International Journal of Business and Society, Vol. 25 No. 1, 2024, 27-48

ICTS AND LABOUR PRODUCTIVITY NEXUS IN DEVELOPING COUNTRIES: EVIDENCE FROM PANEL ESTIMATION APPROACH

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ABSTRACT

This study examines the impact of information and communication technologies (ICTs) on labour productivity in developing countries from 2000 to 2019, using the two-step System GMM estimation and dynamic panel quantile regression. The empirical results present new evidence on the moderating effect of ICTs with human capital, financial development and trade openness on labour productivity in developing countries. The interaction terms between ICTs and these three moderators show positive and statistically significant determinants of labour productivity. These three interaction terms have a greater influence on labour productivity than the impact of each variable assessed individually. The dynamic panel quantile regression results revealed that ICTs statistically significant to enhance labour productivity in lower and intermediate quantiles than in the highest quantiles in developing countries. This finding suggested that ICTs play an essential role in improving productivity at the lower and average labour productivity levels. This study can help policymakers develop a long-term strategy in terms of ICTs adoption and usage more intensively in developing countries as they strive to achieve the goals of industrial 4.0.

Keywords: Information and Communication Technologies (ICTs), Labour Productivity, Two-steps System GMM, Dynamic Panel Quantile Regression

Submission: 7th June 2023
Accepted: 26th September 2023
https://doi.org/10.33736/ijbs.6868.2024

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1. INTRODUCTION

The recent digital shift, driven by technology, urbanization, and globalization, has reshaped the 21st-century job market, necessitating a mix of cognitive, social-emotional, and technical abilities to boost national labour productivity. Notably, many countries have seen a stagnation in productivity growth over the past decade. Yet, with the fast pace of digital transformation, incorporating new business models, upgraded infrastructure, and enhanced human capital, there's an anticipated revival of labour productivity to support sustainable economic growth. Information and Communication Technologies (ICTs), regarded as a general-purpose technology, are fundamental in propelling innovation and productivity, especially in developed countries. In essence, labour productivity evaluates the efficient use of resources to produce goods and services over time. The International Telecommunication Union (ITU) highlighted in 2020 that while 98% of young adults in developed countires use the internet, only 66% do so in developing countries, suggesting underutilization of ICTs in the latter. ITU emphasizes that optimizing ICTs is pivotal for developing countries to achieve certain Sustainable Development Goals by 2030, focusing on labour productivity and employment. Supported by the rapid youth demographic growth, who are major ICT users, there's potential to revolutionize labour productivity digitally. The Covid-19 pandemic accelerated this digital transition, pushing firms towards automation to boost productivity (World Economic Forum, 2021). Thus, understanding the influence of ICTs on global labour productivity is of paramount importance.

This study examines the influence of Information and Communication Technologies (ICTs) on labour productivity across 84 developing countries from 2000 to 2019. These countries were chosen based on their Gross National Income (GNI) per capita and the availability of data, as categorized by the World Bank Atlas method. We employed the Generalized Method of Moments (GMM) estimator alongside other advanced analytical techniques to explore how certain variables, such as human capital, financial development, and trade openness, interact with ICTs in shaping labour productivity. This research stands out for several reasons. Unlike studies from the 1990s, which primarily emphasized a microeconomic perspective focusing on firm-level insights into the relationship between ICTs and productivity, this work offers a broader, national macroeconomic view. Furthermore, while earlier research largely targeted developed countries, our study is focused on developing countries that the World Bank classified as upper-middle and lower-middle-income in 2016. This approach not only provides a comprehensive understanding of the ICT-productivity nexus in these specific countries but also delivers valuable empirical evidence that can guide policymakers when formulating strategic ICT investment plans.

Thirdly, a few control variables at the national level, such as human capital, financial development, and trade openness, are included to ensure robust results and support empirical research on ICTs and labour productivity nexus. Besides the direct effect, this study consists of the interaction effect between ICTs and three potential moderator variables: human capital, financial development, and trade openness. This interaction effect will reveal how these three moderators affect the impact of ICTs on labour productivity. Finally, the dynamic panel quantile regression approach used in this study will shed light on the influence of ICTs on labour productivity at various productivity levels in developing countries, including low, average and high labour productivity levels. In contrast to previous studies that relied heavily on methodologies such as panel cointegration and panel long-run estimations, the vector error-correction model (VECM), this study fills a gap in the literature and provides new insight. The remainder of this study is organized as follows. Section 2 reviews the previous literature. The empirical model, econometric methodology, and the data are presented in Section 3. Section 4 discusses the empirical findings and interprets them, while the concluding section discusses the implicat ions of the results.

2. LITERATURE REVIEW

The neoclassical growth theory is the famous theory that illustrates the relationship between ICTs and labor productivity. Robert Solow and Trevor Swan created the neoclassical growth theory in 1956, which comprises three key contributors to economic growth: labour, capital, and technology. According to the theory, labour and capital in the production function produce short-term equilibrium. It also highlighted the enormous economic influence of technological progress. In addition, the neoclassical growth theory posits that both capital accumulation and how individuals utilize capital are crucial for economic growth. Furthermore, an economy's output is determined by the relationship between capital and labour, and it's also believed that technology can help increase worker productivity and production capacity. Consequently, the production function of the neoclassical growth theory is Y = A.F. (K, L), where Y is an economy's gross domestic product, K represents its share of capital, L indicates the proportion of unskilled labour in an economy, and A describes a determining degree of technology. Due to the labour and technology nexus, an economy's production function is commonly reformulated as Y = F (K, AL).

Prior research has extensively explored the ICT-productivity link both at firm and industry levels. Notably, Brynjolfsson and Hitt (2003) and Bartel et al. (2007) found a positive influence of computers and ICT on Total Factor Production (TFP) at the firm level. Fukao (2009), Fukao et al. (2013), and Jung et al. (2013) further cemented this perspective, highlighting the positive outcomes of ICT investment on TFP growth, especially in Korean ICT industries. However, the broad applicability of these findings, especially to national-level outcomes, is debated (Kim et al., 2021). While some studies focus on firm and industry-level impacts, others emphasize national productivity driven by ICTs. Fukao et al. (2009) found high ICT manufacturing productivity growth in Japan and Korea from 1995-2005 but lower in ICT services. Fukao (2013) noted Japan's inefficient ICT capital accumulation in non-ICT sectors, reducing TFP. Kim et al. (2019) revealed Korea's greater ICT investment impact on productivity than Japan across various sectors. Kijek et al. (2019) confirmed the technological innovation's moderating role in the ICT-productivity relationship among Polish firms. Lee et al. (2020) highlighted that older workers in Japan and Korea's ICT-rich sectors enhance labor productivity. Lastly, Li et al. (2021) identified a strong positive link between ICT and TFP in Chinese manufacturing, with multiple contributing factors like R&D.

