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Digitalisation and structural change: Evidence from cross-country analysis

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ABSTRACT

This study examines digitalisation as a driver of Structural Change (SC), a core mechanism of economic development. Using a cross-country panel of 51 economies from 1990 to 2018, and panel data methodologies of Fixed Effects estimation and two-step System GMM, we find that digitalisation significantly accelerates economy-wide structural change. A doubling of internet penetration is associated with a 0.14 to 0.18- unit increase in the SC component of labour productivity growth, holding other factors constant. However, the effects of digitalisation on SC are heterogeneous across countries, with stronger effects noted for low and lower-middle income economies, structurally under-developed economies, and countries with higher forward linkages in global value chains (GVCs) than their counterparts. Moreover, digitalisation reduces manufacturing employment shares, pointing to a pattern of digital-led (de)industrialisation in developing countries. Overall, our findings contribute new evidence that digitalisation facilitates a form of leapfrogging in which developing countries transition directly from agriculture to digitally enabled services, bypassing traditional manufacturing-led industrialisation pathways.

1. Introduction

Digitalisation -the diffusion of digital technologies, such as broadband Internet, mobile connectivity, platforms and data-driven applications – has become a defining feature of contemporary economic transformation. While there is extensive literature examining the development outcomes of digitalisation, its effect on Structural Change remains under-examined in the extant literature. In development economics, Structural Change has been traditionally conceptualised as a process driven by two fundamental forces: differences in productivity across sectors, and the ability of labour and capital to move from low-to high-productivity activities (Kuznets, 1966; Herrendorf et al., 2014; McMillan et al., 2014).

Emerging evidence suggests that digitalisation interacts with the drivers of structural change in complex and potentially contradictory ways (Matthess and Kunkel, 2020). Digital technologies can raise productivity, reduce coordination costs, and open new upgrading opportunities across sectors (Hallward-Driemeier and Nayyar, 2017; Hjort and Poulsen, 2019). The effects of digitalisation on the manufacturing sector have received significant attention in academic studies because manufacturing has long acted as the engine of economic growth and job creation in developing economies (McMillan et al., 2014; Haraguchi et al., 2017). However,

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digitalisation can reduce the tradability of manufacturing, reinforcing a 'technology bias' in favour of high-income economies and limiting learning and upgrading capabilities for developing economies (Banga and te Velde, 2018; Matthess and Kunkel, 2020). While the implicit link between digitalisation and structural change has been examined in some studies (Rodrik, 2018; Newfarmer et al., 2019), only a handful of studies provide an explicit conceptualisation (Matthess and Kunkel, 2020; De Melo and Solleder, 2022; Cook and Rani, 2025), with even more limited empirical evidence on the same.

Our study addresses this gap by empirically examining the impact of digitalisation on structural change (SC) in the period 1990-2018. Our novel cross-country panel matches value-added and employment data for 51 economies, from the latest version of the Economic Transformation Database (ETD),[1] with indicators from UNCTAD EORA, Penn World Tables, Bruegel dataset, and the World Development Indicators (WDI). The combined dataset reports on two aspects of SC: labour productivity growth due to between-sector productivity shifts and changes in manufacturing employment share.

Using quantitative empirical methodologies of Fixed Effects and System Generalised Methods of Moments (GMM), we isolate the causal effect of internet penetration, a proxy for digitalisation, on both economy-wide SC and manufacturing employment share. Thus, we make our first empirical contribution to the nascent literature on digitalisation and structural change. We add fresh perspectives to key debates on 'unconditional convergence' in manufacturing and 'catch up' in developing countries (Rodrik, 2013), specifically in relation to digitalisation. Second, we extend the literature on digitalisation and SC by empirically showing that the structural effects of digitalisation are highly context specific. We find heterogeneity in the effects of digitalisation across both countries' income levels and stages of their structural transformation journey. For the latter, we use Sen's (2019) categorisation and divide the countries in our sample into structurally underdeveloped, structurally developing, and structurally developed countries to examine the heterogeneity in digital-led structural change. Third, we contribute new knowledge on how the relationship between digitalisation and SC is moderated by global value chains (GVCs).[2] While international trade is an important driver of SC, its effect has often been overlooked in studies (Matsuyama, 2019). Together, digitalisation and trade can have important interactions in shaping SC, but these effects remain understudied.

