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Digital de-industrialization, global value chains, and structural transformation

Empirical evidence from low- and middle-income countries

Karishma Banga,[1] Pankhury Harbansh,[2] and Surendar Singh[3]

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Abstract: Digitalization and shifting patterns of globalization are fast changing the rules of the game for countries embarking on a path of industrialization. In this study, we empirically examine the impact of digitalization and global value chains on structural transformation using a cross-country panel of 51 economies in the GGDC/UNU-WIDER Economic Transformation Database for the period 1990–2018. The analysis is based on a novel cross-country panel combining information from the Economic Transformation Database with the UNCTAD EORA data set, World Development Indicators, and Penn World Tables. Structural transformation is examined through changes across three variables: changes in manufacturing labour productivity, manufacturing employment share, and country-level structural change. To address issues related to endogeneity and country fixed effects, we use methodologies of fixed effects with instrumental variables and the two-step system GMM estimator. Results indicate that digitalization has a positive impact on structural change and manufacturing labour productivity but a negative impact on manufacturing employment share, indicating a reallocation of labour from the agricultural sector into services. Overall global value chain participation, and particularly forward participation, has a positive impact on structural change and manufacturing labour productivity.

Key words: industrialization, digital technologies, structural transformation, global value chains

JEL classification: O14, F6, F14, C23

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[1] Digital and Technology Cluster, Institute of Development Studies (IDS), UK, K.Banga@ids.ac.uk; [2] Climate Change, Just Transition, & Green Jobs, Enterprise Department, International Labour Organization (ILO), Geneva, Switzerland; [3] FORE School of Management, New Delhi, India

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Information and requests: publications@wider.unu.edu

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

1 Introduction

Economic transformation can be understood as the continuous process of raising within-sector productivity growth through the reallocation of resources from low- to high-productivity firms/farms within a given sector or through productivity improvements within existing firms/farms by moving into more efficient product lines (McMillan et al. 2017; Woodruff 2014). It can also be achieved through structural change—the shift of workers/economic activity from the agricultural sector to higher productivity sectors of manufacturing and services—which has been the traditional path towards economic growth and job creation (Kuznets 1966; Herrendorf et al. 2014). Evidence from high-income countries in North America, Europe, and some parts of East Asia suggests that, in the early stages of development, agriculture contributes to a large portion of employment opportunities. Subsequently, manufacturing employment rises, peaking at a certain level, and thereafter declines, giving rise to a 'hump-shaped' curve (Duarte and Restuccia 2010). In the later stages of development, the services sector acts as the main engine of job creation (Syrquin and Chenery 1989).

In this transformation process, several scholars have identified the manufacturing sector as the key engine of economic growth, with developing economies industrializing at different rates (McMillan et al. 2014; Haraguchi et al. 2017). Others argue that low- and middle-income countries are 'prematurely de-industrializing', wherein there is a decline in manufacturing at lower peak levels of industrialization and gross domestic product (GDP) per capita compared to the past (Rodrik 2016; Atolia et al. 2020; Felipe et al. 2019). For instance, in Africa, the share of industry in GDP has declined from 29.9 per cent to 26.8 per cent in the period 1990–2019 (Banga 2023). This is concerning since the tradability of manufacturing goods has played an important role in the 'unconditional convergence' of labour productivity, enabling catch-up of developing economies to the developed economies (Rodrik 2013). A recent study, however, debunks the de-industrialization hypothesis, showing that the manufacturing employment share has been increasing in many low-income countries in Asia and sub-Saharan Africa (SSA) post-2000, indicating an industrial naissance (Kruse et al. 2022). At the same time, 'smokestack-less' industries have emerged, such as tourism, information and communication technology, food processing, and horticulture, sharing similar characteristics to manufacturing, with the potential to act as new engines of economic growth in the coming decades (Newfarmer et al. 2019). A new pattern of structural transformation is also being observed in low-income countries, with workers moving directly from agriculture to non-business services (Sen 2019).

Whether developing economies can still pursue the manufacturing-led development strategy for economic transformation continues to be strongly debated. In this paper, we argue that opportunities for manufacturing-led structural transformation in low- and middle-income countries are importantly shaped by the level of digitalization,[1] especially in the context of changing patterns of globalization. Advanced digital technologies have permeated across sectors at a fast rate, as evidenced by the 14 per cent year-on-year growth in active industrial robots worldwide (IFR 2022). Digitalization can unlock new opportunities for manufacturing-led job creation in developing economies by lowering the costs of communication, coordination, transportation, and information procurement, facilitating productivity gains, trade, and export expansion (Hallward-Driemeier and Nayyar 2017; Hjort and Poulsen 2019), serving as powerful new tools for accelerating innovation and structural transformation (Andreoni and Roberts 2020; Sturgeon

[1] Digitalization constitutes a range of existing and emerging technologies, such as robots, sensors, machine learning, and IoT, which have cross-cutting applications across and along sectoral value chains.

2021). However, growing digitalization has been linked to job polarization in developed economies, wherein jobs in low- and high-end services are rising at the expense of routine-intensive manufacturing jobs (see, e.g., Goos and Manning 2007). A persistent digital divide between developed and developing economies could also mean reduced incentives for developed economies to offshore future manufacturing tasks to low- and middle-income countries through global value chains (GVCs), leading to the loss of 'could-have-been jobs' (World Bank 2017). Digital technologies, such as 3D printing, can further contribute towards shortening GVCs (Rehnberg and Ponte 2018), with developed economies 'near-shoring' or 'friend shoring'[2] production.

While an implicit link between digitalization and structural change can be found in some studies (e.g., Rodrik 2018; Newfarmer et al. 2019), there are only a handful of studies that provide an explicit conceptualization of digitalization as a driver of structural transformation (see Matthess and Kunkel 2020; De Melo and Solleder 2022) and even more limited empirical evidence on the same. In this study, we address the research gap by empirically and simultaneously examining the impact of digitalization and GVCs on structural transformation using a cross-country panel in the period 1990–2018, combining information on 51 economies from the GGDC/UNU-WIDER Economic Transformation Database, UNCTAD EORA data set, World Development Indicators, and Penn World Tables. To address issues related to endogeneity, we use methodologies of fixed effects with IV estimation and system generalized method of moments (system GMM) estimation. Important policy implications emerge from unpacking the heterogenous effects of digital technologies and GVCs on structural transformation across levels of digital development and structural compositions of the economy.

Section 2 presents a literature review, focusing on digitalization and GVCs as drivers of structural transformation. Section 3 presents data sources used for analysis and descriptive statistics. Section 4 presents the econometric models and identification strategy adopted to deal with econometric issues faced during empirical analysis. Section 5 presents empirical results, and Section 6 concludes the study with policy implications.

2 Drivers of structural transformation

2.1 Digital-led structural transformation

Three separate strands of literatures are relevant to the study of digital-led structural transformation. The first strand focuses on productivity effects of digital technologies, automation, and robotics in the manufacturing sector, which in turn leads to higher manufacturing output and job creation. Gal et al. (2019) find a positive effect of digital adoption on firm-level productivity, with a stronger effect for manufacturing industries compared to services. Andreoni et al. (2021) argue that digital technologies have the potential to foster production systems that respond in real time to manufacturing conditions, supply-chain disruptions, and demand fluctuations, while automation and robotization can boost manufacturing productivity and jobs. Several firm-level studies confirm the positive link between digitalization and manufacturing productivity. Using a data set of 40,154 manufacturing firms across 91 developing and transition economies, Cariolle and Le Goff (2021) find that a 10 percentage-point increase in email use in locations where firms operate raises their sales and sales per worker by 36 per cent. In Korea, firms using the internet in production and business processes have about a 1.5 per cent higher annual labour productivity

[2] A shift of manufacturing trade towards allies.

growth rate than a firm not using the internet (Mun et al. 2014). Similarly, in Africa, internet penetration has a sizable and considerable impact on SSA's real per capita GDP growth and productivity at both the sectoral and aggregate levels (Simione and Li 2021), with internet access boosting labour productivity by 3.7 per cent (World Bank 2016). However, gains from digitalization vary across income levels. Farhadi et al. (2012) note a lower effect of ICT penetration on GDP growth for low-income countries compared to high-income countries, while Banga and te Velde (2018) find a lower impact of internet penetration on manufacturing labour productivity in low-income and SSA countries compared to their counterparts. Similarly, productivity gains differ across the type of technology/measure for digitalization used. Broadband adoption is found to not have any significant impact on firm productivity in the works of Bertschek et al. (2013) and Colombo et al. (2013).