The second strand of the literature discusses the impact of ICTs on productivity at the country level (Meijers, 2007; Chansarn, 2010; Sniukiena & Sarkane, 2014; Venturini, 2015; Wamboye et al., 2016; Relich, 2017; Herman, 2020; Kim et al., 2021; Ceccobelli et al., 2021). Meijers (2007) found positive externalities from ICT investment on economic growth and productivity using cross-country analysis. Chansarn (2010) assessed the influence of education, health, and technology on labour productivity growth in 30 countries, noting that China's impact inflated results for eastern developing countries and that technological advancement was crucial for productivity. Venturini (2015) highlighted the positive indirect effects of ICTs on productivity growth in OECD nations using dynamic OLS for long-run spillovers. Similarly, Wamboye et al. (2016) established that ICT penetration boosted labour productivity in 43 sub-Saharan African countries, while Relich (2017) found that certain software applications had a more pronounced effect on productivity in transitional compared to developed EU countries. Conversely, Herman (2020) showed a significant positive relationship between digitization and productivity in Romania, emphasizing the need for the EU workforce to enhance digital skills.

Several studies offer opposing views on ICT's impact on worker productivity, suggesting potential negative effects (Maiulyt-Sniukiena & Gaile-Sarkane, 2014; Ceccobelli et al., 2016; Hawash & Lang, 2020; Abramova & Grishchenko, 2020; Kim et al., 2021). Maiulyt-Sniukiena and Gaile-Sarkane (2014) analyzed 27 EU nations, finding mixed results between ICT development and labour productivity among countries with varying productivity levels. Hawash and Lang (2020) noted a minimal ICT impact on productivity in 76 developing nations from 1991 to 2014. Supporting this, Abramova and Grishchenko (2020) didn't find a robust connection between ICT and productivity in Russia. Conversely, Ceccobelli et al. (2021) identified a negative effect of ICT capital on labour productivity in 14 OECD countries from 1995 to 2005. Diverging slightly, Kim et al. (2021) categorized ICT as mobile or wired, concluding mobile ICT boosts national productivity, while wired ICT doesn't. Another study by Kim et al. (2021) found that ICT benefits the productivity of IT industries producing ICT-related products in the EU, the US, and Japan.

3. DATA, EMPIRICAL MODELS AND ECONOMETRIC METHODOLOGIES

3.1 Data

This article adopts panel data that includes annual data of 84 developing countries (46 upper-middle-income and 38 lower-middle-income) from 2000 to 2019. Labour productivity is the dependent variable in this study that is commonly used as the proxy to measure performance. Meanwhile, the independent variables include the initial labour productivity to explain the convergence, ICTs consisting of fixed telephone, mobile cellular and internet subscriptions per 100 people (Kim et al., 2021). Apart from that, control variables include human capital (measured by the human capital index), financial development (measured by domestic credit to the private sector as GDP share) and trade openness (measured by the ratio sum of imports and exports to real GDP per capita) are applied in this study. All variables are processed in logarithmic forms to reduce variations in the data. Table 1 shows the descriptive statistics of the variables. Data for ICTs is obtained from the ITU World Telecommunication database; the human capital index is collected from Penn World Table. The data for control variables-trade openness and financial development are obtained from the World Development Indicators (WDI), the World Bank database. The descriptive statistics of the full sample are illustrated in table 1.

3.2 Empirical Models

The Cobb-Douglas (1928) production function was referred in this study as the linear estimation of the fundamental production function to the relationship between ICTs and labour productivity

(Kurt & Kurt., 2015; Mamun et al., 2015). It is a neoclassical model of economic growth, as shown below.

$$Y = f(K, L) \tag{1}$$

where, Y denotes output (GDP), K denotes capital, L stands for labour. As referring to Romer (2006), since most of these economies are open economies and modern technologies are readily available to improve the knowledge stock of domestic laborers, it is assumed that labour in these sample countries is effective labour. As a result, the output per unit of effective labour is expressed as below:

$$\frac{Y}{L} = F\left(\frac{K}{L}, \frac{L}{L}\right) = F\left(\frac{K}{L}, 1\right) \tag{2}$$

where $\frac{Y}{L}$ denotes as the output per unit or labour productivity, $\frac{K}{L}$ represents the capital per unit of effective labour. Assume that $Y = \frac{Y}{L}$, $k = \frac{K}{L}$, and thus, it can be rewritten as $Y = f(K)$. In this study, the impact of ICTs on labour productivity will be captured by adopting the Cobb-Douglas production function as follows by adding the ICTs at the right side of the equation. Including the ICTs in the production function of the neoclassical function helps to explain the observed increase in productivity that has involved the ICTs adoption. The modified function enables the estimation of ICTs' contributions to labour productivity and establishes the best distribution of ICTs throughout the production process.

$$Y = f(K, ICTs) \tag{3}$$

This function is converted into logarithm form as follows.

$$\ln(Y) = \alpha + \beta_1 lnICTs + \beta_2 \ln(K) \tag{4}$$

Thus, the specific model for this study is adopted an intercountry production function to assess the impact of ICTs on country-level productivity which is based on the studies of Kim et al. (2021) and Dedrick et al. (2013), as shown in model below.

$$lnY_{it} = \beta_0 + \beta_1 lnY_{it-1} + \beta_2 lnICT_{it} + \beta_s lnZ_{it} + \eta_i + \varepsilon_{it} \tag{5}$$

Where, *i* signifies observation representing a country and *t* implies the time index. lnY_{it} represents labour productivity. All the variables are converted into logarithms. lnY_{it-1} represents lagged labour productivity. Based on Barro's (1991) explanation, lagged dependent variable is included in the model to capture the convergence effect of developing countries to developed countries. β_1 coefficient is projected to be statistically significant to verify the dynamic process of this model, which means the previous labour productivity might influence the current labor productivity. β_2 implies the estimated parameter of ICTs variables that consist of fixed telephone, mobile cellular and internet subscriptions per 100 people. By referring to other literature in the field, β_s represents the estimated parameters of each control variable. lnZ_{it} presents the value of human capital (β_3), financial development (β_4) and trade openness (β_5). Four independent variables are set in this study, including lagged dependent variable, ICTs and three control variables for each equation that will be estimated. Their coefficients are expected to be positive based on neoclassical growth theories and previous literature. η_i implies unobserved specific terms of each country and ε is the error term.