The remainder of the paper is organised as follows: Section 2 discusses the relevant literature on drivers of SC, with a focus on digitalisation. Section 3 presents the research methodology and data used for the empirical analysis. Section 4 presents the empirical results, and Section 5 discusses the results and concludes with policy implications for developing countries.

2. Literature review and theoretical framework

In this section, we first conceptualise structural change and then develop a mechanism-based theoretical framework to clarify how digitalisation affects structural change. Matthess and Kunkel (2020) provide pioneering conceptual work on understanding the mechanisms through which digitalisation can facilitate or obstruct structural change. In the short term, the adoption of digital tools can increase within-sector productivity and alter firms' demand for different types of labour, triggering employment shifts across sectors. Over the long term, digitalisation can reshape countries' comparative advantages, the relative size of agriculture, manufacturing, and services, and their position in GVCs (Matthess and Kunkel, 2020; McMillan et al., 2014).

2.1. Conceptualising structural change

Structural change refers to the reallocation of labour and economic activity across sectors with varying productivities. Classic development theory links this process to the movement of workers from low-productivity agriculture to higher-productivity manufacturing and modern services (Kuznets, 1966; Syrquin and Chenery, 1989). Empirical evidence from high-income countries in North America, Europe, and East Asia confirms that agriculture initially dominates employment, followed by a rise and eventual decline in manufacturing employment, producing a characteristic 'hump-shaped' curve (Duarte and Restuccia, 2010). Services then become the main engine of job creation in the later stages of development (Syrquin and Chenery, 1989).

However, many developing economies have not followed this path, experiencing premature de-industrialisation, with manufacturing peaking at lower GDP per capita levels (Rodrik, 2016). Contemporary research recognises multiple forms of structural change rather than a single linear trajectory. Some economies experience service-led growth, others resource-driven transitions, and many follow mixed paths shaped by initial conditions, human capital, and institutions (McMillan et al., 2014; Newfarmer et al., 2019). Recent literature has also extended this concept to include upgrading within sectors, shifts toward more complex and technology-intensive activities, and changes in sectors' contributions to aggregate value added (Herrendorf et al., 2014).

In terms of measurement, structural change is most often captured through shifts in sectoral employment shares weighted by productivity differentials, although value-added shares, productivity growth decompositions, and structural change indices are also used to capture the pace and quality of transformation (McMillan and Rodrik, 2011; Timmer et al., 2015).

[1] The ETD is a collaboration between Groningen Growth and Development Centre's (GGDC) and UNU-WIDER (Kruse et al., 2022).

[2] GVCs refer to trading networks that bring a product from the design stages to delivery, and in the process span several countries.

2.2. Digitalisation as a driver of structural change

2.2.1. Changes in relative productivity levels across sectors

Digitalisation primarily influences structural transformation by reshaping relative productivity levels and growth rates across economic sectors. At the micro level, the adoption of digital technologies by firms can reduce information asymmetries, lower transaction and coordination costs, and enable more efficient use of capital and labour. Empirically, a positive and stronger effect of digital adoption on firm-level productivity has been observed in manufacturing compared to services (Gal et al., 2019). Digitalisation has increased manufacturing labour productivity by the lowering costs of production, communication, coordination, transportation, and information procurement, as well as by facilitating trade and productivity gains (Hallward-Driemeier and Nayyar, 2017; Hjort and Poulsen, 2019; Andreoni and Roberts, 2020; Sturgeon, 2021). Specifically, email use has been found to boost sales and sales per worker across manufacturing firms in 91 developing and transition economies (Cariolle and Le Goff, 2021). In Africa, internet penetration has had a sizeable and considerable impact on 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).

At the macro level, the uneven adoption of digital technologies across sectors can generate new productivity differentials that shape relative prices and profits. Baumol (1967) argued that labour typically shifts away from technologically dynamic sectors into more stagnant ones characterised by less technological advancement and slower productivity growth, such as health and education sectors. Digitalisation, however, complicates this dynamic by generating significant productivity differences within the services sector itself. In developing countries with lagging skills and industrial policies, this could induce a leapfrogging of manufacturing, with labour moving directly from agriculture into low productivity non-tradable services.

