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Article

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The Effect of foreign direct investment on structural change in developing countries: an examination of the labor productivity dimension

Ezo Emako^{1*}, Seid Nuru¹ and Mesfin Menza¹

Abstract: Developing countries require overall labor productivity to sustain their economic growth. Overall labor productivity, on the other hand, cannot be achieved without structural change. Because developing countries lack sufficient resources, foreign direct investment (FDI) is recommended for them to realize structural change. Therefore, the primary purpose of this study is to estimate the effect of FDI on the structural change in labor productivity in developing countries from 1990 to 2018 using Driscoll and Kraay's estimation. The study found that foreign direct investment boosts overall labor productivity by facilitating “structural change” and



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PUBLIC INTEREST STATEMENT

Productivity differences account for a lion's share of countries' ability to be developed and stay poor. Developing countries have been known to have economies with very low productivity labor pools that are largely concentrated in the agriculture sector. Therefore, simply shifting labor from the low-productive agriculture sector to the industry sector is able to promote economic growth and development without real productivity improvements in either sector. However, developing countries have a marginalized industry sector that is not in a position to lead this structural change well. For developing countries to carry out structural change in their economies, foreign direct investment (FDI) has been recommended. However, neither the structural change effect nor the within-sector effect of FDI on labor productivity has been studied. Therefore, this study is motivated to examine the effect of FDI on overall labor productivity via within-sector and structural change effects in 35 developing countries from 1990 to 2018 using Driscoll and Kraay's (1998) estimation. The finding indicates that FDI is an important tool to boost overall labor productivity via either a within-sector effect or a structural change effect, but the within-sector effect is the most important channel through which FDI promotes overall productivity. Since it is important for the labor productivity of developing countries, developing countries should pay attention to attracting a sufficient amount of FDI, particularly those motivated by exports, by providing different incentives, such as providing well-trained labor.

improving “within-sector” labor productivity. Furthermore, variables such as export, population size, domestic capital, human capital, and the usage of chemical fertilizer all have a positive and significant effect on labor productivity. *On the contrary*, government expenditure, the development of infrastructure, and the utilization of large areas of land have all been discovered to have a negative effect on labor productivity. However, per capita income has a negligible effect on it. Therefore, developing countries should not only pay attention to the quantity of FDI but also to its quality by putting an emphasis on FDI in the manufacturing sector and export-based FDI. Additionally, increasing domestic capital through the mobilization of domestic savings and strengthening the use of technology, such as chemical fertilizer, may be essential policy directions to increase labor productivity.

Subjects: Economics; Finance; Industry & Industrial Studies

Keywords: Driscoll and Kraay; labor productivity; foreign direct investment; structural change; within sector

1. Introduction

Globally, productivity differences account for 90 percent of per capita income differences (Bernanke & Rotemberg, 1997). “Productivity” refers to the amount of goods and services produced by a worker over a given period of time (Le et al., 2019). Because it accounts for the lion’s share of economic growth, there will be no sustainable economic growth and development unless productivity improves (Anyanwu, 2014; Suri & Undry, 2022; World Bank, 2022). Improving labor productivity is also the most practical way to reduce poverty by raising income, investing in human capital, and generating new jobs in developing countries (Devlin, 2013; Gollin et al., 2014; Rohima et al., 2013; United Nations Conference on Trade and Development (UNCTAD), 2022). Therefore, there are two ways in which labor productivity can surge: (1) improvements that occur “within the sector”—through capital accumulation and technological progress within that sector, and (2) improvements stemming from “structural changes.”

Structural change is the shift of workers from low-productive sectors to high-productive ones that stimulates economic growth (McCullough, 2017). Structural change is typically characterized by a declining agricultural employment share over time, an increasing service employment share, and a hump-shaped pattern for industrial employment share (Duarte & Restuccia, 2010). Structural change is successfully completed in three stages. Agricultural employment dominates the economy at first, and as the economy develops, labor reallocation associated with structural change is generally associated with early reallocation from agriculture to industry and services, and later reallocation from agricultural and industry to services (Ghose, 2021). This means that countries should move from agriculture-led to industry-led growth, and then onto a service-led growth model. In developing countries, agriculture employs the most labor and produces the least, making it the least productive sector. Due to this low labor productivity, it is difficult to achieve development in an economy that is dominated by agriculture. Consequently, the industry sector is needed to boost development. Because of its technological dynamism, high productivity level, and fast pace of growth (due to high returns to scale), the industry sector is the most crucial sector for development (Rodrik, 2016). Moreover, it is also at the center of structural change because of its wide scope of specialization, its ability to produce tradable products, and its potential to make links with other sectors (Bah, 2011).

However, the real problem in developing countries is the large productivity gap between agriculture and industry (McMillan et al., 2014). For instance, non-agricultural labor in African countries is six times more productive than agricultural labor (Gollin et al., 2014). This suggests that there is a significant allocative inefficiency in developing countries, which reduces overall labor productivity

and development. Thus, structural change is required to address this inefficiency and ensure long-term economic growth by simply relocating agricultural workers to the industrial sector in developing countries. It implies that shifting labor and other resources from less productive to more productive sectors promotes economic growth even if no productivity gain occurs within the sector.

Nonetheless, achieving structural change in developing countries' economies remains a challenge. It has been particularly challenging for Africa and Latin America to achieve structural change due to a lack of technology, an infant industry sector, inadequate finance and capital, and a shortage of human capital (Jayne et al., 2018). Different theories, recent experiences, and the structural transformation histories of Asian tigers (South Korea, Taiwan, Singapore, and Hong Kong) show that foreign direct investment (FDI) is an essential tool for developing countries like Africa to undergo structural change by increasing labor productivity, addressing resource gaps, boosting manufacturing industry, transferring technology and knowledge, utilizing large labor pools, and strengthening the domestic economy's linkage to the global market (Asada, 2020). It is derived from multinational enterprises (MNEs), which are companies that invest in at least two separate countries (one is the FDI sending country called the "home country" and the other is the "host country"—an FDI receiving country).

However, FDI has been a topic of debate in both theoretical and empirical studies over the years. For instance, the Harrod-Domar (Domar, 1946; Harrod, 1939) theory and Rostow's (1960) linear-stage theory contend that FDI increases labor productivity and structural change by increasing savings and accelerating capital accumulation, particularly during the "take-off" period, which is an essential part of structural change and industrial development. The growth theory of Solow (1957) argues, in contrast, that capital accumulation has no long-run growth effects. Thus, FDI, according to this theory, promotes long-term economic and productivity growth by facilitating technological advancements, managerial innovations, and information sharing. According to structuralist theories developed by Lewis (1954) and Chenery (1960), FDI increases labor productivity by stimulating capital accumulation in the industrial sector, enabling labor to transfer from agriculture to industry. A further argument Kuznets (1966) made was that through FDI, agriculture-dominated poor countries can promote their non-agricultural sectors (because non-agricultural labor productivity grows more rapidly than agricultural labor productivity).

In contrast, dependency theories proposed by authors such as Dos-Santos (1970) contend that MNEs may drive domestic enterprises out of the local market entirely, a phenomenon known as the "crowding out effect". Because of their large capital and high level of technology, they produce comparatively high-quality and low-priced goods, making local enterprises less competent in the domestic market. Frank (1967), another narrator of dependency theory, states that FDI destroys labor productivity and development through profit repatriation and natural resource depletion. Alternatively, the new growth theory proposed by Romer (1990) and Grossman and Helpman (1991) suggests that FDI facilitates structural change and increases labor productivity through the transfer of knowledge and technology via horizontal and vertical spillover. A horizontal spillover effect (intra-industry effect) occurs when technology and knowledge flow from MNEs to local companies within the same industry via imitation, professional labor mobility, and competition (Fosfuri et al., 2001; Gorg & Strobl, 2005; Lutz & Talavera, 2004; Zhu & Tan, 2000). The vertical spillover effect, on the other hand, can be visualized by a forward link (MNEs as suppliers and domestic enterprises as customers) or a backward link (domestic firms as suppliers and MNEs as customers). The vertical linkages are more likely to result in knowledge spillovers than the horizontal linkages; thus, they are important channels for technology and knowledge transfer compared to the horizontal spillover effects (Amendolagine et al., 2013; Jude, 2015).