3.3 Two-Step System GMM Method

One of the methods used to analyse the relationship between ICTs and labour productivity is the Two-Step System Generalized Method of Moments (GMM) estimation. There are numerous advantages of employing GMM versus conventional static estimation models such as OLS. The conventional methods may introduce a fixed effect and endogeneity problem that is difficult to resolve. The GMM technique addressed difficulties such as country effect, serial correlation, and endogeneity (Arellano & Bond, 1991). To overcome country-specific effects, the equation must first be differentiated (Arellano & Bover, 1995). Meanwhile, instrumental variables can address the issue of endogeneity between difference-lagged dependent variables and error terms. This study applies the two-step System GMM estimator. The use of the instrumental variables is suggested to solve the issue of endogeneity between differences in lagged dependent variables and error terms. However, the differenced GMM is the lagged levels become weak instruments if the explanatory variables show persistence, which may lead to biases in coefficients estimated. (Blundell & Bond, 1998; Alonso-Borrego et al., 1999). The biases caused by differenced GMM can be reduced through a two-step System GMM estimator where both level and first differenced regressions are estimated into a single system. Furthermore, most studies prefer to apply a two-step system GMM estimation instead of a one-step estimation because it uses optimal weighting matrices when the assumption of independence and homoscedasticity to the estimated parameters does not hold.

In addition to that, this study also intends to investigate the impact of ICTs on labour productivity which adopts the interaction terms in the model as shown in model 6 below:

$$lnY_{it} = \beta_0 + \beta_1 lnY_{it-1} + \beta_2 lnICT_{it} + \beta_s (InICT \text{ X } lnZ)_{it} + \beta_s lnZ_{it} + \eta_i + \varepsilon_{it} \quad (6)$$

Model 6 signifies that each ICT proxy, namely the sum of fixed telephone, mobile phone and internet subscription, will interact with some control variables, lnZ_{it} that includes human capital (HC), financial development (FD) and trade openness (TO). For instance, ICT x human capital (HC) and the rest of the control variables. The interaction term is the cross-product of the two independent variables. The interaction term into the multiple regression and the original independent variable will assist in investigating the effect of ICTs on labour productivity that depends on the respective control variables. The interaction term between ICTs and control variables allows us to examine if the control variables, such as human resources (HC), are a complement or alternative for increasing labor productivity. A positive and significant β_s denotes that human capital is the main factor in the ICTs and labor productivity nexus. Therefore, a positive coefficient is expected for each interaction.

The specific models will be shown below:

$$lnY_{it} = \beta_0 + \beta_1 lnY_{it-1} + \beta_2 lnICTs_{it} + \beta_s (InICTs^* \, lnHC)_{it} + \beta_s lnZ_{it} + \eta_i + \varepsilon_{it} \quad (7)$$

$$lnY_{it} = \beta_0 + \beta_1 lnY_{it-1} + \beta_2 lnICTs_{it} + \beta_s (InICTs^* \, lnFD)_{it} + \beta_s lnZ_{it} + \eta_i + \varepsilon_{it} \quad (8)$$

$$lnY_{it} = \beta_0 + \beta_1 lnY_{it-1} + \beta_2 lnICTs_{it} + \beta_s (In \, ICTs^* \, lnTO)_{it} + \beta_s lnZ_{it} + \eta_i + \varepsilon_{it} \quad (9)$$

3.4 Dynamic Panel Quantile Regression

This study also adopted the dynamic panel quantile regression estimator for panel data (QRPD) with nonadditive fixed effects by Powell (2016). Quantile regression is extended from a classical least-squares approach of the conditional mean to a collection of models for different conditional quantile functions. Unlike traditional least square regression, quantile regression can provide information about the points in the conditional distribution other than the conditional mean that fully represents this distribution (Buchinsky, 1994, 1995; Eide & Showalter, 1997). The traditional least square regression only provides information on the conditional mean and median located at the center of the distribution, giving an incomplete description of a conditional distribution (Mosteller & Tukey, 1977). Furthermore, quantile regression analysis can provide information on conditional variables' asymmetric and non-linear effects on the dependent variable (Baur, 2013). In this study, the QRPD with nonadditive fixed effects retains the non-separable disturbance term generally linked with quantile estimation and resolves the fundamental problem by excluding individual fixed effects that could change the interpretation of the estimated coefficient on the treatment variable. The QRPD was also developed to provide reliable estimates of long-term cover for complex persistence patterns. This method is adequate for quantile estimators with fixed effects (μ_i) that relies on the estimation of the distribution of $Y_{it}/X_{it}(Y_{it} given \, X_{it}$.

Following Powell's approach, the model specification is stated as follows:

$$Y_{it} = \sum_j X_{it}^{'} \, \alpha_j(\varepsilon *_{it}), \varepsilon *_{it} \sim \varepsilon(0,1) \quad (10)$$

Where Y_{it} is the labour productivity, $X_{it}^{'}$ is the main independent variables, the α_j is the parameter of interest, and, $\varepsilon *_{it}$ is the error terms and the susceptibility for the outcome that can be explained by different error terms such as some time is varying and some time-fixed. The coefficient is considered linear in this model and $X_{it}^{'} \, \alpha_j(\emptyset)$ is firmly rising in $\emptyset$. As for the $\emptyset^{th}$quantile of Y_{it}, quantile regression depends on the conditional restriction as follows:

$$P(Y_{it} \leq X_{it}^{'} \, \alpha_j(\emptyset|X_{it}) = \emptyset, \emptyset \epsilon [0,1] \quad (11)$$

Equation 4 states that the latent outcome factor has a lower probability than the quantile function, is equal to all $X_{it,}$and is identical to $\emptyset$. Powell's QRPD allows this probability to vary by unit and within the unit as long as the fluctuation is orthogonal to the instrument. Thus, Powell's estimator, which is built on conditional and unconditional constraints, is as follows:

$$P(Y_{it} \leq X'_{it}\alpha_j(\emptyset|X_i) = P(Y_{is} \leq X'_{is}\alpha_j(\emptyset|X_i), X_i = (X_{i1,\dots,}X_{iT}) \quad (12)$$

Lastly, the quantile regression model can estimate generalized quantile regressions using Markov Chain Monte Carlo methods or grid-search methods.

Table 1: Descriptive Statistics: 84 Developing Countries

Variable	Description	Mean	Max	Min	Std Dev
Labor Productivity	GDP divided by the total number of labor	1185371	1.12e+08	738.3074	1.08e+07
Mobile	Mobile cellular subscriptions	90.21	252.81	0.029	64.76
Fixed Telephone	Fixed Telephone subscriptions	10.72	48.10	0.053	9.12
Internet	Internet subscriptions	22.54	84.2132	.0001517	21.47
Human Capital	Human Capital Index (years of schooling, weighted)	2.29	3.61	0.51	0.53
Financial Development	Domestic credit to private sector (% of GDP)	39.38	165.40	1.27	29.73
Trade Openness	Ratio sum of imports and exports to real GDP per capita	79.72	220.41	0.17	33.97

4. EMPIRICAL RESULTS AND DISCUSSION

Table 2 illustrates the correlation matrix of the variables employed in the analysis. Although most of the coefficients are less than 0.6, it is noticeable that the economic growth variable appears to be highly correlated compared with other variables.

