importing country to be processed and re-exported.

The backward GVC participation is given by:

$$GVCb_{sr} = \frac{V_s(I - A_{ss})^{-1} \sum_{j \neq s}^{G} A_{sj} B_{js} E_{sr} + \sum_{j \neq s}^{G} V_t B_{js} E_{sr}}{U_n E_{sr}} \tag{2}$$

Where
V_s is the value added share in each unit of gross output produced by country s.
A is the matrix of intermediate inputs coefficients, obtained by dividing intermediate inputs produced in country i and used in country j by gross output produced in country i. Then $(I - A_{ss})^{-1}$ so-called inverse of leontif matrix.
B accounts for all the gross output produced in all the rounds of production.
E_{sr} total export or bilateral trade flow from country s to country r.

In other words $GVCb_{sr}$=FC(Foreign Content)+DDC(Domestic Double Counting) and the forward GVC participation can be written:

$$GVCf_{sr} = \frac{V_s(I - A_{ss})^{-1} A_{sr} (I - A_{ss})^{-1} (\sum_{j \neq s}^{G} Y_{rj} + \sum_{j \neq s}^{G} A_{rj} \sum_{K}^{G} \sum_{K}^{G} B_{jk} Y_{kl})}{U_n E_{sr}} \tag{3}$$

Where U_nE_{sr} is the gross exportation, given by:

$$
\begin{aligned}
U_nE_{sr} =& DC + FC \\
=& V_sBssE_{Es*} + \sum_{j\neq s}^{G} V_tBtsE_{Es*} \\
=& V_sBssE_{Es*} + V_sBss\sum_{j\neq s} A_{sj}BjsE_{Es*} + \sum_{j\neq s}^{G} V_tBtsE_{Es*} + \sum_{j\neq s}^{G} V_tBts\sum_{j\neq s} A_{sj}BjsE_{Es*}
\end{aligned} \tag{4}
$$

Table 1 describes all the variables used in this analysis, whereas their average value in the considered sample is presented in descriptive statistics Table 2 below.

Variable	Obs	Mean	Std. Dev.	Min	Max
Employment to population ratio	330	54.30381	9.647582	32.026	76.069
$GVC_{backward_t}$	330	37561.01	48319.61	629.79	205181.6
$GVC_{forward_t}$	330	16650.02	17220.7	368.7	77732.3
$ICTimport$	330	9.61048	6.873303	1.112616	32.87227
VA	330	303535.6	413308	7069.556	2786193

Table 2: *Descriptive statistics.*

More specifically, the importation of ICTs and backward participation value chains are positively correlated with the employment variable as present on Table 3.

	Employment Rate	ICTimport	$GVC_{backward_t}$	$GVC_{forward_t}$	VA
Employment Rate	1				
ICTimport	0.2624	1			
$GVC_{backward_t}$	0.1146	0.7878	1		
$GVC_{forward_t}$	0.3842	0.6679	0.4501	1	
VA	0.1059	0.5052	0.7993	0.1303	1

Table 3: *Correlation matrix.*

Therefore, our empirical specification seeks to answer the question: is there a relationship between employment and technology as a result of developing countries' participation in global value chains? Our basic hypothesis is that backward GVC participation is closely related to product innovation which can lead to an increase in the employment while forward GVC participation is a synonym for process innovation and therefore it could lead to decrease labour demand [14]. In bulk phrase, the above analysis aims to evaluate the technological effects involved in the product/process innovation dichotomy.

Although, to answer the previous question, we apply a dynamic panel model estimated by bootstrap-corrected fixed-effects (BCFE).

The BCFE estimator is useful for solving problems that can arise from including dependent variable with a lag, due to its ability to resample data, the bias omitted by a variable, convergence, cross dependence and heteroskedasticity that compromise analytical error correction procedures are controlled by BCFE. The main advantage of using the BCFE method is that it does not require an analytic expression of the fixed-effects estimator (FE) bias, in the sense that it has been evaluated numerically using the bootstrap resampling method. Furthermore, introducing lags on dependent variables is useful for solving endogeneiety problems. Moreover, our study illustrates a striking example in dynamic panel data, because labour demand is known in developing countries to react slowly to the movements of explanatory variables such as technology.