Similar to the contradicting theoretical argument, the findings of previous empirical studies on the effect of FDI on labor productivity are mixed and inconclusive. First, it is claimed that FDI increases labor productivity by promoting structural change in developing countries. For example,

according to Lutz and Talavera (2004) in Ukraine, FDI has a positive and considerable effect on productivity because of technology transfer, catch-up, competition effects, linkages, and training effects. They noted that the magnitude varies depending on the type of industry; for example, the metal processing and woodworking industries have high productivity, whereas the construction materials and light industries have low productivity. Based on cointegration analysis, Ramirez (2006) argues that FDI is beneficial to labor productivity because of spillover effects via technology and management know-how transfer. The Turkey experience, as presented by Arisoy (2012), also demonstrates that FDI boosts productivity growth by increasing capital accumulation and serving as a major source of technology spillovers. Due to its strong backward links with local firms, Amendolagine et al. (2013) describe FDI as an essential contributor to labor productivity in SSA. Evidence from Wamboye et al.'s (2016) study, conducted in 43 Sub-Saharan African (SSA) countries using the Roodman-GMM (Generalized method of moments), shows that FDI has a positive effect on labor productivity while government expenditure and fixed telephone subscriptions per 100 people have a negative effect due to a lack of sufficient technological absorption of new technology.

According to Demena and Murshed (2018), the evidence from SSA highlights FDI's role as a major driver of labor productivity, but its size depends on the type of technology transfer channels, the technical level of domestic firms, and their absorption capacity. Technological transfer improves labor productivity through demonstration and labor mobility (a relatively lower effect and the only way for firms with low technology levels to increase their labor productivity), although competition impact supports the existence of an impeded pecuniary spillover effect. Similarly, Demena and Murshed (2018) in Uganda found FDI to be an important factor in labor productivity due to technology and knowledge transfer. In India, Das and Chaudhuri (2018) discovered substantial evidence of FDI's horizontal spillover effect by compelling indigenous enterprises to increase their resource and technology usage. In Vietnam, the Autoregressive Distributive Lag Model (ARDL) analysis by Vinh (2019) and Asada (2020) indicates that FDI and exports have a significant positive effect on labor productivity. This is because the FDI inflows mainly consist of "Greenfield" investment, which involves new finance, new production, technology, job creation, and the strong absorption capacity of the country. Based on the experience of European Union (EU) countries, Derando and Horvatin (2019) claim that Greenfield investment does not always bring up-to-date technology and can fail to have a major positive influence on local productivity, even in the long run. On the other hand, merger and acquisition (M & A)—the purchase of existing industries or mergers with them—is motivated by high-profit expectations, which aids in efficient knowledge transfer locally and the future extension of beneficial spillover effects.

Some scholars, on the other hand, claim that FDI adversely affects labor productivity. For example, Aitken and Harrison (1999) investigated 4000 Venezuelan enterprises and came to the conclusion that increased foreign ownership has a detrimental effect on domestically owned firm productivity because MNEs are more likely to locate in more productive sectors. Similarly, the empirical evidence of Zhou et al. (2002) from China shows that FDI reduces local companies' production efficiency by diverting the best employees away from domestic firms competing for the same market. According to empirical evidence from Malaysia by Ismail et al. (2012), FDI has a negative effect on labor productivity due to a large technological gap between MNEs and domestic companies, which makes technology and knowledge transfer difficult for local firms because local firms have a low absorption capacity, resulting in a crowding-out effect for local firms. Herzer and Donaubaauer (2018)'s co-integration analysis shows that FDI has a negative significant effect on productivity growth, which is even more pronounced in countries with lower levels of human capital and financial development and a less open economy.

The third claim is that FDI has no effect on raising labor productivity. For instance, Elmawazini (2014) discovered a negative but weak effect of FDI on productivity growth in Gulf Cooperation Council (GCC) countries from 1995 to 2001 using Blundell-Bond dynamic panel GMM estimation. It

was justified by the fact that the majority of FDI inflows to the region went to natural resources and construction, which are less important for technology transfer and labor productivity. According to Vuksic (2015), FDI has little effect on labor productivity in Croatia due to insufficient capacity for FDI absorption and insufficient FDI inflow. By using a two-step system GMM for 45 African countries for the period 1980–2012, Malikane and Chitambara (2018) also found a positive but weak effect of FDI on total factor productivity (TFP).

In light of this, the vital but poorly addressed question is, “Does FDI improve labor productivity in developing countries?” In what ways does it affect labor productivity? These questions were not adequately covered in the earlier studies. There have been a few empirical studies that attempted to examine the effect of FDI on overall labor productivity in developing countries, but the results are inconclusive and require further investigation. As previously stated, overall labor productivity can be raised by raising worker productivity in a specific sector (within-sector effect) and through structural change (structural-change effect). However, no study has examined the effect of FDI on labor productivity in developing countries via the “within-sector effect” or “structural-change effect.” Hence, by examining the effect of FDI on labor productivity via within-sector effects and structural change effects, this study may be the first to contribute novel insights to the existing literature. This will help in the review of policy concerns in developing countries and the worldwide research community. In order to achieve this aim, the study attempted to test the null hypothesis, which contends that FDI has no effect on labor productivity via structural change, against the alternative hypothesis, that FDI has a significant positive effect on the improvement of labor productivity in developing countries.

The remainder of this paper is structured as follows: Section 2 addresses the methodology part of the study, which includes estimation techniques and econometric model specification. The study output’s descriptive and econometric analyses are both presented in Section 3. Section 4, the last section, presents the study’s conclusion remarks.

2. Methodology

2.1. Data and econometric model specification

The study used a panel dataset of 35 developing countries between 1990 and 2018. The selection of 35 countries is based on the availability of data (for a list of countries, see Appendix). They are all from Asia, Africa, and Latin America, which are thought to be the home of developing countries. Based on data retrieved from United Nations Conference on Trade and Development (UNCTAD; 2022), they are distinguished by a mean government expenditure of 13.79 percent, with countries with the most government intervention experience, such as China (36 percent), Indonesia (24.36 percent), and South Africa (22.57 percent), and countries with low government consumption, such as Malaysia (4.25 percent of GDP), Burkina Faso (5.06 percent), and Senegal (6.57 percent). Inflows of FDI into these countries averaged 2.58 percent of GDP. Mozambique (10.17 percent), Vietnam (6 percent), Costa Rica (4.57 percent), Namibia (4.52 percent), and Malaysia (4.30 percent) were among the best performers, while Bangladesh (0.79 percent), Burkina Faso (1.02 percent), Pakistan (1.06 percent), and Indonesia (1.07 percent) were among the least. In terms of economic standards, the countries covered in this study had an average per capita GDP of 4463.82 USD in 2018, with Argentina (14,260.88 USD), Costa Rica (12,505.37 USD), and Malaysia (11,067.85 USD) at the top of the list. At the bottom of the list are Malawi (563.09 USD), Mozambique (602.53 USD), Burkina Faso (718.98 USD), and Ethiopia (727 USD). Below, in Table 1, selected variables for econometric analysis are described in terms of their definition, symbols, measurement, sources, and expected signs.