Table 2: Correlations

	Labour Productivity	ICTs	HCl	FD	TO
Labour Productivity$_{t-1}$	1.0000				
ICTs	0.2728	1.0000			
Human Capital (HC)	0.3838	0.3772	1.0000		
Financial Development (FD)	0.1913	0.5012	0.3054	1.0000	
Trade Openness (TO)	0.1542	0.2715	0.1268	0.2665	1.0000

4.1 Two-step System GMM Result

This section explores the impact of ICTs on labour productivity through a two-step system-GMM estimation. Table 3 presents the estimate of the impact of ICTs and other independent variables on labour productivity which covers 84 developing countries from 2000 to 2019. There are four models shown in table 3. Model (1) illustrates the estimated result of the two-step system GMM on the full sample of developing countries without the interaction terms. Models (2), (3) and (4) examine the interaction terms of ICTs and human capital, ICTs and financial development as well as ICTs and trade openness on labour productivity, respectively.

In light of the model (1) result, the two-step system GMM estimation suggests that the lag labour productivity is significant and confirms this model is the dynamic model. The result established that the coefficient ICTs is positive and statistically significant at the one percent significance level. This finding shows that ICTs have a favourable effect on labour productivity in developing countries. The ICTs coefficient implies that a 1% increase in ICTs usage results in a 0.0144 increase in labour productivity. This outcome is consistent with a few findings in the literature (Chansarn, 2010; Venturini, 2015; Wamboye et al., 2016; Relich, 2017; Herman, 2020). Their papers have contributed to the similar effects where the ICTs positively impacts labour productivity. This could be attributed to structural developments in developing countries, as labour is shifting away from agriculture and moving towards industry and services. The finding proves that ICTs solve labour-market problems rather than social and economic issues (Beck, 2018).

Table 3: Dynamic GMM Estimates (Two-Step System GMM)

Variable	Model 1	Model 2	Model3	Model 4
Labour Productivity$_{it-1}$ (Lag)	0.901***	0.881***	0.902***	0.861***
	(0.00684)	(0.00813)	(0.00630)	(0.00833)
ICTs$_{it}$	0.0144***	0.0175***	0.0175***	0.0172***
	(0.00107)	(0.00112)	(0.000950)	(0.00113)
Human Capital$_{it}$ (HC)	0.0390***	-0.0668***	-0.0221**	0.0260*
	(0.0141)	(0.0128)	(0.00892)	(0.0150)
Financial Development$_{it}$ (FD)	-0.107***	-0.109***	-0.126***	-0.110***
	(0.00367)	(0.00445)	(0.00512)	(0.00462)
Trade Openness$_{it}$ (TO)	0.0119***	0.0107***	0.0101***	0.00228*
	(0.00178)	(0.00130)	(0.00101)	(0.00133)
ICT$_{it}$*HC$_{it}$		0.123***		
		(0.00887)		
ICT$_{it}$*FD$_{it}$			0.0748***	
			(0.00352)	
ICT$_{it}$* TO$_{it}$				0.122***
				(0.00754)
Sargan(P-value)	0.1121	0.1468	0.1084	0.1408
AR2 (P-value)	0.4418	0.4393	0.4434	0.4428
Constant	1.082***	0.670***	0.559***	0.401***
	(0.0643)	(0.0958)	(0.0622)	(0.0965)
Observations	1,219	1,219	1,219	1,219
Number of Country	84	84	84	84

Notes: The standard errors are informed in parentheses. The symbols of ***, ** and * signify significance levels of 1%, 5% and 10%. AR (2) represents the Arellano-Bond test, whose null hypothesis is no second-order autocorrelation in the first difference. For the Sargan test, p-values are closer to 1, indicating that the instruments are valid.

Human capital has a positive and significant coefficient of 0.0390 at a one percent significance level. The argument is consistent with the study of Dua and Garg (2019), where human capital is the essential factor affecting the productivity of developing countries. Meanwhile, financial development has a significant but negative impact on labour productivity. The negative coefficient of 0.107 is significant at a one percent significance level to signify that a 1 percent increase in financial development will lead to a 0.107 percent decrease in labour productivity. This outcome indicates that the quality and efficiency of intermediary financial services enhancement in developing countries is required to improve labour productivity. Trade openness shows a positive and significant impact on labour productivity. The positive coefficient of 0.0119 indicated that a 1 percent increment of trade openness would lead to a 0.0119 percent rise in labour productivity. The positive influence of trade openness on labour productivity signifies that the spillover effect from trade is able to enhance labour productivity in developing countries. This result is similar to the study of Dua and Lang (2019).

Furthermore, this study examines the moderating effect of three control variables (human capital, financial development, and trade openness) on the ICTs and labour productivity nexus in developing countries through interaction terms between ICTs and the three independent variables mentioned above. The outcomes of the interaction terms are presented via model (2) to model (4) in table 3. In model (2), the significance level of ICTs and all other variables are the same as shown in model (1). All the three interaction terms between ICTs and other control variables indicated positive and significant impacts on labour productivity. All the coefficients of ICTs and human capital, ICTs and financial development and ICTs and trade openness are significant at a one percent significance level. In other words, the moderating effects of human capital positively impacted the ICTs and labour productivity nexus in developing countries as well as the moderating effect of financial development and trade openness.

The interaction terms between ICTs and human capital have a positive and significant coefficient of 0.123. This finding implies that ICTs would help improve labour productivity if the country has good human capital planning. The coefficient of the interaction term between ICTs and human capital on labour productivity is greater than when the human capital is investigated individually on labour productivity, as shown in model (1). This result indicates that ICTs significantly influence labour productivity when both skilled and unskilled workers are involved. The effect of ICTs is enhanced through human capital to improve labour productivity in developing countries. This outcome may be due to the ICTs used in developing countries to improve efficient employee interaction, increase flexibility, enhance performance, and reduce cost (Levi-Bilech et al., 2018).

According to model (3), the interaction effect between ICTs and financial development is strong and favourable, with a coefficient of 0.0748. The interaction effect between ICTs and financial development will enhance labour productivity in developing countries. This scenario is intriguing as the interaction effect of ICTs and financial development positively impacted labour productivity in developing countries. In contrast, financial development has a negative impact on labour productivity when financial development is investigated individually on labour productivity in the model (1). This scenario can be explained where ICTs can improve labour productivity in developing countries with the support of a solid financial framework. Financial development in the industrial 4.0 era has created a more stable institutional environment, allowing developing countries to reap the benefits and increase labour productivity.