The second, and substantial, strand of literature focuses on the employment effects of digitalization and automation across sectors. Studies document both a 'labour-augmenting' effect of digital technologies, including through the productivity effects discussed above, and a 'labour substitution' effect (see Hauge 2021 for a recent review). Some scholars argue that in the Global South, manufacturing is more intensive in routine tasks that are susceptible to automation than services, indicating a higher threat to these jobs from automation (OECD 2016; Frey and Rahbari 2016; Hallward-Driemeier and Nayyar 2017; Manyika et al. 2017; Schlogl and Sumner 2020). Graetz and Michaels (2018) argue that digitalization negatively impacts low-skilled, low-wage jobs and contributes to job loss, but at the same time, it also creates net gains in well-paid jobs, reflecting a redistribution of labour across sectors and increase in wage inequality. Less-automated manufacturing sectors may still act as windows of opportunity for low- and middle-income countries to undertake local manufacturing production, but this window is narrowing with the fast-declining cost of digital technologies (Banga and te Velde 2018). The impact of automation on the labour market will continue to differ across countries, depending on several factors, including globalization, new product demand, occupational structure in employment, labour frictions, and institutional differences affecting relative wages (Banga and te Velde 2018).

The third, and recent, strand of literature focuses on a digital-led restructuring of the labour force (Acemoglu and Restrepo 2019; Hauge 2021). Scholars argue that digitalization will make services more tradable (Baldwin and Forslid 2020; Mayer 2020). In the digital age, the services sector can act as a 'new and alternative engine' for growth (Hallward-Driemeier and Nayyar 2017; International Monetary Fund 2018; Loungani et al. 2017; Miroudot and Cadestin 2017; Owusu et al. 2020). In line with this, there is evidence of large-scale internet adoption being inversely correlated with the share of industry in the economy and positively correlated with the share of services in the economy (Simone and Li 2021). Using a panel of 171 countries and panel vector autoregressive models in a generalized method of moment approach, Saba and Ngepah (2022) find that ICT expansion has led to a decline of manufacturing value added as a share in GDP.

2.2 GVC-led structural transformation

The rise of digital technologies is taking place in the context of globalization and fragmentation of production systems in GVCs. The literature has paid little attention to the role of international trade in structural change (Matsuyama 2019). Based on the theory of comparative advantage, international trade can create productivity gains through specialization. These productivity gains from trade can be amplified through integration into GVCs, which enables specialization in core tasks, access to imported intermediate inputs, and knowledge spill-overs (Matthess and Kunkel 2020; Alessandria et al. 2021; Criscuolo and Timmis 2017). Focusing on modern high-income agrarian economies, Lim (2021) finds that increasing participation in agricultural GVCs leads to increasing shares of GDP and employment in the agricultural and services sector at the expense of manufacturing. For European Union (EU) economies, Stöllinger (2016) finds that GVC participation has a significant but differentiated effect on manufacturing-led structural change. GVCs have led to developed economies specializing in specific high value-adding tasks and production stages, keeping core competencies in-house, while offshoring low value-added tasks to developing economies (Amador and Cabral 2016). Kumar (2022) finds no significant impact of GVCs on structural transformation in developing economies using a cross-country panel of 40 countries.

A country's GVC participation and level of digitalization can importantly interact to shape its structural transformation journey. The large-scale adoption of digital technologies by lead firms in GVCs has contributed to the rise of 'digital lead firms' and digital labour process transformations (Lopez et al. 2022). The rapidly falling rate of 3D printers, robots, and digital capital in the Global North, coupled with a persistent digital divide across developed and developing economies, could reduce the comparative advantages of Southern suppliers in labour-intensive low-cost manufacturing, decreasing gains from manufacturing GVCs. The rising digitalization and automation of manufacturing production in the Global North could, in part, also explain the declining role of Northern partners in developing countries' GVC trade and the subsequent rise of 'polycentric trade' (Horner and Nadvi 2018). Further, trade in value chains is governed by lead firms and is largely driven by higher technical and quality standards that are generally associated with advanced technologies (Rodrik 2018). This could undermine the possible opportunities of low- and middle-income countries to leverage the benefits of GVC-led trade. On the other hand, digitalization could facilitate technology and knowledge transfer from linking into GVCs, thereby increasing productivity gains from trade. For Indian manufacturing GVC firms, an increase in digital capabilities was found to increase the average product sophistication levels of firms (Banga 2022). Use of digital platforms and e-commerce, combined with participation in GVCs, can also significantly increase 'servification of manufacturing' (Lanz and Maurer 2015), contributing towards growth-enhancing structural change.

3 Data sources and descriptive statistics

The analysis on structural transformation is based on the recently released Groningen Growth and Development Centre's (GGDC) and UNU-WIDER's Economic Transformation Database (ETD) for 1990–2018 (Kruse et al. 2022). A novel cross-country panel is created, matching employment and real value-added data for 51 economies in the ETD with indicators from the UNCTAD EORA data set, Penn World Tables, Brugel data set, and World Development Indicators (WDI). The construction of key variables is given below. Table A1 provides further details on the construction of control variables.

3.1 Dependent variable: structural transformation

Three different indicators are constructed to capture structural transformation using the ETD: a) **manufacturing labour productivity**, calculated as manufacturing value added (constant 2015 prices) divided by manufacturing employment; b) **share of manufacturing employment in total employment**; and c) **economy-wide 'structural change'**.

To measure structural change, we follow McMillan et al. (2014) and decompose country-level labour productivity using:

$$\Delta P_t = \sum_{i=n} \theta_{i,t-k} \Delta p_{i,t} + \sum_{i=n} p_{i,t} \Delta \theta_{i,t}$$

where P_t and $P_{i,t}$ refer to economy-wide and sectoral labour productivity levels, respectively, and $\theta_{i,t}$ is the share of employment in sector i. The Δ operator denotes the change in productivity or employment shares between t-k and t. The first term in the decomposition is the 'within-sector' component of productivity growth, calculated as the weighted sum of productivity growth within individual sectors, with the weights equal to the employment share of each sector at the beginning of the time period. The second term is the 'structural change', calculated as the inner productivity levels (at the end of the time period) with changes in employment shares across sectors. When changes in employment shares are positively correlated with productivity levels, this term will be positive.

3.2 Key independent variables

Digitalization level: we use country-level internet penetration (per cent of the population who has access to internet) as a proxy for the level of digitalization, extracting data for the period 1990–2018 from ITU's ICT statistics database. This indicator has the advantage of capturing the general effects of digitalization on structural transformation rather than the effect of a particular digital technology, such as robotics or 3D printing. Another useful indicator to capture the digital development level is the internet server penetration, measured as secure internet servers per million people. Collected from the WDI, this indicator uses data on the number of distinct, publicly trusted TLS/SSL certificates found in the Netcraft Secure Server Survey.

Digital trade integration: we measure the level of a country's digital trade integration (DTI) as the value added by the post and telecommunications sector in a country's gross exports, divided by the value added by post and telecommunications in global exports. This is calculated for each year separately in the period 1990–2018, using input-output matrices from UNCTAD's EORA database.

GVC participation: we use three different indicators from the UNCTAD EORA database to capture a country's participation in global networks. Backward linkages or backward GVC participation are calculated as the share of foreign value added (FVA) in gross exports (Koopman et al. 2014); forward linkages or forward GVC participation are captured as the domestic value added in intermediate exports, as a share in gross exports; overall GVC participation of a country is calculated as the sum of backward and forward linkages.