Based on labor productivity theories (Yellen, 1984), we present the following quantitative model assessing the effect of FDI on labor productivity:

$$SC_{it} = \beta_0 + \beta_1 FDI_{it} + \sum \beta_j X_{it} + \varepsilon_{it} \quad (1)$$

Table 1. Definition of the variables

Variable	Symbol	Definitions & Hypothesis	Source
Structural Change	SC	It is the result of a “static structural change effect” plus a “dynamic structural change effect” in labor productivity growth. In the econometrics analysis, it serves as a dependent variable.	GGDC
Foreign Direct Investment	lnFDI	It is the amount of equity capital, earnings reinvestment, and other intra-firm loans represented as net FDI inflows in the balance of payments. It is measured in millions of USD at current prices. It is a well-known source of physical capital augmentation as well as technological and knowledge spillovers (Arisoy, 2012). Hence, it is expected to increase labor productivity.	UNCTAD
Human Capital	lnHC	Human capital is measured using an index based on years of education and returns on investment in education. Its value ranges from zero to one, and as it approaches one, it indicates that the country has adequate human capital. Workers with qualified education and skills have the potential to use technologies in novel ways and improve production techniques (Baharin et al., 2020), which is expected to boost labor productivity.	PT10.0
Physical Capital	lnK	It is calculated using the logarithm of capital stock at current purchasing power parities (in millions of 2017 USD). Physical capital, such as new machines, tractors, photocopiers, shovels, and other equipment, greatly aids workers in producing more; thus, having more physical capital is expected to have a positive effect on labor productivity.	PT10.0

(Continued)

Variable	Symbol	Definitions & Hypothesis	Source
Total Population	lnPoP	It is measured in terms of the number of people (in millions), and the logarithmic form was used. Having a large population will reduce per capita capital (Samargandi, 2018), which is expected to have a negative effect on labor productivity.	PT10.0
Fertilizer Utilization	lnFU	Nitrogen nutrient fertilizer used in agriculture was measured in tons as a proxy for fertilizer utilization and was expressed in logarithmic form. Because the agriculture sector absorbs a large share of employment in developing countries, fertilizer utilization is an important variable to boost labor productivity by improving agricultural land (Sun & Li, 2021). As a result, it is expected to have a positive effect on labor productivity.	FAO
Arable Land	lnAL	It is a plot of land that will be used for agriculture. It is measured in hectares (1000 hectares) and is written in logarithmic form. A small farm allows the farmer to efficiently use family labor and close follow-up with good farm management (Rada & Fuglie, 2019). Thus, a large farm size is expected to have a negative effect on labor productivity.	FAO
Income	lnPCGDP	Increasing income allows for more investment in family education; the maintenance of workers' health through adequate medication and feeding; and the motivation to work hard (Yellen, 1984). The GDP per capita in the current USD was used to calculate income for the purposes of this study. It was used in the form of a logarithm. Therefore, it is hypothesized that labor productivity will rise as income rises.	UNCTAD

(Continued)

Table 1. (Continued)

Variable	Symbol	Definitions & Hypothesis	Source
Infrastructure	INF	The number of fixed telephone subscriptions per 100 people is a proxy for infrastructure. Infrastructure development is used to facilitate production and reduce both production and transaction costs, as well as to aid in the adoption of technology, easy communication, and quick transportation (Wan & Zhang, 2018). Hence, it is expected to increase labor productivity.	WDI
Government Expenditure	lnGE	It is government investment in infrastructure, education, health, agriculture, peace and security, and other areas. It is currently measured in millions of USD and expressed in logarithmic form. Investing in education, health, information, and communication technology has a direct effect on labor productivity (Wan & Zhang, 2018). Thus, it is expected to increase labor productivity.	UNCTAD
Export	EXP	Exports are goods and services produced in one country and shipped to another. It is measured in the percentage of GDP. Exports have the potential to boost labor productivity by fostering backward linkages and technological spillover (Dine & Chalil, 2021). Thus, it is expected to increase labor productivity.	UNCTAD

Note: GGDC = Groningen Growth and Development Centre, UNCTAD = United Nations Conference on Trade and Development, FAO = Food and Agriculture Organization, WDI = World Development Indicators, & PT10.0 = Pen Table 10.0

Where: “t” represents the year (1990–2018), “i” represents the country included in the study, “SC” denotes the labor productivity growth due to structural change, and X represents the composite of control variables presented in Table 1, and “ β_j ” indicates their coefficients, and β_0 refers to the intercept coefficient, β_1 indicates the coefficient parameter of FDI, and ϵ_{it} is an error term.

There are two mechanisms for increasing labor productivity: (i) within economic sectors through capital deepening, technological progress, or reduced misallocating of labor across plants—this is

called the “within-sector effect,” and (ii) labor can move across sectors—this is referred to as the “structural change effect” which makes up the interesting dependent variable in our FDI-labor productivity analysis. The labor productivity growth, which is a dependent variable in econometric analysis, was obtained by decomposing it under the effect of “structural change”. There are many different ways to decompose productivity growth into “within-sector effect” and “structural change effect”. McMillan et al. (2014) provide an explanation of aggregate labor productivity growth by considering the decomposition equation expressed in Equation 2:

$$\Delta L_t = \sum_{i=n} l_{i,t-k} \Delta A_{i,t} + \sum_{i=n} A_{i,t} \Delta l_{i,t} \quad (2)$$

Where L_t and $A_{i,t}$ are the overall and sectoral labor productivity levels, respectively, and $l_{i,t}$ is the share of employment in sector i . Agriculture (agriculture, forestry, and fishing); industry (mining and quarrying, manufacturing, electricity, gas, water supply, and construction); and service (trade, transportation, finance, real estate, government services, and other services) are the three sectors. A sector’s employment share is the ratio of sectoral employment to overall employment, while labor productivity is calculated by dividing the sector’s output by its employment. The Δ operator represents the difference in employment or productivity between $t-k$ and t . The first term (on the right-hand side) in Equation (2), called “within-sector effect,” is the weighted sum of the productivity growth within each sector, where the weights correspond to each sector’s employment share at the beginning of the period. In Equation 2, the second term, the “structural-change effect,” describes the productivity effects of labor re-allocations across sectors, which will be positive when changes in employment shares are positive, and structural change will boost aggregate productivity growth.

The decomposition analysis presented in Equation 2 has been criticized for overestimating the contribution of within-sector productivity growth while underestimating the effect of structural changes. As a result, some scholars have used Haltiwanger’s (2000) decomposition analysis which results in Equation 3.

$$\Delta L_t = \sum_{i=n} l_{i,t} \Delta A_{i,t} + \sum_{i=n} A_{i,t} \Delta l_{i,t} \quad (3)$$

In contrast to Equation 2, Haltiwanger (2000)’s decomposition analysis used the contemporary share of employment in order to obtain the weighted sum of the within-sector effect. However, it has been criticized for incorrectly enlarging the structural change effect. Timmer and de Vries (2009) then applied their decomposition as expressed in Equation 4 by using the average share of employment instead of either initial or contemporary timeshares.

$$\Delta L_t = \sum_{i=n} \bar{l}_i \Delta A_{i,t} + \sum_{i=n} \bar{A}_i \Delta l_{i,t} \quad (4)$$

In Equation 4, \bar{l}_i is the average employment share of sector- i , while \bar{A}_i represents sector- i ’s average labor productivity level. de Vries et al. (2015) criticized the fact that Equations 2–4 capture only static measures of the reallocation effect (differences in productivity levels between sectors) but ignore the reality that different sectors grow at different rates of productivity (i.e. dynamism). de Vries et al. (2015) developed a decomposition method in Equation 5 to capture the dynamic effect of structural change on labor productivity, and it has been adopted for by most researchers.

$$\Delta L_t = \sum_{i=n} l_{i,t-k} \Delta A_{i,t} + \sum_{i=n} A_{i,t} \Delta l_{i,t} + \sum_{i=n} \Delta A_{i,t} \Delta l_{i,t} \quad (5)$$

The first term (on the right-hand side) in Equation 5 indicates “within-sector effect”—similar to that in Equation 2; the second term indicates “static structural change effect”—the capability of a country to move labor from less productive activities to higher-producing ones; and the third term indicates “dynamism effect of structural change”—the potential of a country to reallocate its labor towards industries with high productivity growth. Alternatively, it is the combined effect of changes in sector employment and productivity levels. Therefore, to determine the dependent

variable of this study, called labor productivity growth due to structural change (summation of static and dynamic structural change effects), we employed de Vries et al.'s (2015) decomposition method.