Model (4) presented the interaction terms of ICTs and trade openness on labour productivity. The interaction coefficient between ICTs and trade openness is positive and significant with a coefficient of 0.122, demonstrating that ICTs significantly affect labour productivity when the country opens to world trade. Trade openness is vital as foreign investment through international trade provides a channel to introduce new knowledge transfer and ICTs skills into different countries, improving productivity and promoting growth (Bloom et al., 2012). ICTs are a vital key factor that significantly impacts labour productivity. Additionally, human capital, financial development and trade openness have positively moderated the ICTs and labour productivity nexus in developing countries. The impact of ICTs on labour productivity is strengthened through the interaction effect between human capital, financial development and trade openness. The interaction effect of ICTs with these variables has a greater influence on labour productivity than the impact of each control variable assessed independently.

4.2 Dynamic Panel Quantile Regression Result

Table 4 presents the result of the dynamic panel quantile regression estimation on the effect of ICTs on labour productivity. The outcomes are shown in the nine quantiles of labour productivity correspondently in q10, q20, q30, q40, q50, q60, q70, q80 and q90. The 10th percentile model (q10), 20th percentile model (q20) and 30th percentile (q30) are employed to illustrate the impact of ICTs in the developing countries with low labour productivity, the 40th percentile (q40), the 50th percentile (q50) and the 60th percentile (q60) to specify the impact of ICTs in the countries with the average labour productivity. Meanwhile, the 70th percentile (q70), the 80th percentile (q80) and the 90th percentile (q90) state the effect of ICTs in the developing countries with high labour productivity.

The estimated coefficient of ICTs is significant at a one percent significance level at all quantiles except for the 40th quantile, as shown in Table 4. The effect is diverse at different quantiles. The ICTs have positive and significant coefficients from low to upper quantile levels except for the 40th quantile. The result signifies that every increase in ICTs plays a substantial role in improving labour productivity in developing countries. This result is comparable to the two-step System GMM estimation result and corroborates a few published findings (Chansarn, 2010; Venturini, 2015; Wamboye et al., 2016; Relich, 2017; Herman, 2020). The effect of ICTs on labour productivity is more significant at lower quantiles (q10, q20 and q30) than at upper quantiles (q60, q70, q80 and q90). This implies that ICTs have a greater impact and are more significant for developing countries with low and moderate levels of labour productivity than in developing countries with high levels of labour productivity. Apart from that, there is a positive and significant coefficient of lag labour productivity for all quantiles from lower to upper quantiles.

In the case of human capital, the result shows a positive and significant coefficient at most of the quantiles except for the 30th, 40th, and 50th quantiles. However, the influence of human capital is more extensive at the upper quantiles (q60, q70, q80 and q90). This finding indicated that human capital positively impacted labour productivity in high labour productivity countries. The result is consistent with the study of Hawash and Lang (2020) who suggested that human capital plays a crucial role in the labour productivity of developing countries. This result also supports the GMM estimation, where human capital is a significant factor for labour productivity in developing countries.

The finding of financial development shows that the coefficient of financial development is significant but negative in all quantiles except for the 20th quantile. The negative impact of financial development on labour productivity is more significant in the middle quantiles (q30, q40 and q50) than upper quantiles. This result is in keeping with the result reported in the GMM estimation, where financial development reduces labour productivity, especially in developing countries with average labour productivity. Thus, a revolution in financial structure through digitalization should be explored to boost labour efficiency in developing countries.

On the contrary, the finding of trade openness is clearly heterogeneous. The impact of trade openness is significant at most of the quantile levels except for the 20th, 60th and 80th quantile levels. Trade openness has a positive and significant coefficient at most quantiles except for the upper quantiles (q80 and q90), indicating that trade openness is essential in most developing countries, especially those with low and average labour productivity. The positive influence of trade openness is more impactful at the middle quantiles (q30 and q40). This finding is in line with the outcome of Dua and Garg (2018), who suggested that trade openness has a positive impact on labour productivity in developing countries. The corresponding Powell's dynamic panel quantile diagram for ICTs is displayed in Figure 1. The illustrated figure reveals that the ICTs show a decreasing pattern, and it decreases rapidly from lower quantiles to upper quantiles.

Figure 1: Quantile process coefficient estimation ICTs with 95% confidence intervals Powell (2016)