3.3 Construction of control variables

Foreign direct investment (FDI): we use inward FDI flows, as a share of GDP, to control for the impact of FDI on a structural transformant variable. The impact of FDI on ST is ambiguous; studies by Samouel and Aram (2016) for Africa, Jie and Shamshedin (2019) for Ethiopia, and Muhlen and Escobar (2020) and Thirion (2020) for Mexico find that FDI enables the reallocation of labour effectively from the primary to the industrial sector, leading to industrialization. Similarly, for 44 developing countries and four newly industrialized economies, Emako et al. (2022) find that FDI boosts overall labour productivity by facilitating both structural change and within-sector labour productivity. In contrast, in South Asia and SSA, FDI appears to have a significantly negative effect on industrial development due to repatriation of profits and market-setting effects (Maroof et al. 2019; Oduola et al. 2022; Muller 2021).

Gross capital formation: we use gross capital formation as a share of GDP to control for the impact of increasing real investment in physical capital on the annual labour reallocation process (Matias and Mathilde 2021). While infrastructure development can facilitate the reallocation of labour from less productive to more productive sectors as well as the entry and growth of new industries in the modern sectors, investment in labour-saving physical capital in the early stages of development could lead to premature de-industrialization, adversely affecting structural change (Kumar 2022).

Skill development: we use the human capital index from the Penn World Tables to control for the impact of human capital development on ST. Accumulation of human capital has been linked to facilitating the structural change process of an economy (Li et al. 2019; Pinto et al. 2020; Bye and Faehn 2021). The HCI index is based on both years of schooling and returns to education.

Agricultural employment share: we use the initial share of agriculture in total employment, obtained from WDI, to account for existing structural gaps in the economy (McMillan and Rodrik 2011). It is expected that countries with a higher agricultural share in employment experience faster structural change.

Changes in REER: we use data on the annual changes in REER as a measure of currency overvaluation (or undervaluation), which is expected to impact ST (Stöllinger 2016; Kumar 2022). The REER data against 170 trading partners are taken from Bruegel data set. A negative coefficient is expected on the variable since sustained overvaluation of REER will hurt the structural change process through its impact on the competitiveness of the tradable sectors (Rodrik 2008).

GDP per capita: we control for the lagged GDP per capita levels, obtained from WDI. Increasing levels of GDP per capita are expected to slow down the structural change process, also known as the convergence hypothesis (Stöllinger 2017).

3.4 Descriptive statistics

Summary statistics are given in Table 1. It is observed that in our cross-country panel in the period 1990–2018, the log of manufacturing labour productivity varies between 6 and 11.08, with an average value of 9.12. The share of manufacturing in total employment varies between 0.88 per cent to 31.5 per cent, with an average value of 11 per cent. The average SC in the sample is 0.2 per cent and average internet penetration sits at 15 per cent. The digital trade integration share ranges from less than 1 per cent to 2.43 per cent. The digital divide across income groups is quite stark; on average, internet penetration is roughly 43 per cent in high-income countries but as low as 3.72 per cent in low-income countries (see Table 2). Similarly, in high-income countries, the average value of DTI is 0.72 per cent and over 5,000 people per million have access to secure servers, compared to a DTI value of 0.02 per cent in low-income countries and less than 10 people having access to secure servers. The average manufacturing labour productivity and manufacturing employment share appear to increase with income status, while structural change decreases with income status. The average yearly structural change between 1990 and 2018 has been higher in low- and lower-middle-income countries, as compared to upper-middle-income and high-income countries, rendering support to the convergence hypothesis.

Table 1: Summary statistics

	Obs	Mean	SD	Min	Max
Digital integration (%)	1,400	0.24	0.365	0.001	2.436
FVA ratio	1,392	0.20	0.135	0.001	1.000
GVC participation index	1,392	0.48	0.504	0.228	18.810
Internet penetration (%)	1,431	15.61	22.700	0.000	96.023
Structural change (%)	1,398	0.29	3.060	-38.390	17.280
Man_va (% of GDP)	1,353	15.09	6.186	0.972	33.346
HCI index	1,450	2.16	0.597	1.030	4.154
TFP	1,160	0.58	0.228	0.116	1.510
Capital/labour ratio	1,450	97.22	120.205	1.152	661.485
GCF (% of GDP)	1,279	23.26	6.557	9.983	53.122
Man_emp (% of total emp)	1,450	10.94	5.805	0.884	31.487
Man_va (% of GVA)	1,450	15.25	6.326	1.043	32.493
FDI inflow (% of GDP)	1,412	3.34	5.011	-6.898	58.519
Forward linkages (%)	1,392	0.28	0.477	0.093	17.810
Log (GDP per capita)	1,297	7.88	1.319	5.210	11.020
Population	1,450	3.28	1.488	0.054	7.264
Man_labour productivity	1,421	9.13	1.160	6.097	11.879
Real wage	842	17.21	1.589	13.104	20.108
Country labour productivity	1,449	14.82	17.531	0.678	88.420
Servers per million	450	837.33	5,188.329	0.020	84,713.860

Note: real wage, population, and manufacturing labour productivity are in logs.

Source: authors, cross-country panel (1990–2018).

Table 2: Mean values, across income status

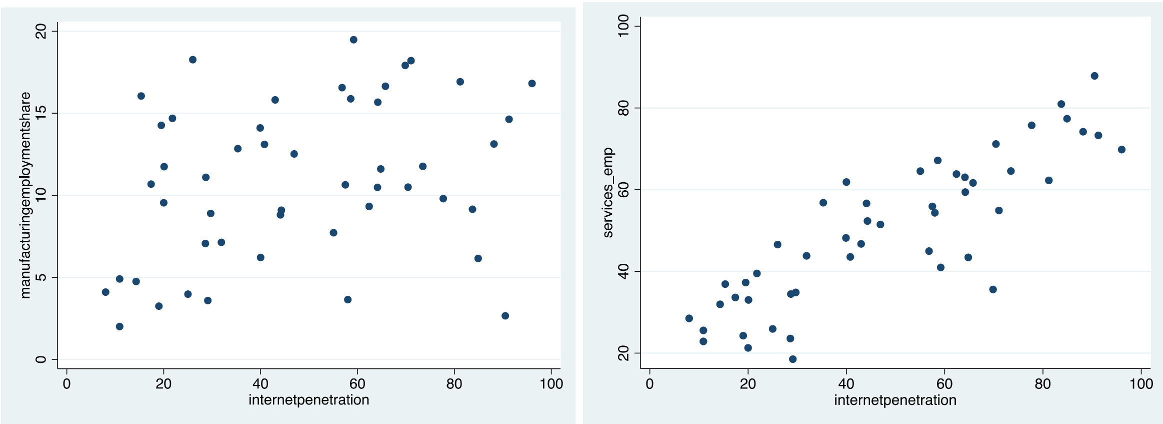
Country income level	**Log (man_LP)**	**Structural change**	**Within-sector productivity growth**	**Man_emp share (%)**	**Internet pen. (%)**	**Digital integration (%)**	**Secure servers per 1 million**
Low income	7.92	0.48	2.44	4.55	3.72	0.02	9
Lower-middle income	8.54	0.42	2.41	10.12	8.71	0.15	68
Upper-middle income	9.84	0.13	1.76	14.00	19.77	0.30	52
High income	10.79	0.02	1.99	14.96	43.41	0.72	5,340

Note: the panel contains six high-income countries, nine low-income, 19 lower-middle-income, and 16 upper-middle-income.

Source: authors, cross-country panel (1990–2018).