2.2. Estimation techniques

There have been three most common panel data estimation methods: pooled OLS, fixed effects (FE), and random effects (RE); however, several preliminary tests on the variables were frequently performed to ensure the suitability of the methodology used and the robustness of the results. Homoskedasticity, no serial correlation, and cross-sectional independence assumptions are all required for OLS estimation (Poveda, 2011). Despite this, our data are heteroskedastic and serially correlated, with a cross-sectional dependence problem, as mentioned in section 3.2, therefore, using OLS for this panel data is not advised. Based on the results of some statistical tests, FE and RE are used instead of OLS, but the fixed effect estimators remove the unobserved heterogeneity problem from the dataset. In RE, the unobserved heterogeneity term is merged with the idiosyncratic error term, yielding a composite error term, which becomes serially correlated and is not well addressed (Hoque et al., 2015). If non-spherical errors are not addressed properly, they can cause inefficiency in coefficient estimation and bias in standard error estimation (Reed & Ye, 2011). Because our data does not meet the homoskedasticity and autocorrelation assumptions, conventional techniques such as OLS, FE, and RE are not appropriate estimation methods.

The robust estimation of standard errors produced by Eicker (1967) and White (1980) is typically used when the homoskedasticity assumptions of OLS are violated. It does not, however, take cross-sectional correlation into account (Hoechle, 2007). Parks (1967) made the first attempt to solve the problem using the feasible generalized least squares (FGLS) method. This method, however, works only when the number of time periods (T) in a panel data set is greater than or equal to the number of cross sections (N), so it is not recommended for this study because the N relative to T is large. Moreover, it produces unacceptable levels of standard error. Alternatively, the Beck and Katz (1995) method is used, which is based on panel-corrected standard errors (PCSE). The PCSE approach, unlike FGLS, has limited robustness when the N of panel data exceeds the T (Hoechle, 2007). Hence, because our panel has N = 35 and T = 29, it is inapplicable in our case. To cope with such issues, Driscoll and Kraay (1998) developed a method that is insensitive to very general cross-sectional and temporal dependence. Unlike the other techniques mentioned above, it has multifaceted purposes. It makes standard errors robust to heteroscedasticity and serial correlation. It estimates the parameters by considering the variables with one lag, which allows them to control for potential endogeneity issues between variables (Cerra & Saxena, 2008). The DK covariance estimator can handle missing values and works with both balanced and unbalanced panel data (Baloch et al., 2019). Due to these characteristics, DK regression estimation is employed in this study. STATA 16.0 software was used for statistical analysis.

3. Result and discussion

3.1. Descriptive analysis

This section tries to shed light on the main stylized facts about structural change related to employment share change and productivity growth in three sectors (agriculture, industry, and service) in 35 developing countries from 1990–2018.

The agriculture employment declined considerably during the study period, on average by 19.22 percent from 52.23 percent in 1990 to 33 percent in 2018. According to Table 2, Senegal (42.29 percent), Burkina Faso (39.58 percent), China (33.99 percent), Vietnam (38.95 percent), and Bolivia (30.92 percent) are among the top five countries that have experienced more than 30 percent reduction in agricultural employment share over the study period. Contrary to this, Lesotho (1.22 percent), Argentina (5.42 percent), South Africa (7.51 percent), Botswana (8.67 percent), and Mexico (9.9 percent) are among the bottom five countries with shrinkage of less than 10 percent in agriculture employment share. From this, we can see that the countries that are at the top in

Table 2. Sectoral share of employment over (1990–2018)

Country	Agriculture			Industry			Service		
	1990	2018	Change	1990	2018	Change	1990	2018	Change
Senegal	65.75	23.46	-42.29	8.17	19.74	11.57	26.07	56.8	30.73
Burkina Faso	88.3	48.72	-39.58	3.47	17.66	14.19	8.24	33.62	25.38
Viet Nam	76.67	37.72	-38.95	9.17	26.7	17.53	14.16	35.57	21.41
China	60.1	26.11	-33.99	24.86	32.94	8.08	15.04	40.95	25.91
Bolivia	58.65	27.73	-30.92	11.09	19.96	8.87	30.26	52.32	22.06
Rwanda	91.5	62.38	-29.12	2.11	11.7	9.59	6.39	25.92	19.53
Kenya	71.21	43.88	-27.33	7.15	18.86	11.71	21.64	37.26	15.62
Bangladesh	65.75	39.85	-25.9	14.13	20.66	6.53	20.12	39.49	19.37
India	64.78	38.9	-25.88	15.39	28.09	12.7	19.84	33.01	13.17
Thailand	57.97	32.2	-25.77	17.54	22.85	5.31	24.49	44.95	20.46
Namibia	47.31	23.05	-24.26	14.94	15.1	0.16	37.74	61.86	24.12
Indonesia	54.67	30.46	-24.21	14.07	21.36	7.29	31.26	48.18	16.92
Ethiopia	89.18	65.35	-23.83	2.49	13.37	10.88	8.34	21.28	12.94
Nigeria	69.43	46.45	-22.98	12.83	9.74	-3.09	17.74	43.81	26.07
Malawi	86.1	64.1	-22	4.89	7.4	2.51	9.01	28.5	19.49
Ghana	54.95	33.31	-21.64	16.48	19.97	3.49	28.57	46.72	18.15
Cameroon	74.68	54.03	-20.65	7.69	11.12	3.43	17.63	34.85	17.22
Sri Lanka	40.82	25.5	-15.32	17.85	27.94	10.09	41.32	46.56	5.24
Tanzania	84.57	69.7	-14.87	3.86	6.04	2.18	11.57	24.26	12.69
Malaysia	24.46	10.63	-13.83	25.02	27.11	2.09	50.53	62.26	11.73
Costa Rica	28.91	15.51	-13.4	27.77	19.94	-7.83	43.31	64.55	21.24
Mozambique	85.67	72.95	-12.72	4.15	4.17	0.02	10.18	22.87	12.69
Egypt	34.36	21.66	-12.7	22.54	26.86	4.32	43.1	51.47	8.37
Colombia	31.21	18.99	-12.22	18.69	18	-0.69	50.1	63.02	12.92

(Continued)

Table 2. (Continued)