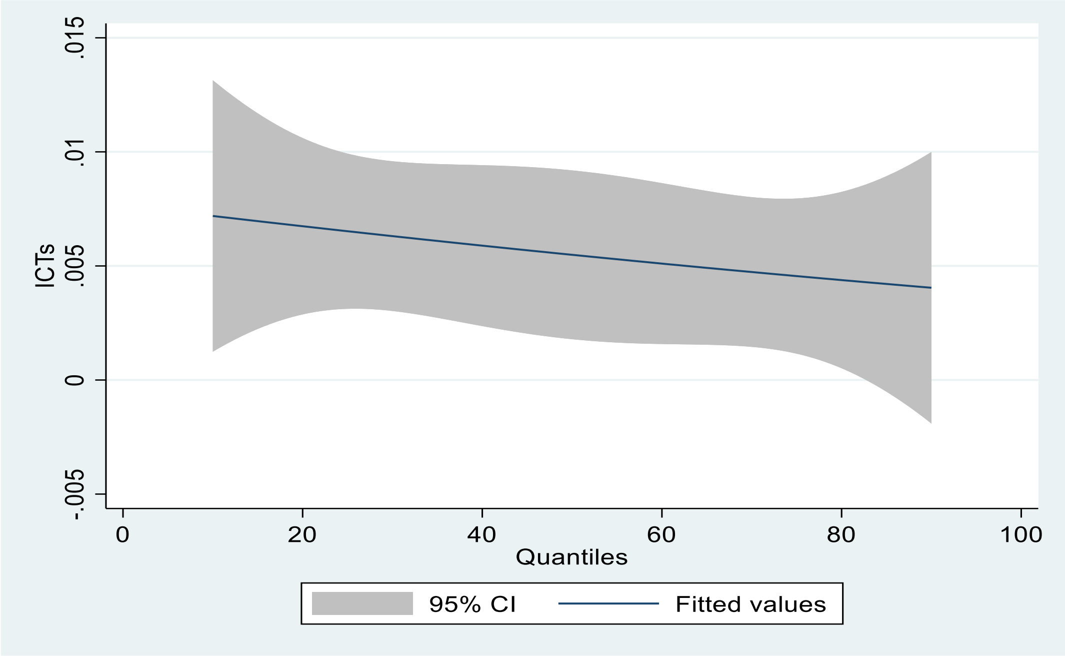


Table 4: Quantile Regression Result

D.var LP					**Quantiles**				
Variables	**10th**	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
Labour Productivity$_{it-1}$ (Lag)	0.932***	0.979***	0.975***	0.972***	0.960***	0.974***	0.968***	0.967***	0.985***
	(0.0105)	(0.00131)	(0.0121)	(0.00449)	(0.00612)	(0.00524)	(0.00224)	(0.00179)	(0.00163)
ICTs$_{it}$	0.00859***	0.00604***	0.0071***	0.000240	0.00854***	0.00515**	0.00644***	0.00583***	0.00195***
	(0.00208)	(0.000437)	(0.00197)	(0.000182)	(0.00196)	(0.00204)	(0.000643)	(0.00121)	(0.000463)
Human Capital$_{it}$ (HC)	0.0956**	0.0345***	0.0581	-0.0204	0.0145	0.0713***	0.0901***	0.0704***	0.0349***
	(0.0411)	(0.00301)	(0.0403)	(0.0143)	(0.0202)	(0.0223)	(0.00621)	(0.0150)	(0.00313)
Financial Development$_{it}$ (FD)	-0.0168***	0.00165	-0.0196***	-0.019***	-0.0167***	-0.013***	-0.0063***	-0.0108***	-0.0130***
	(0.00469)	(0.00136)	(0.00394)	(0.00431)	(0.00276)	(0.00313)	(0.00107)	(0.000758)	(0.00155)
Trade Openness$_{it}$ (TO)	0.0222**	0.00154	0.0216***	0.0301***	0.0166***	0.00373	0.00477***	-0.00426	-0.0027***
	(0.0109)	(0.00154)	(0.00683)	(0.0107)	(0.00512)	(0.00344)	(0.00112)	(0.00306)	(0.000567)
Observations	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219

Note: ***, ** and * denote significance at 1%, %% and 10% levels respectively.

4.3 Robustness Check

4.3.1 Adding one explanatory variable

This study conducts robustness checks to examine the sensitivity of the results to alternative estimation strategies. First, this study has added the new variable, which is population growth (pg) as an extra control variable for the robustness check as reported in Table 5. Model (5) indicates the two-step System GMM, where the ICTs suggest a positive and significant impact on labour productivity. Meanwhile, model (6), model (7) and model (8) show the results of the interaction terms between ICTs and human capital, financial development and trade openness with the additional control variables of population growth. These three interaction models present the positive and significant coefficient at a 1 percent significance level. The findings show the sign and significance of the ICTs and labour productivity are consistent with the outcomes stated in Table 3. Thus, this finding can be concluded that the quantitative nature of the result in this study is robust when a different variable is added.

Table 5: Dynamic GMM Estimates (Two-step system GMM)

Variable	Model 5	Model 6	Model 7	Model 8
Labour Productivity (Lag)	0.921***	0.897***	0.913***	0.873***
	(0.00702)	(0.00803)	(0.00691)	(0.00873)
ICT	0.0148***	0.0172***	0.0170***	0.0170***
	(0.00109)	(0.00120)	(0.00122)	(0.00121)
Human Capital (HC)	-0.0347***	-0.0798***	-0.0509***	0.000179
	(0.0112)	(0.0122)	(0.0104)	(0.0156)
Financial Development (FD)	-0.100***	-0.105***	-0.118***	-0.108***
	(0.00411)	(0.00472)	(0.00584)	(0.00485)
Trade Openness (TO)	0.0138***	0.0122***	0.0112***	0.00342***
	(0.00170)	(0.00151)	(0.00136)	(0.000884)
Population Growth (PG)	-0.0393***	-0.0244***	-0.0274***	-0.0161***
	(0.00474)	(0.00530)	(0.00491)	(0.00481)
ICT*HC		0.0893***		
		(0.00906)		
ICT*FD			0.0590***	
			(0.00403)	
ICT* TO				0.108***
				(0.00811)
Sargan(P-value)	0.1653	0.1480	0.1092	0.1445
AR2 (P-value)	0.4393	0.4381	0.4402 |	0.4425
Constant	0.959***	0.722***	0.613***	0.437***
	(0.0683)	(0.0924)	(0.0652)	(0.103)
Observations	1,219	1,219	1,219	1,219
Number of Country	84	84	84	84

Notes: The standard errors is informed in parentheses. The symbols of ***signify significance levels of 1%. AR (2) represents the Arellano-Bond test, whose null hypothesis is that there is no second-order autocorrelation in the first difference. For the Sargan test: when p-values are closer to 1, indicating that the instruments are valid.

4.3.2 Dynamic Panel Quantile Regression with an Interaction Term

In the previous section, this paper applies the two-step GMM estimation with interaction terms to analyze the impact of ICTs and other interaction variables on labour productivity. The robustness of the findings is tested by running the dynamic panel quantile regression with those interaction terms between ICTs and three control variables (human resources, financial development, and trade openness). The results are presented in Tables 6, 7, and 8 below.

Table 6 illustrates the result of the interaction between ICTs and human resources. The interaction effect of ICTs and human capital is heterogeneous, where the estimated coefficient of the interaction is significant at the 10^{th},40^{th}, 70^{th} and 90^{th} quantiles. Part of the results aligns with baseline model (2), where the interaction between ICTs and human capital will enhance labour productivity, as shown n the 10^{th} and 90^{th} quantile. Meanwhile, Table 7 shows the interaction between ICTs and financial development on labour productivity. Most of the estimated coefficients of the interaction between ICTs and financial development are significant except for the 30^{th}, 50^{th} and 70^{th}. The positive and significance of the estimated coefficient at most of the quantiles are consistent with the findings where the interaction between ICTs and financial development can improve labour productivity. Lastly, Table 8 shows the result of the interaction terms between ICTs and trade openness. There is a positive and significant estimated coefficient for the interaction between ICTs and trade openness at some quantiles (q30, q60, q90). This outcome is in line with the baseline model (4), where GMM results show that the interaction effect between ICTs and trade openness stimulates labour productivity. Figure 2 presents the graphs for quantile process estimates of the interaction term between ICTs and three moderators. Figure 2 reveals that the interaction between ICT and human capital (ICTHC) as well as ICT and financial development (ICTFD) show a U-shaped pattern. In contrast, the interaction between ICT and trade openness (ICTTO) shows an inverted pattern where it increases up to the middle quantile and decreases to the right.