2.2.2. Increase in relative tradability of services

The second, and related, mechanism is concerned with the relative tradability of services compared to manufacturing. Some scholars argue that digitalisation can impact structural change by making services more tradable than manufacturing (Baldwin and Forslid, 2020; Mayer, 2020). Advancements in digital technologies, including the rise of online platforms and progress in collaborative software have significantly reduced the costs of delivering services across borders. This has ushered in an era of services delivered over the Internet, such as business process outsourcing (BPO) services, IT services, telemedicine, online education, and e-commerce (Baldwin and Forslid, 2020; Kan et al., 2022). The increased use of digitalisation has been linked to the rise of new 'smokestack-less' industries in developing countries, such as tourism, information and communication technology, food processing, and horticulture, which share similar characteristics to manufacturing (Newfarmer et al., 2019).

The rise of digital platforms is often viewed as a panacea for generating employment, fostering development, and accelerating structural change (Matthess and Kunkel, 2020). These platforms have facilitated the expansion of firm creation, particularly in services and platform-mediated activities, and can expand opportunities for self-employment and entrepreneurship. Digital technologies lower the entry costs for firms into service provision by reducing fixed investments in information, marketing, and coordination.

At the macro level, increased service tradability creates the possibility of service-led structural change, in which labour reallocates toward digitally deliverable services rather than manufacturing. Services are therefore the 'new and alternative engine' for economic growth (Hallward-Driemeier and Nayyar, 2017; Miroudot and Cadestin, 2017; Owusu et al., 2020). In line with this, Simione and Li (2021) find empirical evidence of internet adoption being inversely correlated with the share of industry in the economy and positively correlated with the share of services. De Melo and Solleder (2022), however, refute the hypothesis that the rise of robotics favours services sector-led industrialisation at the expense of manufacturing in MENA and SSA.

2.2.3. Changes in labour demand and task composition

The third key mechanism operates through changes in labour demand and task composition. Traditionally, technology has been skill-biased, increasing the demand of high-skilled workers relative to low-skilled workers. However, in developed countries, there is strong evidence of digitalisation restructuring the labour force of developed economies by 'hollowing out' the middle-skilled workers (Acemoglu and Restrepo, 2019; Goos and Manning, 2007). Digitalisation has automated routine cognitive and manual tasks, leading to a decline in labour involved in medium-skilled jobs across sectors, such as clerical workers and machine operators. Employment has subsequently expanded in high-skill, knowledge-intensive services and low-skill personal services, while routine medium-skilled jobs have declined.

However, in developing economies, the rate of digital-led polarisation has been much lower (Carlos Molina and William, 2019), potentially due to labour being concentrated in low-skilled, low-routine occupations, growing informal work, and a slower decline in the relative price of investment compared to developed countries (Banga and te Velde, 2019). Even so, the reduced global demand for low-skill manufacturing labour and reduced labour intensity of production is likely to undermine the comparative advantage of developing countries in labour-intensive manufacturing, threatening to worsen premature de-industrialisation. These shifts in skills and task structures can lead to the reallocation of workers within firms and across sectors. Labour may instead flow directly from agriculture into services, many of which are informal and low productivity, with ambiguous implications for long-term growth in the economy. The rise of platformisation and gig work is likely to intensify the expansion of low-productivity service work in developing countries by promoting micro-task-based employment, such as delivery, data annotation, and other digital piecework (Cook and Rani, 2025). Such tasks involve low barriers to entry, limited skill development, and minimal opportunities for broader and structural changes.