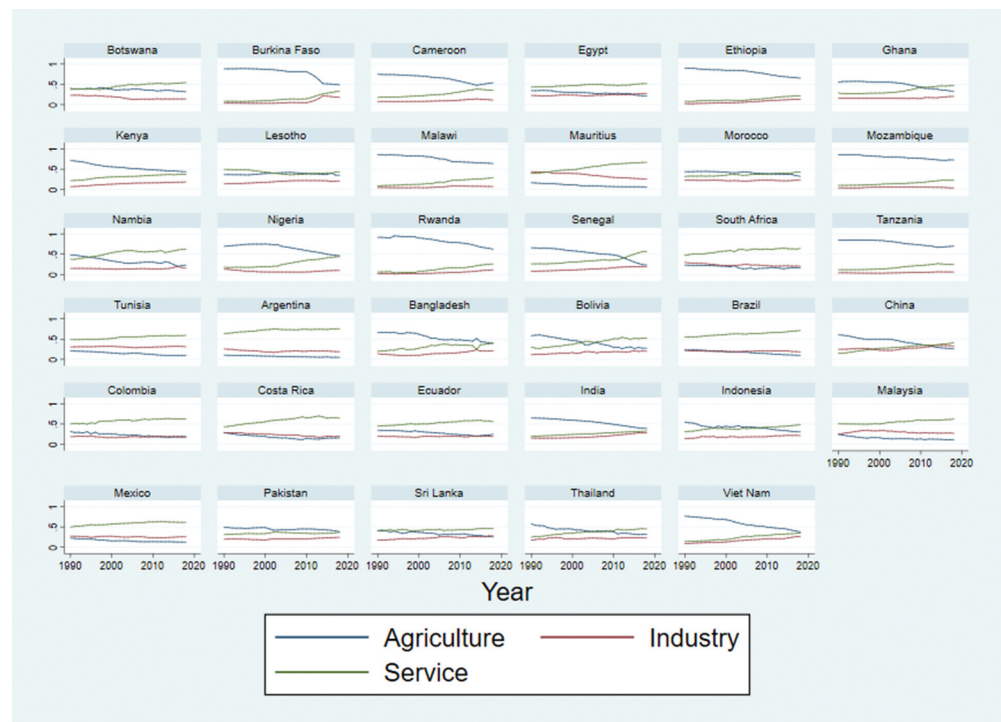
Country	Agriculture			Industry			Service		
	1990	2018	Change	1990	2018	Change	1990	2018	Change
Brazil	22.25	10.17	-12.08	23.16	18.66	-4.5	54.59	71.16	16.57
Morocco	44.1	32.73	-11.37	23.58	23.84	0.26	32.32	43.43	11.11
Tunisia	20.58	9.39	-11.19	30.71	31.21	0.5	48.71	59.4	10.69
Pakistan	49.01	38.49	-10.52	19.78	24.62	4.84	31.21	36.88	5.67
Mauritius	16.72	6.37	-10.35	43.77	26.48	-17.29	39.51	67.15	27.64
Ecuador	35.07	24.86	-10.21	19.95	19.24	-0.71	44.99	55.89	10.9
Mexico	22.61	12.71	-9.9	27.49	25.64	-1.85	49.9	61.65	11.75
Botswana	40.24	31.57	-8.67	22.87	14.09	-8.78	36.89	54.33	17.44
South Africa	23.22	15.71	-7.51	29.62	20.48	-9.14	47.17	63.82	16.65
Argentina	10.56	5.14	-5.42	25.7	19.13	-6.57	63.74	75.73	11.99
Lesotho	36.55	35.33	-1.22	13.77	21.13	7.36	49.68	43.54	-6.14
Average	52.23	33.00	-19.22	16.76	19.76	3.00	31.01	47.23	16.22

terms of reducing agricultural employment are those that started with a relatively high share of agricultural employment, while the bottom-ranked countries started with a relatively low share of agricultural employment. This suggests that structural changes become more difficult as the economy advances. However, despite a declining trend in agricultural employment share, as illustrated in Figure 1, Ethiopia, Malawi, Mozambique, Rwanda, and Tanzania continue to have a disproportionately large share of agricultural employment.

For a structural change to take place, it is not only important to realize the shrinkage of employment, but it is also important to know where displaced workers will go once they have been displaced from agriculture. On a normal path, the path pursued by so-called industrialized countries, displaced agricultural employees are expected to shift to the industry sector, but once the industry sector matures, both agricultural and industrial workers are expected to move to the service sector. The latter is referred to as deindustrialization; it is a necessary stage of structural transformation. Because we are concerned with developing countries, the majority of displaced agricultural workers are expected to be placed in the industrial sector. However, only 3 percent of the 19.22 percent of displaced agricultural workers moved into the industrial sector, while the majority (16.22 percent) went into the service sector. For example, agricultural employment was displaced by more than 30 percent in those countries (Senegal, Burkina Faso, Vietnam, China, and Bolivia), but only 8.08 percent to 11.57 percent of this displacement entered the industrial sector.

On the basis of Table 2, three categories of structural changes can be identified. The first type of structural change is called “culled structural change”. This is marked by a large percentage of employees remaining in agriculture but workers moving directly from this sector to the service sector as economic conditions improve, bypassing the industrial sector. This type of structural change has occurred in the majority of the countries included in this study. Bangladesh (6.53 percent from 25.9 percent), Namibia (0.60 percent from 24.26 percent), Mozambique (0.02 percent from 12.72 percent), and Malawi (2.51 percent from 2.51 percent) are good examples of “culled

Figure 1. Structural change trends across countries.



structural change” because very few displaced workers moved from agriculture to industry. It was called “Premature Service-led Growth” by Ghose (2021) in India. This category includes countries that are still in the early stages of structural change and have the potential to switch to industry-led structural change. However, various arguments have been advanced in support of premature service-led growth. de Vries et al. (2015) argue it is due to inadequate industrial development and pro-market policies implemented in the 1990s that intensified wholesale and retail trade, as well as imports and exports. Ghose (2021) argues that the current growth of digital technology boosts the expansion of service sectors such as banking and business services more than the expansion of industry businesses. Dasgupta and Singh (2005) argue that in developing countries, a structural change driven by services is as normal as structural change driven by industry in developed countries. Rodrik (2016) also speculates that this is due to the shift in global demand from manufacturing to services and also the inability of developing countries to break out of the lucrative global market for manufacturing goods. This structural shift also runs counter to the classic Lewis-type dual economy model, in which workers leave subsistence agriculture to work in modern manufacturing (Lewis, 1954).

“Immature deindustrialization” is the second type of structural change. Another way to state it is that developing countries are transitioning to service economies without having experienced adequate industrialization. Deindustrialization began when manufacturing employment accounted for 30 percent of total employment in advanced countries (Asyraf et al., 2019). Deindustrialization started in newly industrialized countries as well, such as Japan, where manufacturing employment peaked at 25–30 percent of total manufacturing employment, close to 25 percent in South Korea, and close to 35 percent in Taiwan (Grabowski, 2017). Thus, premature deindustrialization refers to the early stages of deindustrialization prior to this turning point. Nigeria is experiencing this type of structural change, with agriculture still accounting for a large share of employment and the industrial sector’s development level is low, but workers have moved from both the agricultural and industrial sectors to the service sector.

The third is “the conventional type of structural change” that advanced countries have experienced. The agriculture sector’s employment is small and industry employment is relatively large in this category. As a consequence, workers move both from agriculture and industry to services. The economies of Argentina, South Africa, Mexico, Mauritius, and Tunisia are good examples of this category. In general, this suggests that the path of structural change experienced by developing countries does not have a single pattern, as developed countries had. It is consistent with the findings of Bah (2011), who discovered a multi-channel path of structural transformation in developing countries. Furthermore, they have seen a decrease in agriculture and an increase in industry, but the speed of structural change in developing countries has been very slow when compared to the Asian Tigers because they were developed over a three-decade period from the 1960s to the 1990s.