Certainly, there are a variety of estimators used, like the generalized moment method (GMM) recommended for this type of study [37, 14]. Except that, the GMM method under appropriate assumptions, asymptotically unbiased when N tends to infinity and T is finite, however, the instrumental variable injected by this technique leads often to poor characteristics for small samples like our study. In other words, the proliferation of instruments leads to over-identification.

Also, some studies have shown that Least Square Dummy Variable estimator (LSDV) outperforms GMM estimators in the case of $T > 30$ [24, 23], although it has relatively low variance. However, it is still inconsistent for dynamic panel models with fixed time dimension T as our sample [16].

Moving from this consideration, Kiviet (1995) proposes a corrected LSDV estimation procedure to calculate the bias of Fixed Effects estimator. This procedure outperforms other estimators for smaller T [7, 6, 38]. In fact, Škrabić Perić [38] shows that when panel dimensions consist of T larger than N ($N = 10$, $T = 15$ or 30), the LSDVc estimator has lower Root Mean Squared Error (RMSE) not only in comparison to LSDV but also to GMM estimators. In the same context, Buddelmeyer, H. et al. [6] suggest that LSDVc performs well, even if T is smaller than N, when the coefficient of the lagged variable is $\gamma = 0,4$.

But a practical downside of Kiviet's correction is the strict set of assumptions (homoskedasticity) which do not allow cross-sectional correlations and correlation between lagged dependent variable and the error term.

Henceforth, the BCFE estimator is more suitable than LSDVc for our dataset , as demonstrated by Monte Carlo simulations conducted by DeVos et al. [13]. In fact, the Monte Carlo simulations show that the small sample properties of BCFE are similar to those of the LSDVc, but it has the potential to be applicable in non-standard cases through an adequate modification of the bootstrap resampling to account for general heterosckedasticity, endogeneiety and cross-sectional dependence.Therefore, BCFE estimator resolves the problem of endogeneiety at the level of the lagged variable, and at the level of the other explanatory variables.

The estimation with FE controls unobserved effect, but it is biased when T is lower than 30 in estimation of dynamic panel models, it is inconsistent and inefficient.

Empirically, we implement Pooled OLS estimate (POLS), fixed effect estimate (FE) and LSDVc as the robustness check. POOLS and FE as an additional check to establish a plausible range, where the autoregressive coefficient of the BCFE estimation should be established as suggested by De Vos et al. [13].

3.2. Results

We note that backward and forward GVC participation are used separately as mentioned in Table 4 and Table 5. The coefficient of the employment rate per population (expressed in %) is always positive and significant confirming the persistence of employment variable over time. Similarly, as is commonly pointed out in the literature, the coefficient of value added is significant and positively related to the employment rate in all estimates. The coefficient of backward participation (lagged) is positive, smaller than one and statistically significant. This can be explained by the fact that the backward position of developing economies have a relevant impact on their employment in so far that technological interdependencies increase labour demand through product innovation, as it was previously demonstrated in the literature review [27, 9, 14, 43, 10, 45].

Regarding the forward participation (lagged) reported in Table 2, we notice a negative and non-significant relationship with employment. According to this result, we can not identify the interplay between forward participation and employment. Developing countries invest far less in research and development than developped countries, it is pecisely the difference in the type of innovation that create the divergence. Developped countries go for process innovation with advanced technologies while developing countries are content of using product innovation.

Concerning the ICT imports, our results highlight its positive impact on employment. It means that the increase of imports including electronic equipment and components increase employment in developing countries. It goes with the previous results showing the positive effect of backward GVC participation in countries using imported inputs to export carried out by technological interdependencies.