Table 6: Panel Quantile Regression Result (Interaction between ICT and Human Resource)

D.var LP					**Quantiles**				
Variables	**10th**	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
Labor Productivity$_{it-1}$	0.977***	0.970***	0.953***	0.968***	0.975***	0.956***	0.978***	0.989***	0.965***
	(0.00376)	(0.00894)	(0.0101)	(0.00512)	(0.00368)	(0.0107)	(0.00199)	(0.000596)	(0.0142)
ICTs$_{it}$	0.00624***	0.00810***	0.00646***	0.00515***	0.00520***	0.00398**	0.000121	0.00425***	0.00303
	(0.000745)	(0.00256)	(0.00206)	(0.00122)	(0.000939)	(0.00194)	(0.000485)	(0.00101)	(0.00196)
ICT$_{it}$* HC$_{it}$	0.0271***	-0.00203	0.0362	-0.00879*	0.00870	0.0465	-0.0232***	-0.00336	0.0465***
	(0.00613)	(0.0233)	(0.0238)	(0.00459)	(0.00604)	(0.0308)	(0.00591)	(0.00294)	(0.0118)
Human Capital$_{it}$ (HC)	-0.0360***	0.122***	-0.0591***	0.00735	0.0755***	0.0225	0.105***	0.0160***	-0.0298**
	(0.00491)	(0.0238)	(0.0214)	(0.0166)	(0.0198)	(0.0279)	(0.0109)	(0.00602)	(0.0145)
Financial Development$_{it}$ (FD)	-0.0192***	-0.00503	-0.0183***	-0.0130***	-0.0163***	-0.0142***	-0.00464	-0.00342	-0.0203***
	(0.00253)	(0.00918)	(0.00277)	(0.00154)	(0.00231)	(0.00218)	(0.00302)	(0.00299)	(0.00489)
Trade Openness$_{it}$ (TO)	-0.0058***	-0.0112*	0.0114***	0.0170***	0.00170	0.0195***	-0.00337***	-0.0103***	0.0199
	(0.00127)	(0.00573)	(0.00351)	(0.00521)	(0.00600)	(0.00371)	(0.00125)	(0.00137)	(0.0138)
Observations	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219

Note: ***, ** and * denote significance at 1%, %% and 10% levels respectively.

Table 7: Panel Quantile Regression Result (Interaction between ICT and Financial Development)

D.var LP					**Quantiles**				
Variables	**10th**	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
Labor Productivity$_{it-1}$	0.977***	0.983***	0.968***	0.970***	0.961***	0.968***	0.964***	0.986***	0.970***
	(0.00191)	(0.00138)	(0.00292)	(0.00338)	(0.0152)	(0.00313)	(0.00401)	(0.000327)	(0.00550)
ICTs$_{it}$	0.00303***	0.00316	0.00377	0.00427***	0.00386**	0.00472***	0.00419***	0.000576***	0.00220***
	(0.00109)	(0.00222)	(0.00235)	(0.00131)	(0.00166)	(0.000608)	(0.000699)	(0.000200)	(0.000673)
ICT$_{it}$* FD$_{it}$	0.0260***	0.0139***	0.00680	0.0177***	0.0518	-0.0134**	-0.00664	0.00404**	0.0327***
	(0.00430)	(0.00252)	(0.0119)	(0.00296)	(0.0359)	(0.00646)	(0.00681)	(0.00182)	(0.00798)
Human Capital$_{it}$ (HC)	-0.000295	-0.00218	0.0257*	0.0103	0.110**	0.107***	0.0885***	0.0336***	0.00584
	(0.00491)	(0.00304)	(0.0153)	(0.00729)	(0.0474)	(0.0306)	(0.0127)	(0.00216)	(0.0122)
Financial Development$_{it}$ (FD)	-0.0288***	-0.0158***	-0.0108*	-0.0142***	-0.0119**	-0.0131***	-0.0108***	-0.00113	-0.0209***
	(0.00868)	(0.00553)	(0.00617)	(0.00282)	(0.00578)	(0.00213)	(0.00262)	(0.00174)	(0.00325)
Trade Openness$_{it}$ (TO)	0.00972	0.00438*	0.0197***	0.0182***	0.0108*	0.000581	-0.00465	-0.00670***	0.0236***
	(0.00945)	(0.00262)	(0.00340)	(0.00310)	(0.00623)	(0.00388)	(0.00318)	(0.000453)	(0.00652)
Observations	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219

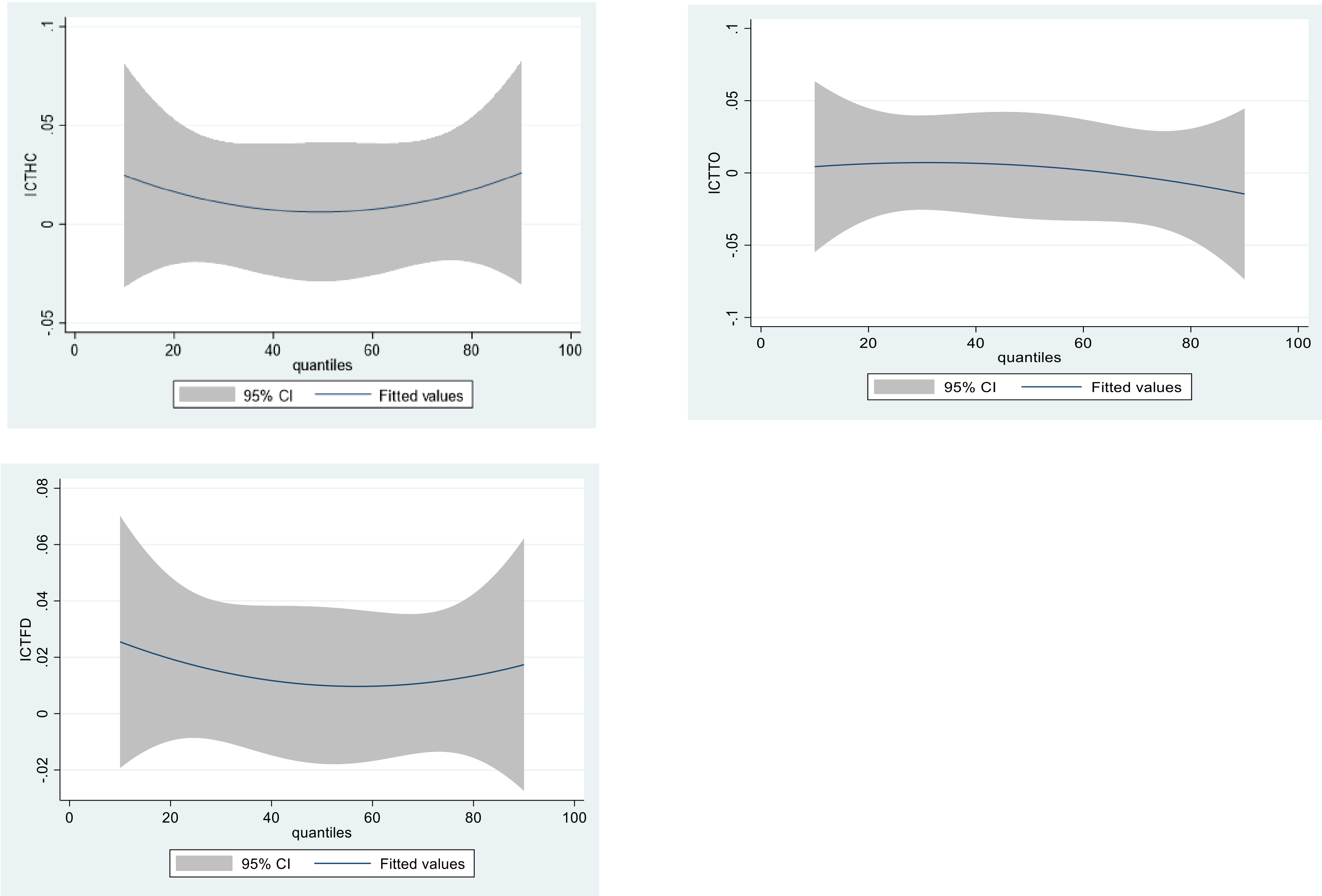
Note: ***, ** and * denote significance at 1%, %% and 10% levels respectively.