2.2.4. Changes in input-output structures

Digitalisation can also affect structural change through its macro-level effects on the input-output structure of international trade. The majority of trade today occurs through GVCs, which allow countries to specialise in their core competencies, while offshoring other tasks to countries according to their comparative advantages. In high-income agrarian economies, agricultural GVCs have led to increased employment in the agricultural and services sectors at the expense of manufacturing (Lim, 2021). There is also evidence of Central European manufacturing countries benefitting from manufacturing-led structural change through GVCs (Stöllinger, 2016). However, no strong evidence of GVC-led SC has been found for developing countries (Rohit, 2023), potentially because developed countries specialise in high value-adding tasks and production stages, while offshoring low value-added tasks through GVCs to developing economies (Amador and Cabral, 2016).

Some scholars are of the view that digitalisation can increase gains from linking into GVCs by facilitating economic upgrading. For instance, digitalisation has a significant and positive effect on both productivity and product upgrading of Indian manufacturing GVC firms (Banga, 2022, 2023w). Internet penetration has also significantly improved Chinese firms' positions in GVCs by lowering transaction costs and improving resource allocation efficiency (Gan et al., 2025). Even in the services sector, digitalisation has boosted productivity and innovation, leading to upgrading of services GVCs from low to high value-added activities (Kan et al., 2022). However, a persistent digital divide across developed and developing countries can lead to changing comparative advantages and reduced incentives for developed economies to offshore future manufacturing tasks through GVCs (Hallward-Driemeier and Nayyar, 2017). Therefore, the interaction between digitalisation and GVCs in shaping SC merits further empirical exploration.

2.3. Gaps in the literature

Despite the growing interest in how digitalisation reshapes structural change, there are important gaps in the existing literature. First, there is a dearth of empirical studies undertaking a casual analysis of the impact of digitalisation on structural change in developing countries. The extant literature either provides evidence on advanced economies or tends to focus on firm-level outcomes in a particular developing economy or set of economies. For example, focusing on sub-Saharan Africa, Fabrice et al. (2024) find that internet use is conducive to structural change, especially when it comes to tools that require specific, sophisticated skills and have a wide range of applications, such as the Internet. For China, Li et al. (2022) find that the rapid use of the new generation of information technology since 2000 has accelerated the process of structural labour adjustment, with labour moving away from the agricultural sector into services. This finding is echoed in the study of Han et al. (2025), which examines micro-level changes in the Chinese labour market due to digitalisation, and finds that digital technology development has significantly facilitated labour movement from the primary sector to consumer services.

Second, there is limited theoretical and empirical research on heterogeneity in digital-led SC. From the discussion above, the effects of digitalisation on structural change can vary widely across developing economies, depending on initial conditions, capabilities, and integration into global markets. In developing countries, digitalisation interacts with unique structural features, such as large agrarian sectors, high informality, limited manufacturing bases, and uneven digital infrastructure. Therefore, it is critical to analyse the heterogeneity in the effects of digitalisation on SC.

2.4. Other drivers of SC

Our review of the literature reveals other important drivers of SC, which are important to consider in the empirical analysis of the impact of digitalisation on SC. Several studies have documented foreign direct investment (FDI) as a key enabler of SC in developing economies, including in Africa (Samouel and Aram, 2016) and Mexico (Thirión, 2020). FDI has enabled the effective reallocation of labour from the primary to the industrial sector, leading to industrialisation. For 44 developing countries and four newly industrialised economies, Emako et al. (2022) find that FDI boosts overall labour productivity by facilitating both SC and within-sector labour productivity. However, in South Asia and SSA, FDI appears to have a significantly negative effect on industrial development due to profit repatriation and market-setting effects (Maroof et al., 2019; Oduola et al., 2022; Müller, 2021).

Another important driver of SC is the accumulation of human capital and skills (Li et al., 2019; Pinto et al., 2020; Bye and Fæhn, 2021). Skilled workers enhance the overall productivity of the economy but with a clear polarisation of skills and wages resulting chiefly from the structural shift from manufacturing to services (Bárány and Siegel, 2018; Asik et al., 2020).

Infrastructure development can also facilitate the reallocation of labour from less productive to more productive sectors, but investment in labour-saving physical capital in the early stages of development can lead to premature de-industrialisation (Rohit, 2023). Therefore, controlling for the impact of increasing real investment in physical capital on the annual labour reallocation process is crucial (Matias and Mathilde, 2021). In addition, growth-enhancing SC is affected by competitive exchange rates (Haile, 2019; Iasco-Pereira and Missio, 2022). Some studies use the annual change in the real effective exchange rate (REER) as a measure of currency overvaluation and find that a sustained overvaluation of the REER hurts SC through its impact on the competitiveness of the tradable sectors (Rodrik, 2008; Stöllinger, 2016; Rohit, 2023).