To sum up, demand can have two crucial effects: boosting production, that led to higher labour demand (the coefficients of value added justify this effect); on the other hand, the demand increase technological inputs that may induce high job displacement. On the whole, this empirical work seeks to demonstrate that the labour in a context characterized by technological progress seems to be a process that leads to productive structure fueled by fragmentation and inter-sectoral dependencies. The evolution of employment in sectors operating in global value chains is closely linked to product innovation in backward activities providing inputs. Similarly, the positive relationship of technological innovation with employment is generally more evident in activities subject to broad-based innovation policy to encourage productivity and economic growth [33].

$\log E$	Pooled OLS	FE OLS	LSDVc	BCFE OLS
$\log E_{t-1}$	0.405 (0.0029)***	0.804 (0.0385)***	0.025 (0.015)***	0.815 (0.019) ***
$\log GVC_{backward_{t-1}}$	0.025 (0.008)***	0.013 (0.006)**	0.024 (0.007)**	0.02 (0.008)***
$\log ICTimport_{t-1}$	0.003 (0.0023)	0.007 (0.004)*	0.004 (0.006)**	0.009 (0.0082)**
$\log VA_t$	0.002 (.0011)***	0.048 (0.0135)***	0.017 (0.01)***	0.023 (0.0121)***
Observations	330	330	330	330

Note: The dependent variable is the employment rate expressed as the logarithm Log (E). Standard errors are in parentheses. The Pooled OLS method adopts standard errors grouped by country. The BCFE method adopts mche-like resampling (i.e. from the normal distribution with an estimated (cross-section specific) heterogeneous variance). *,** and *** reflect the 10%, 5% and 1% significance levels.

Table 4: *Backward GVC participation, technology and employment. Estimation results.*

$\log E$	Pooled OLS	FE OLS	LSDVc	BCFE OLS
$\log E_{t-1}$	0.495 (0.331)***	0.780 (0.038)***	0.024 (0.015)***	0.808 (0.015)***
$\log GVC_{forward_{t-1}}$	-0.183 (0.120)	0.019 (0.012)	0.018 (0.01)	-0.015 (0.016)
$\log ICTimport_{t-1}$	0.094 (0.153)	0.006 (0.007)	-0.009 (0.008)	0.009 (0.006) **
$\log VA_t$	0.45 (0.081)***	0.30 (0.076)***	0.013 (0.014)***	0.034 (0.014)***
Observations	330	330	330	330

Note: The dependent variable is the employment rate expressed as the logarithm Log (E). Standard errors are in parentheses. The Pooled OLS method adopts standard errors grouped by country. The BCFE method adopts mche-like resampling (i.e. from the normal distribution with an estimated (cross-section specific) heterogeneous variance). *,** and *** reflect the 10%, 5% and 1% significance levels.

Table 5: *Forward GVC participation, technology and employment. Estimation results.*

4. Conclusion

This paper is a contribution to the existing literature inspecting the interplay between technology and employment throughout GVC participation in developing countries. This subject has been discussed extensively for developed countries while it has not been widely examined for developing countries. This justifies our interest to expand our sample by including countries not previously studied.

Drawing from evidence for 33 countries between 2010 and 2020, our econometric analysis based on dynamic panel bootstrap-corrected fixed effects estimation, showed that cross-border technological progress made a profound changes in economies. The empirical results showed positive and relevant impact for Backward GVC participation on employment, which clearly demonstrates the role of product innovation embodied in technological interdependency. In the same way, ICT import shows a positive effect on employment and contributes to the performance of industries in developing countries. As in the literature review, these results claim that employment is increased when the country has a backward participation in GVC.

According to our results, the effect of forward participation on employment is not significant in developing countries. The production in these countries does not rely on a high level of technologies, which can be explained by insufficient investment in R&D activities and weak innovation ability. The study cannot be deepened towards the nature of this interplay between forward participation and employment especially with the lack of data on employment by categories (Like PIAAC and STEP survey) for these countries.

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