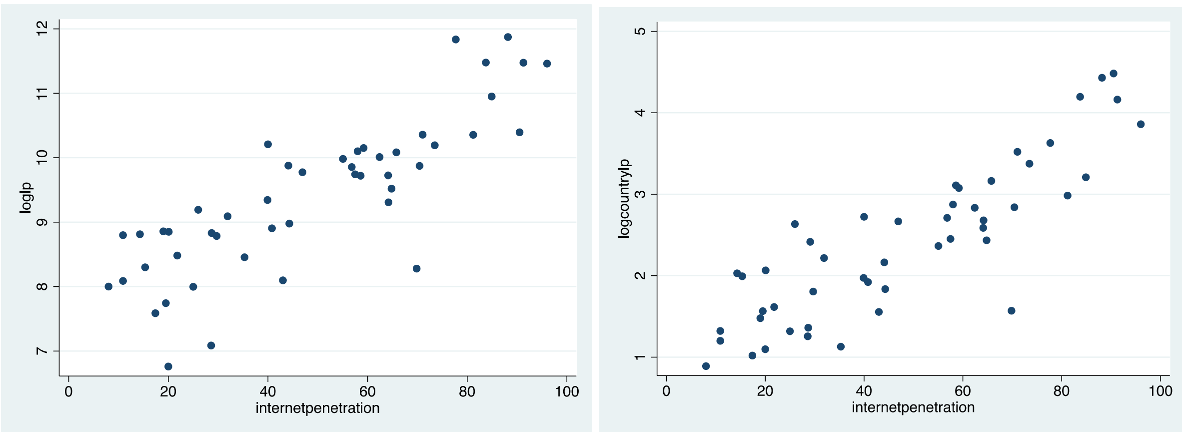
Figure 1 plots the manufacturing employment share and services employment share against internet penetration for the year 2018, the last year of the panel. There appears to be a positive and much stronger association between services employment share and internet penetration than the manufacturing sector. For both manufacturing labour productivity and country-level labour productivity, a positive association is observed from Figure 2.

Figure 1: Manufacturing (left) and services (right) employment shares, 2018



Source: authors' illustration.

Figure 2: Manufacturing LP (left) and country LP (right), 2018



Source: authors' illustration.

4 Econometric model and empirical strategy

We embed the hypothesis that digitalization of the economy will affect structural transformation in a simple regression framework. Importantly, the regression approach is flexible enough to allow for differentiated impacts of digitalization across countries.

For country c at time t, we first estimate the following model:

$$Log(Manufacturing\_lp)_{ct} = a_1 + \gamma_2 Digitalization_{ct} + \vartheta_2 GVC\ participation_{ct-1} + \vartheta_3 Log(real\ wage)_{ct-1} + B_1 X_{ct} + a_c + a_t + u_{ct} \ldots EQ \quad (1)$$

Equation (1) examines the impact of digitalization and GVC participation on manufacturing labour productivity. Digitalization is captured through internet penetration, while measures of backward, forward, and overall GVC linkages are used to measure GVC participation. The productivity effects of participating in GVCs will likely take time to show, and hence, the GVC participation variable has been lagged. The econometric model includes country-level control variables in vector X_{ct}, such as human capital index and FDI, that can affect manufacturing labour productivity; a_c and a_t refer to country and time fixed effects, respectively. A positive value on γ_2 in Equation (1) indicates digital-led manufacturing productivity gains.

Equation (2) measures the impact of digitalization and lagged GVC participation on manufacturing employment share. While the share of manufacturing in total employment is a highly imperfect indicator for the importance of the manufacturing sector in an economy and its performance, it still shows whether resources are relatively attracted to or drawn from the manufacturing sector in the respective economy. Following Kruse et al. (2022), we include log population and its square as well as log GDP per capita and its square in the regression of manufacturing employment share. A positive coefficient on γ will indicate digital-led industrialization, while a negative coefficient will imply digital-led de-industrialization. A positive coefficient on ϑ indicates that growing global integration in GVCs boosts industrialization.

$$(Man\_emp\_shr)_{ct} = a_1 + \gamma_2 Digitalization_{ct} + \vartheta_2 GVC\ participation_{ct-1} + \vartheta_3 \log{(population)_{ct}} + \vartheta_4 \log{(population)_{ct}}^2 + \vartheta_5 \log{(GDP\ per\ capita)_{ct}} + \vartheta_6 \log{(GDP\ per\ capita)_{ct}}^2 + B_1 X_{ct} + a_c + a_t + u_{ct} \ldots EQ \quad (2)$$

Equation (3) uses economy-wide structural change as the dependent variable, i.e. the component of labour productivity growth explained by labour shifts across sectors. Following Konte et al. (2022), we control for the one-year lag of labour productivity, Ln (Productivityit−1), to test for convergence across countries. A positive value of γ_2 indicates that digitalization is increasing growth-enhancing structural change. X_{ct-1} includes lagged values of other control variables, such as human and physical capital, FDI, REER, and GDP per capita.

$$(Structural\ change)_{ct} = a_0 + \delta_1 Labour\ productivity_{ct-1} + \gamma_2 Digitalization_{ct} + \vartheta_3 GVC\ particiaption\ _{ct-1} + B_1 X_{ct-1} + a_c + a_t + u_{ct} \quad (3)$$

In analysing the causal relationship between digitalization and structural transformation in a cross-country panel, the main econometric issue is that of endogeneity caused by reverse causality and simultaneity bias. In Models 1 and 2, our dependent variable is measured at the sector level (manufacturing) while key explanatory variables (digitalization and GVC participation) are at the country level, so we do not expect reverse causality running from the dependent variable to the explanatory variables. Nonetheless, endogeneity can be caused due to simultaneity bias, wherein unobserved variables are affecting both structural transformation of a country and its digitalization and GVC participation level. To tackle endogeneity and country fixed effects in our model, we combine the fixed effects estimation strategy with the instrumental variable (IV) approach. We exploit external instruments such as the average rate of regional internet penetration and secure server penetration and internal instruments (lagged values of internet penetration) in the FE-IV approach. Both regional internet penetration and server penetration are expected to be positively correlated with the explanatory variable (internet penetration) but not with sectoral labour productivity. To test the validity of the instruments, we carry out the *Kleibergen-Paap test* of under-identification of instruments and the *Hansen's test* of over-identification. A *p* value less than 0.05 on the *Kleibergen-Paap test statistic* ensures that the model is not under-identified, while a *p* value greater than 0.05 on the Hansen's test for over-identifying restrictions renders support to the validity of the instruments. Moreover, we check the *Strock-Yogo weak ID* test critical values against the *Cragg-Donal F statistic* to check against weak identification of instruments. We include time fixed effects and robust standard errors, clustered on countries.

For robustness, we also present results using the two-step system GMM estimator, which uses internal lags from the first-difference equation as instruments for the levels equation and vice versa. The validity of instruments in system GMM is checked through the *p* value, the AR (2), and Hansen's test statistic. A *p* higher than 0.05 on AR (2) indicates that there is no problem of autocorrelation in the lagged values, while a *p* value greater than 0.05 on Hansen's test statistic implies that exogeneity of the instrument set cannot be rejected. Together, this ensures that the instrument set is valid. We make a note to keep the instrument count below the number of countries, and we collapse the instrument set to avoid a problem of 'too many instruments' (Roodman 2009).

5 Empirical results

5.1 Digital (de) industrialization?

This section focuses on the impact of internet penetration on manufacturing labour productivity and employment share. Table 3 presents results from fixed effects regressions using log of manufacturing labour productivity as the dependent variable. Model 1 controls for lagged real wage and time fixed effects; Model 2 adds a control for human capital index and lagged GVC participation; Model 3 further controls for gross capital formation and inward FDI flows. From Models 1–3, it is noted that a country's internet penetration, GVC participation rate, and HCI have a positive and significant impact on sectoral labour productivity in the manufacturing sector, indicating that countries can significantly boost their manufacturing labour productivity through investments in digital infrastructure, global linkages, and an adequately skilled workforce. While we do not expect reverse causality from sector-level labour productivity (dependent variable) to country-level explanatory variables, unobserved shocks could affect both the dependent and independent variables, leading to issues of endogeneity. As a result, in Models 4 and 5, we run fixed effects regressions with instrumental variables (FE-IV). In these models, internet penetration is instrumented with the average regional internet penetration rate and secure internet servers per million. Results from FE-IV regressions in Models 4 and 5 confirm the positive and significant impact of internet penetration and lagged GVC participation on manufacturing labour productivity. These results are in line with the findings of internet penetration in Banga and te Velde (2018) and Pahl and Timmer (2020).