Labor productivity growth in the overall economy is divided into growth due to within sector productivity growth and changes in sector employment share. According to Table 3, the average overall productivity growth was 192.18 percentage points, with the “within-sector effect” change accounting for approximately 187.18 percent and the “structural change effect” (static plus dynamic) accounting for approximately 5.01 percent over 1991–2018. The negative sign of the values of “dynamic structural change” in Table 3 indicates that new arriving workers from another sector are less productive than existing workers, whereas the positive sign indicates that new workers are more productive than existing workers. In general, the growth rate appears to be inflated, but this is due to significant growth in Indonesia, Colombia, Vietnam, Namibia, Costa Rica, Tunisia, Burkina Faso, Tanzania, and Sri Lanka, as shown in Table 3. Excluding them, we discovered that overall labor productivity was 13.98 percent on average, with a 12.08 percent within-sector effect and a 1.89 percent structural change effect. This indicates that the “within-sector effect” accounted for the lion’s share of overall labor productivity growth rather than the “structural-change effect,” for example, 97.4 percent in the former case and 86.41 percent in the latter. This is

Table 3. Labor productivity decomposition

County	Overall	Within-sector	Structural Change		Agriculture	Industry	Service
			Static	Dynamic			
Indonesia	2139.7	2085.96	45.38	8.36	-2.83	1027.13	1115.4
Colombia	1090.86	1087.02	9.6	-5.75	-5.14	410.53	685.46
Viet Nam	1073.73	993.3	45.78	34.65	20.18	439.45	614.1
Namibia	781.62	797.09	0.19	-15.66	776.2	2.35	3.08
Malawi	420.1	424.49	0.09	-4.48	411.18	3.06	5.86
Costa Rica	384.25	385.52	3.06	-4.33	2.5	134.6	247.14
Tunisia	269.95	276.6	0.01	-6.66	269.32	0.16	0.46
Burkina Faso	88.46	74.75	22.33	-8.61	71.27	3.12	14.07
Tanzania	76.32	72.72	2.71	0.89	2.5	36.22	37.59
Sri Lanka	51.94	51.61	0.37	-0.05	11.06	10.6	30.27
Mauritius	42.64	42.65	0.54	-0.55	24.85	6.77	11.03
Argentina	40.44	40.55	-0.03	-0.08	0.02	21.05	19.37
Nigeria	35.86	35.1	0.27	0.49	1.33	20.41	14.11
Senegal	33.21	10.08	24.43	-1.3	3.72	10.21	19.28
Cameroon	31.23	12.3	19.99	-1.05	-0.2	10.19	21.24
Egypt	22.25	22.39	0.02	-0.15	18.05	1.73	2.47
Thailand	21.66	20.51	1.41	-0.26	14.08	3.23	4.35
Bangladesh	15.27	16.47	0.4	-1.6	11.39	2.22	1.65
India	14.68	14.49	0.21	-0.02	8.81	1.95	3.93
Rwanda	13.8	10.05	4.53	-0.79	3.07	3.09	7.64
Pakistan	11.85	11.77	0.1	-0.03	1.24	2.64	7.97
Bolivia	11.78	11.97	0.09	-0.28	11.09	0.21	0.48
Mexico	11.62	11.5	0.08	0.04	0.18	4.6	6.84
South Africa	10.94	10.93	0.05	-0.03	4.07	3.05	3.83

(Continued)

Table 3. (Continued)

County	Overall	Within-sector	Structural Change		Agriculture	Industry	Service
			Static	Dynamic			
Kenya	5.94	5.19	0.68	0.07	0.68	1.25	4.01
Botswana	5.56	5.65	-0.03	-0.06	0.43	2.61	2.53
Mozambique	5.31	5.34	0.02	-0.05	4.09	0.68	0.54
Ethiopia	3.36	3.34	0.03	-0.01	3.04	0.1	0.23
Brazil	2.44	2.44	0	0	0.64	0.55	1.25
China	2.43	2.33	0.05	0.04	0.37	1.22	0.83
Lesotho	2.34	2.32	0.02	-0.01	0.4	0.47	1.47
Malaysia	2.26	2.24	0.04	-0.02	0.14	0.95	1.17
Morocco	1.44	1.31	0.14	0	-0.02	0.55	0.91
Ghana	0.86	0.86	0	0	0.37	0.21	0.29
Ecuador	0.34	0.33	0.01	0	0.1	0.1	0.14
Average	192.18	187.18	5.22	-0.21	47.66	61.92	82.60

Table 4. Descriptive analysis of all variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Overall labor productivity growth	1,014	192.33	554.62	-757.18	4744.27
Within-sector effect	1,014	187.32	547.41	-755.60	4645.04
Static-Structural Change effect	1,014	5.22	25.62	-292.44	311.55
Dynamic Structural Change	1,014	-0.21	23.75	-367.597	185.02
lnFDI	991	6.58	2.42	-6.91	11.84
lnPoP	1,015	3.39	1.63	0.05	7.26
lnK	1,015	12.82	2.01	8.30	18.35
lnHC	1,015	0.68	0.26	0.03	1.12
EXP	1,015	28.45	19.07	3.28	121.31
lnPCGDP	1,015	7.59	1.05	5.17	9.64
lnGE	1,015	9.62	1.56	6.19	14.65
lnAL	1,015	8.44	1.72	4.32	12.00
INF	1,013	7.06	7.63	0.06	34.27
lnFU	1,015	11.72	2.54	4.34	17.25

a significant indicator of poor labor reallocation from low-labor productive sectors to high-productivity sectors in developing countries. This finding is consistent with Timmer and de Vries (2009) finding that in Asia and Latin America, productivity increases within sectors account for roughly 75 percent of overall labor productivity growth, while structural change effects account for 25 percent. Observations from Senegal and Cameroon contradict this conclusion because the majority of their overall labor productivity was derived from the “structural change effect” rather than the “within sector effect”.

The services sector, not the industry, is the primary driver of rapid increases in labor productivity. Services contribute 42.98 percent (82.60 points) of total labor productivity growth, while industry contributes 32.22 percent (61.92 points) and agriculture contributes 24.80 percent (47.66 points). The experience of the various countries reveals a variety of productivity growth paths. In countries like Namibia, Malawi, Egypt, Thailand, Bangladesh, Burkina Faso, and Bolivia, agriculture, for example, accounted for a larger share of overall labor productivity than other sectors. Indonesia, Colombia, Vietnam, Costa Rica, Tanzania, and Argentina, on the other hand, experienced substantial productivity growth in the industry and service sectors. Developing countries like Kenya, Pakistan, Senegal, and Sri Lanka rely heavily on the service sector to boost their productivity. Agriculture has greater labor productivity than the industry in countries like Botswana and Argentina. This means that structural change reduces productivity and may slow economic growth. It may be contrary to the theory that states the industry sector has higher labor productivity. There are two possible reasons why this may occur. The first is due to workers leaving the agricultural sector, increasing the marginal productivity of the remaining workers in the sector; the second is due to the industry sector not being more productive than the agricultural sector.

Table 4 shows the descriptive statistics for all of the variables. The logarithm of FDI rose by 6.58 on average throughout the study period, with a minimum and maximum value ranging from -6.91 to 11.84 and a standard deviation of 2.42. Domestic physical capital and human capital accumulation as well as the population have average logarithms of 12.82, 0.68, and 3.39, respectively. The

Table 5. Variance-inflating factor (VIF) output

Variable	VIF	Variable	VIF
lnK	6.38	lnFU	1.9
lnPoP	5.69	lnGE	1.87
lnAL	3.84	lnPCGDP	1.64
lnFDI	3.16	lnHC	1.63
INF	2.11	EXP	1.38

average export share of total GDP for all countries is 28.45 percent. The minimum and maximum ranges for the export share of total GDP are from 3.28 to 121.31 percent, with a standard deviation of 19.07 percent. On average, the logarithm of the per capita GDP and government expenditures for selected countries is 7.59 and 9.62; their minimum values are 5.17 and 6.19, and their maximum values are 9.64 and 14.65, with standard deviations of 1.05 and 1.56, respectively. Additionally, lnAL and lnFU average 8.44 and 11.72, with a minimum value of 4.32 and 4.34, and a maximum value of 12.00 and 17.25, with standard deviations of 1.72 and 2.54, respectively. Telephone fixed subscriptions (per 100 people), which is a proxy for infrastructure development, have an average value of 7.06 per 100 people, with a minimum value of 0.06 and a maximum value of 34.27, and a standard deviation of 7.63.

3.2. Econometric analysis

All needed statistical tests, such as the existence of multicollinearity, heteroskedasticity, autocorrelation, and cross-sectional dependence tests, should be performed to arrive at a valid conclusion.