Table 8: Panel Quantile Regression Result (Interaction between ICT and Trade Openness)

D.var LP	**Quantiles**								
Variables	**10th**	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
Labor Productivity$_{it-1}$	0.982***	0.975***	0.949***	0.950***	0.966***	0.967***	0.970***	0.973***	0.985***
	(0.00136)	(0.00302)	(0.00905)	(0.0109)	(0.0155)	(0.00390)	(0.00562)	(0.000961)	(0.00208)
ICTs$_{it}$	0.00228	0.00886***	0.00509***	0.00555***	0.00560***	0.00509***	0.00192	0.00264***	0.00126***
	(0.00166)	(0.00239)	(0.00142)	(0.000994)	(0.00139)	(0.00102)	(0.00892)	(0.000438)	(0.000419)
ICT$_{it}$* TO$_{it}$	-0.0131	0.00833	0.0229***	0.0282	0.00969	0.0103***	-0.0610	-0.0112***	0.0125***
	(0.00818)	(0.0199)	(0.00710)	(0.0226)	(0.0192)	(0.00331)	(0.100)	(0.00120)	(0.00132)
Human Capital$_{it}$ (HC)	0.0142	0.0831***	0.0572***	0.00307	0.0276	0.0994***	0.0538	0.136***	0.0116***
	(0.0113)	(0.0215)	(0.00925)	(0.0154)	(0.0512)	(0.0122)	(0.0951)	(0.00977)	(0.00221)
Financial Development$_{it}$ (FD)	0.00210	-0.00234	-0.0125***	-0.0170***	-0.0150***	-0.0108***	-0.0178	-0.00769***	-0.0245***
	(0.00336)	(0.00428)	(0.00318)	(0.00328)	(0.00433)	(0.00251)	(0.0109)	(0.00100)	(0.00325)
Trade Openness$_{it}$ (TO)	0.00401	0.00406	0.00571	0.0143**	0.0135*	-0.00451	-0.00577	0.000965	0.00408***
	(0.00831)	(0.00607)	(0.00611)	(0.00641)	(0.00812)	(0.00316)	(0.0108)	(0.00360)	(0.00130)
Observations	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219

Note: ***, ** and * denote significance at 1%, %% and 10% levels respectively.

Figure 2: Quantile process coefficient estimation with 95% confidence intervals Powell (2016)



5. CONCLUSION AND IMPLICATIONS

This study evaluates the impact of ICTs on labour productivity in developing countries utilising data from eighty-four developing countries from 2000 to 2019. The two-step System GMM estimation and dynamic panel quantile regression are used in this study. The empirical results revealed that ICTs have a favourable and significant impact on labour productivity via the two-step GMM system. This finding is consistent with prior studies and supports the evidence that ICTs are critical in enhancing labour productivity in developing countries. Furthermore, this study contributes to the literature on the ICTs and labour productivity nexus by incorporating the interaction term of ICTs and other potential moderating variables, namely human capital, financial development, and trade openness to capture the moderation effect of those interaction terms on labour productivity. The findings revealed that all the interaction terms presented positive and significant impacts on labour productivity. This finding suggested that human capital, financial development and trade openness play essential roles in moderating the effect of ICTs on labour productivity in developing countries. The interaction effect of ICTs and the other three moderators is more pronounced in enhancing labour productivity than the impact of each moderator assessed individually.

Apart from that, the empirical result also demonstrated the effect of ICTs on labour productivity in developing countries by analysing the changes according to different quantiles via dynamic panel quantile regression. This finding provides new insight into the literature as it provides more precise results to impact conditional variables on the dependent variables. ICTs have a significant and positive impact from lower quantile level to higher quantile level except for the 40th quantile, indicating ICTs influence labour productivity in all the developing countries. The effect of ICTs on labour productivity is more significant at lower quantile levels than at the upper quantiles. This result indicates that ICTs have a greater impact on labour productivity in developing countries with low and average labour productivity than in developing countries with high levels of labour productivity. Therefore, ICT-related investments should be a priority for policymakers in developing nations, particularly in those areas or industries where labour productivity is relatively lower. Additionally, education and training programmes to advance digital literacy and technology skills should be offered in countries with lower labour productivity to enable workers make better use of ICT technologies and increase productivity. Lastly, governments in developing countries should encourage the transfer of technology and knowledge from higher to lower productivity countries. International partnerships and collaborations can assist in introducing cutting-edge techniques and methodologies that have been successfully used to increase productivity. In conclusion, both findings from the two-step system GMM and dynamic panel quantile regression support the finding that ICT is one of the critical factors that significantly enhance labour productivity. Furthermore, this result verify that the IT productivity paradox does not exist in developing countries.

In summary, the finding of this study has significant policy implications for developing countries. ICTs have emerged as a critical component and backbone of the fourth industrial revolution in this digital era. Thus, investigating the impact of ICTs is vital for developing policy to support labour markets and generate more benefits for workers, organizations, the economy, and society in developing countries. Policymakers in developing countries should prioritize ICT development by strengthening existing ICT infrastructure and facilities to ensure that all economic and industrial sectors are well prepared to be transformed by ICTs. For example, policymakers should focus on building smart factories or adding industrial IoT capabilities to legacy equipment to provide invaluable insights and improve equipment productivity, especially in developing countries with a low digital economy as well as labour productivity. The importance of ICTs and the interaction effect of other factors such as human capital, financial development and trade openness should not underestimate in improving the labour productivity in developing countries. Developing countries requiring creative and high-skilled workers or ICTs specialists to enhance labour productivity should include ICT knowledge and skills in their earlier education system. Furthermore, a mature financial development system and a welcome trade environment for investors are necessary to improve labour productivity, quality, and efficiency in developing countries.

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