From Table A2, it is noted that the interaction term of internet penetration and GVC participation is positive and significant, albeit at 10 per cent, indicating that digitalization increases manufacturing productivity gains from linking into GVCs. However, productivity gains from internet penetration are found to be significantly lower in low-income countries compared to high-income countries. The lower effect of ICT penetration in low-income countries compared to high-income countries has been previously noted for manufacturing labour productivity by Banga and te Velde (2018) and for GDP growth by Farhadi et al. (2012). Low-income countries benefit relatively less from digitalization due to lower skill development, inadequate access to capital, poorer infrastructure, and lower intangible endowments compared to developed economies (Dedrick et al. 2013; Banga and te Velde 2018). Some scholars argue that benefits from digitalization ultimately depend on the level of sophistication of digital technologies. In South Africa and Tanzania, for example, gains from digitalization were rather incremental for SMEs and did not lead to industrial transformation (Murphy et al. 2014). In East Africa, although firms were able to realize some efficiency gains and better networks through digitalization, it did not improve their positioning in terms of upgrading the production process and executing tasks with higher value added (Foster et al. 2018).

A significantly lower impact of forward GVC participation (FL) on manufacturing labour productivity is noted for low-income countries in Table A2, which could, in part, be explained by the structural composition of these economies, with higher shares of natural resources and mining. A second explanation of the lower impact of FL on manufacturing productivity in low-income countries arises from the changing trade patterns. In today's polycentric trade order of rising GVC trade with Southern end markets (Horner and Nadvi 2018), low-income countries could be passively integrating their local firms into labour-intensive parts of regional value chains with little or no technology and know-how transfer (Matthess and Kunkel 2020).

Table 3: Fixed effects estimation: log (manufacturing labour productivity)

VARIABLES	Model 1 FE	Model 2 FE	Model 3 FE	Model 4 FE-IV	Model 5 FE-IV
Internet penetration	0.00751*** (0.00254)	0.00501* (0.00261)	0.00494* (0.00289)	0.00412** (0.00174)	0.00428** (0.00199)
L.log (real wage)	0.102 (0.0970)	0.0963 (0.0959)	0.143 (0.106)	-0.0396 (0.127)	-0.0325 (0.123)
HCI		0.404*** (0.132)	0.311*** (0.107)	0.116 (0.120)	0.125 (0.118)
L. GVC participation		0.00547** (0.00250)	0.00445* (0.00234)	0.811* (0.480)	1.061* (0.602)
Gross cap. form, % GDP			-0.00190 (0.00295)	-0.000450 (0.00604)	-0.000413 (0.00606)
FDI inflow, % GDP			0.00121 (0.00447)	-0.00288 (0.00666)	-0.00237 (0.00672)
Time FE	yes	yes	yes	no	yes
Observations	795	752	700	296	296
Number of countries	43	41	40	38	38
Standard errors	Robust, clustered on country	Robust, clustered on country	Robust, clustered on country	Robust, clustered on country	Robust, clustered on country

Note: in Models 1–4, yearly FE is included, while in Model 6, period FE is included. Constants are included in all models. Robust standard errors are in parentheses, where *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).

Robustness of the baseline results shown in Table 3 about the use of alternative indicators for measuring GVC participation, digitalization, and choice of instrumental variables are carried out in Table 4. Instead of internet penetration to capture digitalization, Models 1 and 2 use the VA_ICT share to proxy the DTI level of the country. The VA_ICT share measures the global VA by the post and telecommunication sector in the exports of a country as the share of VA by the post and telecommunications in global exports. Model 3 uses internet penetration but replaces the GVC participation rate with a narrower measure of global integration—forward linkages, which measure the domestic value added (DVA) in exports of intermediate goods. Model 4 uses the VA_ICT share and lagged forward linkages. Models 5 and 6 use a different set of instrument variables for internet penetration—the average regional internet penetration rate and country-level lagged internet penetration.

Across all robustness checks, it is noted that internet penetration, GVC participation, and HCI have a positive and significant impact on manufacturing labour productivity. It is further noted that a one per cent increase in digital trade integration increases manufacturing labour productivity by a sizeable 26–28 per cent. Manufacturing labour productivity may be path-dependent and persistent, making it important to check the robustness of results to include one period lagged productivity as a regressor. We check the robustness of results using the system GMM estimator in Table A3, since the inclusion of the lagged independent variable in the FE regression is known to give inconsistent results (Nickell 1981). Even after including lagged productivity as a regressor, a positive and significant coefficient is noted on internet penetration, albeit the GVC participation variable loses its significance.

Table 4: Robustness checks: dependent variable—log (manufacturing LP)

VARIABLES	**Model 1** *FE*	**Model 2** *FE*	**Model 3** *FE*	**Model 4** *FE*	**Model 5** *FE-IV*	**Model 6** *FE-IV*
Internet penetration			0.00494*		0.00544*	0.00544*
			(0.00289)		(0.00291)	(0.00291)
L. GVC participation	0.00672***	0.00502**			0.00422*	
	(0.00232)	(0.00193)			(0.00230)	
Digital integration	0.263*	0.285*		0.285*		
	(0.150)	(0.151)		(0.151)		
L.log (real wage)	0.0597	0.113	0.142	0.113	0.146	0.145
	(0.0963)	(0.103)	(0.106)	(0.103)	(0.101)	(0.101)
HCI	0.418**	0.258	0.311***	0.258	0.308***	0.308***
	(0.191)	(0.159)	(0.107)	(0.159)	(0.104)	(0.104)
GCF % GDP		-0.00671	-0.00190	-0.00671	-0.00153	-0.00153
		(0.00414)	(0.00295)	(0.00413)	(0.00284)	(0.00285)
FDI inflow % GDP		0.00263	0.00121	0.00263	0.00110	0.00110
		(0.00447)	(0.00447)	(0.00447)	(0.00428)	(0.00428)
L.FL			0.00436**	0.00536**		0.00411**
			(0.00210)	(0.00200)		(0.00208)
Year FE	yes	yes	yes	yes	Yes	Yes
Observations	724	673	700	673	698	698
R-squared	0.649	0.675	0.673	0.675	0.673	0.673
Number of countries	41	40	40	40	39	39

Note: constant is included in all models. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).

Next, we analyse the impact of internet penetration on manufacturing employment share. Table 5 presents the results of Equation (2), with the manufacturing employment share as the dependent variable. We closely follow Kruse et al. (2022) and regress the manufacturing employment share on log population and its square, log GDP per capita and its square, and time fixed effects but add internet penetration to the model. Models 1–4 run fixed-effect regressions while Models 5 and 6 run FE regressions using instrumental variables for internet penetration.

Table 5: Dependent variable—manufacturing employment share

VARIABLES	**Model 1** *FE*	**Model 2** *FE*	**Model 3** *FE*	**Model 4** *FE*	**Model 5** *FE-IV*	**Model 6** *FE-IV*
Internet penetration	-0.0782***	-0.0753***	-0.0762***	-0.0596***	-0.0430***	-0.0626***
	(0.0226)	(0.0217)	(0.0220)	(0.0220)	(0.0103)	(0.0236)
Log (population)	-0.912	-2.454	-2.886	1.238	0.493	1.178
	(3.403)	(3.472)	(3.594)	(3.315)	(3.000)	(3.204)
Population_sq	0.328	0.432	0.455	0.412	0.467	0.410
	(0.432)	(0.437)	(0.440)	(0.443)	(0.388)	(0.434)
Log (GDPC)	16.76***	15.99***	15.72***	15.62**	17.23***	14.90***
	(5.046)	(5.180)	(5.230)	(5.871)	(5.814)	(5.694)
GDPC_sq	-1.158***	-1.107***	-1.096***	-1.012***	-1.120***	-0.970***
	(0.352)	(0.359)	(0.363)	(0.361)	(0.363)	(0.354)
L. GVC participation		-0.0361		-0.0297	-0.0674***	-0.0279
		(0.0253)		(0.0192)	(0.0247)	(0.0185)
L.FL			0.0892			
			(0.124)			
L.BL			-3.079			
			(3.074)			
HCI				0.243	-0.154	0.257
				(1.443)	(1.257)	(1.416)
FDI inflow, % GDP				-0.162***	-0.169***	-0.162***
				(0.0220)	(0.0225)	(0.0214)
GCF, % GDP				0.0604	0.0772**	0.0596
				(0.0443)	(0.0382)	(0.0437)
Year FE	yes	yes	yes	yes	no	yes
Observations	1,280	1,181	1,181	1,111	1,105	1,105
R-squared	0.494	0.479	0.482	0.553	0.521	0.553
Number of countries	45	43	43	42	42	42

Note: cluster robust SE is used. The average regional internet penetration and lagged internet penetration are used as instruments. A constant is included in all models. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).