3. Data and methodology

3.1. Data

The analysis of 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 dataset, Penn World Tables, Bruegel dataset, and World Development Indicators (WDI). Since consistent, long-term, and internationally comparable sectoral data on output and employment are available from the ETD database only until 2018, our analysis is restricted to this year. The construction of key variables is given below, with Table A1 providing further details on the construction of control variables.

3.2. Econometric model and empirical strategy

We embed the hypothesis that the digitalisation of the economy will affect SC in a simple regression framework that enables us to isolate the causal effects of digitalisation on SC.

For country c at time t, the baseline specification of our econometric model is as follows:

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

Structural change$_{ct}$ refers to country-wide labour productivity growth owing to productivity shifts between sectors. Following McMillan et al. (2014), we decompose labour productivity growth and calculate country-wide structural change 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 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. This term is positive when changes in employment shares are positively correlated with productivity levels. An increase in SC indicates that a country is moving from low to high productivity sectors.

Labour productivity$_{ct-1}$ controls for a one-year lag of labour productivity, in natural log, to test for convergence across countries. A negative value of δ_1 confirms convergence, wherein countries with a lower level of initial labour productivity grow faster (Konte et al., 2022).

Digitalisation$_{ct}$ refers to country-level Internet penetration (per cent of the population who has access to internet), extracting data for the period 1990–2018 from ITU's ICT statistics database. Our reason for measuring digitalisation through internet penetration is guided by three arguments. First, while digitalisation constitutes a range of existing and emerging technologies, such as robots, sensors, and machine learning, there is limited data on these indicators for developing countries. Using data on internet penetration, as a proxy for digitalsation ensures wide coverage of developing countries over time and has also been a standard way of measuring in cross-country empirical studies (Banga and te Velde, 2018). Second, the choice of this indicator ensures that the results capture the general effects of digitalisation on SC rather than that of a specific technology, such as robotics or 3D printing. Third, as Matthess and Kunkel (2020) point out, it is more fruitful to consider relatively simple digital technologies when analysing developing countries, since the cost of capital is very high for a variety of these economies. A positive value of γ_2 in our equation indicates that digitalisation is increasing SC.

GVC particiaption $_{ct-1}$ refers to one-period lag of a country's GVC participation. Since productivity and employment effects of participating in GVCs will likely take time to show, we control for lagged effects. We use three different indicators from the UNCTAD EORA database to capture a country's participation in GVCs. Backward GVC linkages are calculated as the share of foreign value added (FVA) in gross exports (Koopman et al., 2014); forward GVC linkages are captured as the domestic value added in intermediate exports, as a share of gross exports; and the overall GVC participation of a country is calculated as the sum of backward and forward linkages.

For country c at time t, we also run the following baseline specification to examine the impact of digitalisation on industrialisation:

$$\begin{aligned}(Man\_emp\_shr)_{ct} = {} & a_1 + \gamma_2 Digitalisation_{ct} + \vartheta_2 GVC\ participation_{ct-1} + \vartheta_3 \log\ (population)_{ct} + \vartheta_4 \log\ (population)_{ct}{}^2 \\ & + \vartheta_5 \log\ (GDP\ per\ capita)_{ct} + \vartheta_6 \log\ (GDP\ per\ capita)_{ct}{}^2 + B_1 X_{ct} + a_c + a_t + u_{ct}\end{aligned} \tag{2}$$

Man_emp_shr$_{ct}$ refers to the share of the manufacturing sector in total economy-wide employment. While the share of manufacturing in total employment is an imperfect indicator of the importance of the manufacturing sector in an economy, 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 both the logarithm of population and its square, as well as the logarithm of GDP per capita and its square, as regressors in the model for the manufacturing employment share. Since countries with a higher agricultural share in employment experience faster structural change (McMillan and Rodrik, 2011), we control for the initial share of agriculture in total employment. A positive (negative) value of γ_2 indicates digital-led industrialisation (de-industrialisation).