The VIF is widely used as a multicollinearity indicator by academics. The higher the VIF value, the more “difficult” or “collinear” the variable is. According to Gujarati (2003), multicollinearity is not a problem if the VIF of a variable is less than 10. Thus, all variable VIF values are below 10, as shown in Table 5, so our data is free of multicollinearity. The second crucial test is the Breusch-Pagan/Cook-Weisberg test, which is used to determine whether or not heteroskedasticity exists. The test result indicates the presence of heteroskedasticity because the null hypothesis, which states that variance is constant, was rejected with $\text{prob} > \chi^2 = 0.000$. Third, the Wooldridge test for autocorrelation in panel data was performed, which confirmed the existence of first-order autocorrelation by rejecting the null hypothesis that no first-order serial correlation exists with $\text{Prob} > F = 0.01$. Finally, we checked the existence of cross-sectional dependency by using Pesaran’s test. It also proves the presence of cross-sectional reliance by rejecting the null hypothesis, which claims that cross-sectional dependency does not exist, with a p-value of 0.000. We chose the Driscoll and Kraay (1998) estimation method as a result of these test results, and the estimation outputs are shown in Table 6. Fisher-type unit root tests are important to detect the presence of unit roots for unbalanced data. Since the p-value in Table 7 is less than 0.05, the null hypothesis that states “all panels contain unit roots” is rejected. Therefore, our data is not affected by the unit root problem as shown in Table 7.

As a consequence of these different test outputs, the Driscoll and Kraay (1998) estimation method was applied, and its estimation outputs are presented in Table 6. Our fascinating variable, FDI, has a positive and large effect on overall labor productivity. A 1 percent increase in FDI inflows raises overall labor productivity by 40.87 percent, all else being equal. “Within-sector effect” and “structural change effect” pathways are also important for total labor productivity growth. With a percentage increase in FDI, labor productivity is boosted by 39.05 percent via a within-sector effect, while it is only 1.82 percent via structural change. Both effects are significant. This means that, while FDI has a major effect on labor productivity as a result of structural change, its contribution to overall productivity in developing countries is mostly through improving

Table 6. The Driscoll and Kraay (1998) estimation outputs

Variables	Overall	“within-sector”	“Structural Change”
lnFDI	40.87*** (0.005)	39.05** (0.006)	1.82*** (0.009)
lnPOP	33.55** (0.036)	28.87* (0.070)	4.68*** (0.001)
lnK	180.80*** (0.000)	177.50*** (0.000)	3.30*** (0.001)
lnHC	77.45** (0.043)	83.75** (0.027)	-6.31** (0.043)
EXP	4.63*** (0.000)	4.24*** (0.000)	0.39*** (0.000)
lnPCGDP	-48.78 (0.118)	-49.51 (0.000)	0.73 (0.521)
lnGE	-84.65** (0.017)	-78.87** (0.023)	-5.78** (0.000)
lnAL	-147.63*** (0.000)	-144.67*** (0.000)	-2.96*** (0.011)
INF	-9.91** (0.024)	-9.20** (0.033)	-0.72*** (0.000)
lnFU	-24.43*** (0.006)	-25.22*** (0.004)	0.79*** (0.043)

Note: The symbol *** indicates that the variable is significant at a 1 percent significance level, the symbol ** indicates that the variable is significant at a 5 percent significance level, * indicates that the variable is significant at a 10 percent significance level, and other variables are not significant at all at the 1, 5, and 10 percent significance levels. The value in the bracket is the “p-value”.

Table 7. Unit root test (Fisher-type)

	Inverse chi-square (P)		Inverse Normal (Z)		Inverse Logit (L)		Modified inv. Chi-squared (Pm)	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
L	471.03	0.00	-15.80	0.00	-20.79	0.00	33.89	0.00
L1	454.55	0.00	-15.47	0.00	-19.99	0.00	32.50	0.00
SC	655.83	0.00	-21.37	0.00	-30.63	0.00	49.51	0.00
lnFDI	310.11	0.00	-12.85	0.00	-14.38	0.00	20.29	0.00
lnPoP	1221.53	0.00	-25.11	0.00	-52.79	0.00	97.32	0.00
lnK	209.65	0.00	-5.68	0.00	-7.23	0.00	11.80	0.00
lnHC	583.77	0.00	-7.25	0.00	-15.14	0.00	43.42	0.00
EXP	187.55	0.00	-7.84	0.00	-8.04	0.00	9.94	0.00
lnPCGDP	252.03	0.00	-8.73	0.00	-10.64	0.00	15.38	0.00
lnGE	218.44	0.00	-9.49	0.00	-9.84	0.00	12.55	0.00
lnINF	207.55	0.00	-8.96	0.00	-9.26	0.00	11.63	0.00
lnAL	198.52	0.00	-7.68	0.00	-8.29	0.00	10.86	0.00
lnFU	227.91	0.00	-9.92	0.00	-10.36	0.00	13.34	0.00

Note: L is overall labor productivity, L1 is labor productivity due to “within-sector effect”

productivity in sectors rather than aiding structural change. Positive externalities from FDI, such as increased technology transfer and management know-how, are found to have a significant influence on labor productivity. Theory of Harrod-Domar, Rostow (1960), Solow (1957), Chenery (1960), and Kuznets (1966), and Lewis (1954), and new growth theories appear to hold up in light of this

empirical finding. It also aligns with empirical findings from Ukraine's Lutz and Talavera (2004), Turkey's Arisoy (2012), SSA's Amendolagine et al. (2013) and Wamboye et al. (2016), and Vietnam's Asada (2020). On the contrary, it rejects dependency theories such as those proposed by Dos-Santos (1970) and Frank (1967). This study's findings contradicted the negative narratives about FDI on labor productivity advanced by Aitken and Harrison (1999) in Venezuela, Ismail et al. (2012) in Malaysia, Elmawazini (2014) in the Gulf Cooperation Council, and Herzer and Donaubaue (2018) in developing countries.

Population size is the first and most important control variable, having a strong positive effect on overall labor productivity and, in particular, labor productivity due to a "structural-change effect." All else being equal, a one percent increase in total population results in a 33.55 percent increase in overall labor productivity. Population growth raises labor productivity by only 4.68 percent due to the structural change effect. It has a significant effect on overall labor productivity, particularly through structural change, at a 1 percent significance level. At the 10 percent significance level, the effect of population growth on labor improvement via within-sector effect is significant, and a 1 percent increase in population boosts overall labor productivity by 28.87 percent via enhanced within-sector labor improvement. Higher population growth leads to specialization of labor and forces workers to enhance their quality by educating themselves, attempting to employ modern technology, and innovating something new in order to be competent. Our findings support Adam Smith's theory that higher population growth induces specialization in the workforce and advances in technology, both of which raise labor productivity (Chandra, 2004). It also supports the Neo-Malthusian theory, which claims that as the population grows, land use intensifies with modern inputs, resulting in a greater quantity of technological artifacts (Unat, 2020). However, it contradicts the Malthusian theory, which states that as the population grows, it leads to the utilization of less productive land, resulting in low food per person and poor labor productivity (Chernomas, 1990). It also clearly opposes the Ricardo theory's argument that as the population goes up, so does the need for food, driving up food prices and landlord rents and eventually leading to a shortage of food for consumption, diminishing worker productivity (Koley, 2000). Furthermore, it contradicts the findings of empirical investigations such as Ramirez (2006) and Ismail et al. (2012).

The findings clearly demonstrate that capital intensity has a favorable and considerable effect on labor productivity growth. For every one percent rise in domestic capital accumulation, 180.80 percent of productivity growth is recorded—177.50 percent via the "within-sector effect" and 3.30 percent via the "structural change effect." It is in line with both theoretical predictions and empirical findings by Ramirez (2006) and Vuksic (2015), which discovered the same finding in Chile and Croatia, respectively. It also counters Derando and Horvatin's (2019) negative narrative about the effect of domestic capital on productivity, which could hint at a problematic investment structure in EU countries. In developing countries, human capital is also demonstrated to be a major and statistically beneficial factor in worker productivity. In other words, a 1 percent increase in human capital leads to a 77.45 percent increase in overall labor productivity, *ceteris paribus*. The "within-sector effect" accounted for 83.75 percent of the growth, but it was reduced by 6.31 percent due to the "structural change effect." The "structural change effect" on worker productivity is statistically significant. It indicates that workers acquire human capital primarily through experience rather than formal education and training. It supports the endogenous economic growth theory, which emphasizes the importance of investing in human capital and knowledge to increase productivity. Workers that are well educated, highly competent, and trained are familiar with the operation of new machines and technologies, which improve output quality, lower production costs per unit, and increase productivity. This finding is consistent with Vuksic's (2015) and Vinh's (2019) discoveries in Vietnam and Croatia, respectively.