Like Kruse et al. (2022), across the models, it is observed that GDP per capita has a positive and significant impact on the manufacturing employment share, while its squared term has a significant negative impact. We also note a negative impact of inward FDI share on manufacturing employment share. FDI concentrated in the primary sector, coupled with inadequate institutions, could be restricting FDI-led structural transformation. For SSA, Muller (2021) confirms a negative effect of FDI on industrialization, with the effect amplified by a higher degree of ICT penetration.

In terms of digitalization, we note that internet penetration has a significant and negative impact on the manufacturing employment share. This implies that increasing internet penetration is reducing the share of manufacturing in the country's total employment or leading to digital de-industrialization. One reason could be that manufacturing jobs are more routine-intensive and therefore easier to automate with digital technologies (World Bank 2017). Digitalization is likely to change the structural composition of the labour force in low- and middle-income countries towards non-manufacturing sectors (Matthess and Kunkel 2020). Second, the falling costs of automation may lead to end-to-end digitalization across the manufacturing value chains, further incentivizing 'friend shoring' or 'near-shoring' by high-income countries. This could be reinforcing a 'technology bias' in favour of developed countries, limiting learning opportunities and upgrading capabilities for developing countries (Matthess and Kunkel 2020). Third, digitalization could be reducing trade costs, which is shown to have a negative impact on manufacturing employment (Cravino and Sotelo 2019). Additionally, in the case of China, it has been argued that digitalization is more pervasive in services than manufacturing, and as a result, the productivity growth in the services sector has been relatively fast, leading to a faster decline in the prices of service goods than the prices of manufacturing. Therefore, the services sector, with its higher productivity growth rate, attracts a bigger share of labour in China (Xu and Wang 2021).

Table A4 divides the sample into smaller sub-samples based on income groups and regions. Even after removing the six high-income countries in our sample, we find that digitalization has a negative and significant impact on the manufacturing employment share in low- and middle-income countries. While a negative and significant coefficient is noted for internet penetration on the South Asia sample, the coefficient on internet penetration is not found to be significant for the SSA sample. In the studies of Simione and Li (2021) and Ndubuisi et al. (2021), internet penetration has been found to have a positive and significant impact on the services employment share and negative impact on agricultural employment.

5.2 Digital-led structural change

This section focuses on the impact of internet penetration on economy-wide structural change. Table 6 presents the results of Equation (3), with annual structural change (SC) as the dependent variable. An increase in SC denotes that a country is moving from lower productivity sectors into higher productivity sectors. Following Konte et al. (2022), lagged country-level labour productivity is added to account for the convergence process in the sample where countries with a lower level of initial labour productivity tend to have faster growth. Model 1 is run using fixed effects regression with robust standard errors, clustered on countries. Measures of both backward and forward linkages are used to control for participation in GVCs, with human capital index and inward FDI share added as control variables. Model 2 runs FE with overall GVC participation, gross capital formation, and agricultural employment share added controls. Models 3–6 run FE models with an instrumental variable for internet penetration to reduce endogeneity bias resulting from reverse causality and simultaneity bias. The country-level internet penetration rate is instrumented using the regional average rate of internet, which is expected to be correlated to a country's internet penetration rate but not its SC. Models 7 and 8 also run FE-IV models, additionally controlling for lagged agricultural employment share and the annual change real exchange rate.

Table 6: Dependent variable: structural change (SC)

VARIABLES	**Model 1** *FE*	**Model 2** *FE*	**Model 3** *FE-IV*	**Model 4** *FE-IV*	**Model 5** *FE-IV*	**Model 6** *FE-IV*	**Model 7** *FE-IV*	**Model 8** *FE-IV*
L.log (LP)	-0.591	-0.464	-0.530	-0.559	-0.485	-0.514	-0.414	-0.408
	(0.529)	(0.522)	(0.421)	(0.417)	(0.411)	(0.410)	(0.378)	(0.421)
Log (IP)	0.137*	0.185**	0.217*	0.204*	0.273**	0.258**	0.341***	0.329**
	(0.0759)	(0.0847)	(0.123)	(0.119)	(0.121)	(0.116)	(0.131)	(0.157)
L.FDI inflow % GDP	0.00399	0.00165	-0.00409	-0.00254	-0.00069	0.000505	-0.00130	-0.00059
	(0.0109)	(0.0119)	(0.0151)	(0.0151)	(0.0161)	(0.0158)	(0.0156)	(0.0159)
L.HCI	0.471	0.430	1.011**	0.851**	0.764	0.633	0.567	0.534
	(0.635)	(0.597)	(0.498)	(0.402)	(0.471)	(0.395)	(0.471)	(0.496)
L. GVC participation		0.083***	0.084***		0.074***		0.067***	0.060**
		(0.0248)	(0.0216)		(0.0227)		(0.0234)	(0.0245)
L.GCF % of GDP		0.197			-2.444**	-2.295*	-2.513**	-2.705**
		(1.836)			(1.226)	(1.198)	(1.243)	(1.259)
L.FL	0.227***			0.191***		0.172***		
	(0.0631)			(0.0559)		(0.0547)		
L. FVA share	-3.385**			-2.596*		-2.368*		
	(1.439)			(1.354)		(1.322)		
L.Agri_emp share		0.0321**					0.0383**	0.0374*
		(0.0142)					(0.0185)	(0.0198)
L.Δ REER								-0.00585
								(0.00614)
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1,156	1,149	1,062	1,062	1,062	1,062	1,062	1,036
Number of countryid	47	47	47	47	47	47	47	46
P value K			0	0.00	0	0	0.00	0.00
Hansen *p* val			0.11	0.15	0.24	0.33	0.19	0.12
SE	Robust cluster	Robust cluster	Robust cluster	Robust cluster	Robust cluster	Robust cluster	Robust cluster	

Note: internet penetration is instrumented with average regional internet penetration and lagged internet penetration. Labour productivity is measured at the country level. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).

Results confirm that digitalization can significantly increase economy-wide SC. The positive impact of digitalization on SC could be explained through technology's direct impact on sectoral productivity (as seen in Section 5) but also through its impact on employment, input-output structure, and trade (Matthess and Kunkel 2020). Internet penetration and the resultant reduction in transaction costs through the rise in online platforms and connectivity could be enabling diversification of countries in tasks, products, and sectors and new intermediate inputs and modern services (Matthess and Kunkel 2020).

It is noted that GVC participation is an important driver of SC, but when disaggregated based on type of linkages, backward linkages (BL) (measured by FVA share in exports) are found to have a negative impact on SC, while forward linkages (FL) have a positive and significant impact on SC. The positive impact of FLs on productivity has been confirmed by several studies in the literature, but the negative impact of BLs on SC is somewhat surprising. Some scholars argue that technology transfer and domestic technology development do not occur automatically in GVCs (Korwatanasakul and Intarakumnerd 2020, 2021; Pietrobelli and Rabellotti 2011), and in fact, countries may fall into the trap of a subordinate role or a supporting supplier, which has an adverse impact on labour productivity (Korwatanasakul and Hue 2022; Corredoira and McDermott 2014). The negative association between backward GVC linkages and labour productivity has previously been found for Vietnam (Korwatanasakul and Hue 2022) and Turkey (Altun et al. 2022; Nasser Dine 2022).

For skills development, we note a positive and significant impact of HCI, albeit there is only weak evidence. As per Caselli and Coleman (2001), an increased supply of skilled workers leads to a decrease in the relative price of non-agriculture, which results in labour movements out of agriculture towards industry and services. We find that gross capital formation is reducing structural change. As noted by Kumar (2022), investment in labour-saving physical capital in the early stages of development can lead to premature de-industrialization, adversely affecting structural change (Kumar 2022). Similar to McMillan and Rodrik (2011), we find that countries with a higher agricultural share in employment experience faster structural change. Similar to Mensah et al. (2016) and Gui-Diby and Renard (2015), we find no significant impact of FDI on structural transformation.

Table A5 presents baseline results using the system GMM estimator, which runs Equation (3) in both levels and first differences, instrumenting the endogenous variable values with lagged values. Levels are instrumented with lagged values of first differences and vice versa, while external instruments (average regional internet penetration) are also added. From these sets of regressions, it is noted that lagged SC affects current period SC negatively, rendering support to the convergence hypothesis. In the process of development, the inter-sectoral gaps in productivity disappear, and therefore, structurally developed economies experience lower structural change (McMillan et al. 2014). Internet penetration is found to have a positive and significant impact, with comparable estimates to the FE regressions. Also, like FE regression, a positive impact is noted for FL on SC, while backward linkages have a negative impact. These results hold after accounting for both time and regional fixed effects.

Using Sen's (2019) approach, we divide the countries in our sample into three categories, based on their level of structural development in the latest year of the panel—2018. The first category is structurally underdeveloped economies, or those in which the agricultural share of employment is the highest. The second is structurally developing economies, or those in which the services sector accounts for the largest share of employment, followed by agriculture. The third category is structurally developed economies, or those in which the share of the manufacturing sector in employment is higher than that of agriculture. In our sample, 19 countries are identified as structurally underdeveloped, the majority of which are low- and lower-middle-income economies in Africa and Asia, barring India; 19 are structurally developing economies, including China, Thailand, and Indonesia; and 12 are structurally developed economies, including mostly high-income countries as well as Malaysia, Mauritius, Mexico, and Tunisia. We include a structural transformation (ST) categorical variable in our model, which is =0 for structurally underdeveloped economies; =1 for structurally developing economies; and =2 for structurally developed economies.

From Table 7, it is noted that digitalization increases SC, but the impact is significantly higher for structurally underdeveloped economies than for structurally developing and developed economies. A positive and significant coefficient is noted on the interaction term between FL and internet penetration, indicating that digitalization increases SC by increasing gains from trade in GVCs. The coefficient on the three-way interaction between the ST categorical variable, internet penetration, and forward linkages indicates that digitalization-led SC from the trade channel is faster in structurally underdeveloped economies compared to structurally developing and developed economies. This is corroborated in the findings of Model 5, which shows that digitalization increases the impact of forward GVC linkages on SC, but the impact is higher in low- and lower-middle-income economies compared to upper-middle and high-income countries.

Table 7: Fixed effects estimation: dependent variable: SC

VARIABLES	**Model 1** FE	**Model 2** FE	**Model 3** FE	**Model 4** FE	**Model 5** FE
L.SC	-0.290***	-0.280**	-0.314***		-0.296***
	(0.108)	(0.112)	(0.102)		(0.106)
L.log LP				-1.129*	
				(0.561)	
L. log FL	0.453	1.486	1.688	1.531	1.158
	(0.508)	(2.062)	(2.051)	(1.600)	(1.159)
Log Internet pen.	0.527***	0.167*	1.278***	0.893***	0.606***
	(0.176)	(0.0836)	(0.273)	(0.196)	(0.213)
L.logFL#c.log IP	0.270**		0.793***	0.542***	0.340**
	(0.107)		(0.181)	(0.141)	(0.139)
ST developing #L.logFL		-0.718	-0.891	-0.942	
		(2.127)	(2.134)	(1.646)	
ST developed #L.logFL		-1.657	-2.748	-1.594	
		(2.106)	(2.135)	(1.658)	
ST developing # log IP		-0.140**	-1.244***	-0.781***	
		(0.0670)	(0.296)	(0.231)	
ST developed #log IP		-0.108	-0.897***	-0.624**	
		(0.0651)	(0.321)	(0.236)	
ST developing #L.logFL#log IP			-0.785***	-0.495***	
			(0.185)	(0.149)	
ST developed #L.logFL#log IP			-0.614***	-0.419***	
			(0.192)	(0.149)	
L. HCI	-0.956	0.150	-0.233	-0.0586	-0.397
	(1.054)	(0.829)	(0.875)	(0.647)	(0.765)
L. FDI inward % GDP	0.00259	-0.00439	-0.00687	-0.00534	-0.00149
	(0.0224)	(0.0229)	(0.0223)	(0.0212)	(0.0220)
L. GCF % GDP	1.012	0.593	1.301	1.413	0.796
	(2.968)	(2.830)	(2.628)	(2.072)	(2.763)
HIC-UMIC#L.logFL					-0.595
					(1.209)
HIC-UMIC#.log IP					-0.618**
					(0.267)
HIC-UMIC#L.logFL#c.log IP					-0.350**
					(0.155)
Constant	5.470**	3.617**	3.784**	4.501**	4.503***
	(2.109)	(1.658)	(1.772)	(1.822)	(1.637)
Times FE	yes	yes	yes	yes	yes
Observations	1,241	1,241	1,241	1,286	1,241
R-squared	0.150	0.147	0.187	0.096	0.160
Number of countries	47	47	47	47	47

Note: *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).

6 Conclusion and policy recommendations

Evidence from our panel of 51 economies in the period 1990–2018 shows that digitalization has significantly increased economy-wide structural change. Technology has both a direct impact on sectoral productivity but also an indirect impact through the trade channel. We find that digitalization is facilitating SC by increasing gains from GVCs, particularly from forward GVC participation. However, digital-led structural change is faster in structurally underdeveloped economies. Structural transformation in these economies has followed a different pathway, with workers moving directly from agriculture to non-business services (Sen 2019). Digitalization is likely facilitating this shift towards traditional services, which are neither tradable nor technologically dynamic (Schlogl and Sumner 2020). While the services sector has shown promise in some developing countries, such as India and Rwanda (Behuria and Goodfellow 2019; Kleibert and Mann 2020), the services-led development model is neither employment-intensive nor has the same productivity gains as manufacturing.

For the manufacturing sector, we find that digitalization, measured by internet penetration, can significantly increase labour productivity. Moreover, a one per cent increase in digital trade integration, measured by the value-added share of the post and telecom sector, increases manufacturing labour productivity by a sizeable 26–28 per cent, on average. However, digital-led productivity gains are significantly lower in low-income countries compared to high-income countries, due to lagging overall infrastructure, skills, and access to capital (Farhadi et al. 2012; Dedrick et al. 2013; Banga and te Velde 2018). At the same time, digitalization negatively impacts the share of manufacturing in total employment in low- and middle-income countries. The dissemination of technology through GVCs and the shift towards capital-intensive production will not reduce jobs per unit of manufacturing exports but will destroy the comparative advantage of developing economies in labour-intensive manufacturing activities (Rodrik 2018). Together, our findings indicate that digitalization is likely contributing to de-industrialization in low- and middle-income countries. Given the debate on 'premature de-industrialization' (Rodrik 2013) and slow-down in convergence across developed and developing economies (Banga and te Velde 2018), this creates important concerns over the opportunities for developing economies to 'catch up' in the digital age. Reasons for digital-led de-industrialization include automation of routine-intensive manufacturing jobs in the digital age and subsequent changes in the structural composition of the labour force; falling costs of automation incentivizing 'friend shoring' or 'near-shoring' by high-income countries; and digital-induced reduction in trade costs.

Another key finding of our study is that GVC participation has a positive impact on structural change, but when disaggregated based on type of linkages, we observe that backward GVC participation (measured by FVA share in exports) has a negative impact on SC, while FLs have a positive and significant impact. Hauge (2021) argues that the expansion of digital and GVCs has empowered multi-national corporations in the Global North at the expense of industrialization in the South. We find evidence of both GVC participation and internet penetration having a positive impact on manufacturing labour productivity, but the productivity gains from both are significantly lower in low-income countries. Moreover, GVC participation is negatively impacting the manufacturing employment share in low- and middle-income countries. Together, these findings underpin concerns for manufacturing-led development in low-income economies through GVCs.

Important policy implications emerge from this study. There is a need to develop a coherent trade policy that targets increasing domestic value addition and forward linkages in the economy. Policies on digital development adopted by developing countries need to target maximization of manufacturing productivity gains and maintenance of comparative advantage in labour-intensive manufacturing. For large-scale employment gains from digitalization and GVCs, it is important for industrial policies to focus on the domestic integration of the manufacturing sector with the local tech sector (Rodrik 2018). Additionally, education and skills-development policies need to target skills upgradation and equip the labour force with new skills for the future. Lastly, the digital, trade, and education policies need to fit within the wider industrial policy of the country to ensure structural transformation for job creation.