Exports are also a significant factor in labor productivity. In other words, for every 1 percent increase in exports as a percentage of GDP, there will be a 4.63 percent increase in overall labor productivity, *ceteris paribus*. The within-sector effect is 4.24 percent, while structural change effects account for 0.39 percent; both channels are substantial. It backs up the conclusions of

wagner (2007), Gong (2017), and Acouba et al. (2022) and contradicts Csordas's (2017) finding, which claims it has a negative or minor effect. In developing countries, per capita income has no significant effect on the overall productivity, either through the "within-sector effect" or the "structural change effect". This is in contrast to the theoretical explanation of a direct relationship between income and labor productivity, which is justified by improvements in nutrition and investments in human capital. This empirical study suggests a possible reason for the negligible effect: per capita GDP is still insufficient and people are investing their income in non-productive areas (or for survival). It also contradicts the Mirrlees-Stiglitz theory, which claims that low income reduces a worker's ability to work by lowering consumption (Bliss & Stern, 1978).

On the other hand, government spending has a significant negative effect on labor productivity growth; a one percent increase in government spending reduces overall labor productivity growth by 84.65 percent, *ceteris paribus*. The majority (about 78.78 percent) is due to the "within-sector effect" and the remainder (5.78 percent) is due to the "structural change effect." It agrees with Hansson and Henrekson (1994), Wamboye et al. (2016), and Wu et al. (2017), who suggest that government spending deters labor productivity by reducing private savings and investment and limiting capital accumulation through corruption. It also contradicts Gong (2017), who claims that government spending increases labor productivity by providing infrastructure. Not only does government expenditure have a large and negative influence on worker productivity, but so does fixed-line telephone subscriptions per 100 people (a proxy for infrastructure development). When all else is constant, each additional fixed-line telephone subscription per 100 people reduces labor productivity by 9.91 percent, with the within-sector effect accounting for 9.20 percent and the structural change effect accounting for 0.72 percent. This suggests that developing countries have not made adequate use of information technology, and hence investment in this area yields lower returns on investment. It is in line with the findings of Wamboye et al. (2016) in SSA.

An inverse relationship was discovered between the size of arable land and labor productivity. All other things being equal, every 1 percent increase in arable land size reduces overall worker productivity by 147.63 percent. The "within-sector effect" accounted for 144.67 percent of the reduction, while the "structural change effect" accounted for the remaining 2.96 percent. Our findings corroborate Sen's (1962) theory and Cai and Yan's (2019) empirical finding that small farms have higher productivity than large farms due to the intensive use of family labor in small farms and thus lower labor transportation costs. It also contradicts Byiringiro and Reardon's (1996) findings in Ghana. Similarly, because of the "within-sector effect" fertilizer use has a negative effect on overall labor productivity, but it has a favorable effect due to the "structural change effect." The use of chemical fertilizers was also discovered to be a significant driver of worker productivity. Nitrogen fertilizer use rises by a percentage point, resulting in a 24.43 percent reduction in overall labor productivity. The within-sector effect has a negative 25.22 percent influence on labor productivity change, but the structural labor change effect has a positive 0.79 percent influence on labor productivity. The structural change effect has a large positive value, implying that capital formation in agriculture fuels capital accumulation and labor productivity in the industry sector. In general, it is consistent with Hou et al.'s (2022) finding that justifies the increased use of chemical fertilizer by reducing productivity due to improper application.

4. Conclusion remarks

Labor productivity plays an important role in determining the development level of a country. It implies that achieving sustainable economic growth and transformation without an improvement in labor productivity is difficult. On the one hand, the economies of countries with high labor productivity are more likely to be transformed; on the other hand, those of developing countries with low labor productivity are still struggling to make a difference. The majority of people have been working in agriculture, a sector that produces small amounts of output, resulting in relatively very low labor productivity when compared to the industry sector in developing countries. Due to its highly populated and marginalized labor pool, raising agricultural labor productivity may be difficult without new technology and capital accumulation. However, due to a lack of technology, resources, and human capital, developing countries continue to have difficulties in using new technology and injecting new capital into the economy.

Structure change is the second method of increasing labor productivity, which involves shifting labor from agriculture to industry. Because the industrial sector is more productive, transferring labor from agriculture to industry raises overall labor productivity even if there are no within-sector productivity gains in both sectors. However, the central problem with structural change is that the industrial sector is not mature enough to lead the structural change process, and it requires enormous resources to do so in developing countries. In light of these lessons, Asian tigers' experience and development economists have been recommending the use of FDI as a key strategy to achieve structural change in developing countries. Through the introduction of new capital, managerial skills, and cutting-edge technology, FDI is thought to boost labor productivity. In addition, it's thought that FDI encourages structural change in developing countries by making fresh investments in the industrial sector and fostering the infant domestic industry sector via spillover effects.

However, research on the effect of FDI on labor productivity growth, which is important for long-term economic growth and development, is limited, and no study has been conducted to look at the influence of FDI on labor productivity growth as a result of structural change. Therefore, the primary purpose of this study is to estimate the effect of FDI on the structural change in labor productivity in developing countries from 1990 to 2018 using Driscoll and Kraay's (1998) estimation. The analysis suggests that FDI is a significant and positive factor in total labor productivity growth. The within-sector effect and structural-change effect are two important channels through which FDI promotes overall labor productivity. However, FDI's within-sector effect outweighs the structural change effect. It implies that FDI is still not doing enough to bring about structural change in developing countries. Other important factors of labor productivity are population size, domestic capital (physical and human), exports, arable land size, infrastructure, fertilizer utilization, and government expenditure, while per capita income has a negligible influence.

Therefore, the governments of developing countries should strive to attract a sufficient amount of high-quality FDI by boosting human capital status through technical and vocational education and increasing the economy's openness. To facilitate structural change and increase labor productivity, attention should be paid to FDI in the manufacturing sector and FDI that is export-oriented. Promoting domestic capital potential through saving is another important policy direction for promoting labor productivity and structural change. Moreover, policymakers should pay attention to pro-industry policies and not prioritize excessive land use over advancing technologies, such as chemical fertilizer use.

A shortage of data led to this study's analysis of only 35 countries over a 29-year period, which is a few countries and a short timeframe that may decrease the study's quality. In order to estimate the effects of FDI on labor productivity in the future, we recommend using data from a wider range of countries and a longer period of time. If researchers cannot get more annual data, it would be better to break the data down into quarters. Moreover, during the study period, countries such as Indonesia, Colombia, Vietnam, and Malawi had a miraculous increase in overall labor productivity. It might be useful to conduct further research on these countries' experiences to share best practices with other developing countries. International organizations such as the World Bank and the International Monetary Fund are suitable for this purpose.

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Appendix The List of Countries

Argentina	Costa Rica	Malawi	Rwanda
Bangladesh	Ecuador	Malaysia	Senegal
Bolivia	Egypt	Mauritius	South Africa
Botswana	Ethiopia	Mexico	Sri Lanka
Brazil	Ghana	Morocco	Tanzania
Burkina Faso	India	Mozambique	Thailand
Cameroon	Indonesia	Namibia	Tunisia
China	Kenya	Nigeria	Viet Nam
Colombia	Lesotho	Pakistan	



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