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Appendix

Table A1: Construction of variables

Data source	Variable	Construction	Units
ETD	Manufacturing LP	Manufacturing GVA constant 2015 dollars / manufacturing total employees	per unit worker
ETD	Man_va (% of GVA)	Manufacturing GVA / total GVA in constant 2015 dollars	percentage
ETD	Man_emp (% of total emp)	Manufacturing total employees / total employees	percentage
EORA	FVA in exports	Foreign value added embodied in country's exports or backward GVC participation	USD
EORA	Digital integration	Total VA by post and telecom services in exports / gross exports	Share
EORA	DVA in exports	Domestic value added, which is embodied in this country's exports	US$1,000
EORA	Gross exports	FVA+DVA	US$1,000
EORA	FVA share	FVA in exports / gross exports	Share
EORA	DVX or the DVA in exports of intermediate products	Domestic value added of this country, which is embodied in the exports of other countries; this corresponds to the forward GVC participation component of the participation index	US$1,000
EORA	GVC participation index	(FVA + DVX) / gross exports	Index
WDI	Internet penetration	Percentage of population with access to the internet	Percentage
WDI	Real wage	Compensation of employees in current LCU, divided by CPI to get real compensation, divided by OER	Values in USD
WDI	Secure internet servers	Secure internet servers	Per 1 million people
PWT 9	Human capital index, see human capital in PWT9	Based on years of schooling and returns to education	Value
WDI	GCF (% of GDP)	Gross capital formation as a share of GDP	Percentage
ILOstat/ WDI	Real wage in USD	Compensation of employees (in local currency) from WDI for 1990–2018, divided by CPI and then divided by the OER	

Note: customer price index (CPI) reflects changes in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used for this. Data are period averages. The result obtained by dividing compensation by CPI is in USD value.

Source: authors, cross-country panel (1990–2018).

Table A2: Dependent variable—manufacturing LP

VARIABLES	Model 1	Model 2
Internet penetration	-0.00468	0.00377
	(0.00568)	(0.00311)
L. GVC participation	-0.0432	
	(0.0273)	
Internet penetration*L. GVC	0.0165*	
	(0.00939)	
L.log (real wage)	0.127	0.109
	(0.106)	(0.103)
HCI	0.255**	0.313***
	(0.115)	(0.112)
GCF. % GDP	-0.00153	-0.000272
	(0.00282)	(0.00289)
FDI inflow % GDP	0.00221	-0.000840
	(0.00424)	(0.00496)
L.FL		-0.0867
		(0.414)
IP*LIC		-0.0161**
		(0.00681)
IP*LMIC		0.000562
		(0.00308)
IP*UMIC		-0.00193
		(0.00222)
L. (FL) *LIC		-6.458***
		(1.604)
L. (FL) *LMIC		-1.270
		(0.969)
L. (FL) *UMIC		0.0925
		(0.414)
Time FE	yes	yes
Observations	700	700
R-squared	0.682	0.705
Number of countries	40	40

Note: *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).

Table A3: Two-step system GMM results: log (man_LP)

VARIABLES	(1)	(2)	(3)	(5)	(4)	(6)
L.loglp	0.955***	0.888***	0.882***	0.920***	0.923***	0.940***
	(0.0617)	(0.140)	(0.103)	(0.0796)	(0.112)	(0.0577)
L.log (real wag)	0.0553*	0.0448	0.0441*	0.0252	0.0334	0.0197
	(0.0324)	(0.0323)	(0.0267)	(0.0370)	(0.0385)	(0.0333)
FL	0.00185	-0.00117				
	(0.0105)	(0.0113)				
L.FL			0.0158	0.0227		
			(0.0287)	(0.0316)		
L.GVC participation					0.0133	0.0165
					(0.0322)	(0.0290)
Log (internet pen.)	0.00248*	0.00318**	0.00237*	0.00232*	0.00279*	0.00243*
	(0.00137)	(0.00156)	(0.00142)	(0.00128)	(0.00150)	(0.00127)
FDI inflow (% GDP)		-0.00420	-0.000187	-0.000683	-0.000458	-0.000101
		(0.00262)	(0.00245)	(0.00160)	(0.00224)	(0.00154)
K/L		0.000593	0.000509	0.000680*	0.000478	0.000547*
		(0.000982)	(0.000493)	(0.000394)	(0.000480)	(0.000320)
HCI			0.0293	-0.0182	-0.0130	-0.0170
			(0.0805)	(0.0634)	(0.0807)	(0.0567)
Constant	4.302**	4.841*	4.847**	4.325	3.838	3.972*
	(2.182)	(2.755)	(2.270)	(3.171)	(2.762)	(2.374)
Time trend	yes	yes	yes	yes	yes	yes
Regional FE				yes		yes
Observations	752	748	748	748	748	748
Number of countryid	41	41	41	41	41	41

Note: *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).

Table A4: Dependent variable: manufacturing employment share

VARIABLES	**Model 1** *Low and middle income*	**Model 2** *Low and middle income*	**Model 3** *South Asia*	**Model 4** *SSA*
Internet penetration	-0.0707***		-0.301***	0.000309
	(0.0242)		(0.0626)	(0.0637)
Server penetration		-0.116***		
		(0.0364)		
Log (population)	1.329	2.608	65.07*	22.70**
	(4.587)	(6.706)	(29.42)	(9.863)
Population_sq	0.288	0.827	-5.224**	-0.413
	(0.457)	(0.737)	(1.801)	(0.342)
Log (GDP per capita)	14.64*	12.39	10.75	6.410
	(8.580)	(10.35)	(8.038)	(9.906)
GDP per capita_sq	-0.969	-0.645	0.215	-1.052
	(0.576)	(0.583)	(0.650)	(0.802)
L. GVC participation	-0.0347	-7.567	34.81	-0.0864***
	(0.0216)	(4.978)	(25.10)	(0.0229)
HCI	1.394	-0.902	7.657	-0.649
	(1.446)	(1.300)	(3.704)	(1.699)
FDI inflow % of GDP	-0.155***	-0.0209	0.360	-0.0617**
	(0.0432)	(0.0349)	(0.270)	(0.0220)
GCF % of GDP	0.0677	0.0107	-0.0788	0.0384
	(0.0476)	(0.0285)	(0.117)	(0.0304)
Constant	-54.73	-62.24	-265.3	-29.28
	(35.68)	(51.40)	(125.9)	(20.30)
Time FE	yes	yes	yes	yes
Observations	947	324	132	346
R-squared	0.357	0.225	0.795	0.717
Number of countryid	36	36	5	13

Note: *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).

Table A5: Two-step system GMM results: dependent variable is SC

VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
L. structural change	-0.540***	-0.575***	-0.540***	-0.538***	-0.494***
	(0.124)	(0.130)	(0.124)	(0.121)	(0.152)
Log (internet penetration)	0.118*	0.186**	0.118*	0.185**	0.119*
	(0.0709)	(0.0944)	(0.0709)	(0.0862)	(0.0693)
L. inward FDI % gdp	-0.00710	-0.00926	-0.00710	-0.000318	-0.0106
	(0.0202)	(0.0219)	(0.0202)	(0.0328)	(0.0336)
L.FL	0.149***	0.152***	0.149***	0.154***	0.145***
	(0.0483)	(0.0526)	(0.0483)	(0.0456)	(0.0405)
L.FVA share	-1.770*	-2.018*	-1.770*	-2.299**	-2.186*
	(1.044)	(1.072)	(1.044)	(1.122)	(1.153)
L.HCI					0.453
					(1.061)
Constant	0.292	0.0811	0.292	0.0657	-0.862
	(0.333)	(0.367)	(0.333)	(0.700)	(2.922)
Time FE	yes	yes	yes	yes	yes
Regional FE	no	no	no	yes	yes
P Ar (2)	0.30	0.232	0.307	0.294	0.51
Hansen *p* value	0.58	0.657	0.584	0.80	0.67
Observations	1,241	1,241	1,241	1,241	1,241
Number of countryid	47	47	47	47	47

Note: *** p<0.01, ** p<0.05, * p<0.1.

Source: authors, cross-country panel (1990–2018).