In Equations (1) and (2), X_{ct} and X_{ct-1} refer to the vectors of control variables, such as human and physical capital, FDI, REER, and GDP per capita. The detailed construction of all variables used in the analysis is provided in the Appendix (Table A1). The terms a_c and a_t refer to country and time fixed effects, respectively.

Unobservable country-specific time-invariant factors a_c could affect both the structural change of a country and its digitalisation and GVC participation level. There may also be issues of endogeneity caused by reverse causality and simultaneity bias.[3]

Therefore, we estimate a Fixed Effects (FE) model (over a random effect model) and combine our FE estimation strategy with an instrumental variable (IV) approach. We exploit external instruments such as the average rate of regional internet penetration and internal instruments (lagged values of internet penetration) in the FE-IV approach. Regional internet penetration is expected to be positively correlated with the explanatory variable (country-level internet penetration) but not with economy-wide SC. To test the validity of the instruments, we conduct the *Kleibergen-Paap test* of under-identification of instruments and *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 Hansen's test for over-identifying restrictions supports the validity of the instruments. Moreover, we check the *Stock-Yogo weak ID* test critical values against the *Cragg-Donald F statistic* to check against weak identification of instruments. We include time dummies in our model and robust standard errors, clustered by country.

To check robustness against persistency in SC variable, we also present results using the two-step System GMM estimator. It is a dynamic panel data estimator that addresses endogeneity issues by simultaneously running the model in levels and differences, using lagged values of levels as instruments for the first differences and lagged values of the first differences as instruments for levels (Roodman, 2009). The validity of the instruments in system GMM is checked through the *p*-value, 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 the exogeneity of the instrument set cannot be rejected. Together, this ensures that the instrument set is valid. We keep the instrument count below the number of countries, and we collapse the instrument set to avoid the problem of 'too many instruments' (Roodman, 2009).

3.3. Summary statistics

The summary statistics of our dataset are presented in Table 1. In our cross-country panel for the period 1990–2018, the share of manufacturing in total employment varies between 0.88 per cent to 31 per cent, with an average value of 11 per cent. The average SC in the sample is 0.3 per cent and average internet penetration sits at 18 per cent. On average mobile penetration is 45% however, in several cases, it is above 100% reflecting the ownership of multiple devices/cellular subscriptions by individuals.

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 A2). The average manufacturing labour productivity and manufacturing employment share appear to increase with income status, whereas structural change decreases with income status. The average yearly SC between 1990 and 2018 was higher in low- and lower-middle-income countries, than in upper-middle-income and high-income countries, supporting the convergence hypothesis (see Table A2).

Fig. 1 plots the manufacturing 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 the services employment share and internet penetration compared to the manufacturing sector. A positive association is observed between internet penetration and both manufacturing labour productivity and country-level labour productivity (see Fig. 2).

4. Empirical results

4.1. Benchmark results for SC

Table 2 presents the benchmark results of Equation (1) using the fixed-effects (FE) estimator. Model 1 estimates the impact of digitalisation on economy-wide SC, controlling for lagged productivity and inward FDI as a share in GDP. Model 2 adds a control for backward trade linkages, proxied by the foreign value-added share of gross exports. Model 3 adds a control for forward trade linkages (FL). Model 4 adds a control for skills development in the economy. All models are run with robust standard errors, clustered on countries, and include yearly dummies.

From Model 4, we note that digitalisation has a positive and significant effect on economy-wide SC (albeit at the 10%), controlling for other factors. A doubling of internet penetration is associated with a 0.14-unit increase in the SC component of labour productivity growth, holding other factors constant. The negative coefficient of LP confirms convergence. We find that forward linkages can boost growth-enhancing SC, while backward linkages have a negative effect on SC.

The positive impact of digitalisation on SC can be explained through technology's direct impact on sectoral productivity as well as 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, enable the diversification of countries in tasks, products, and sectors and new intermediate inputs and modern services (Matthess and Kunkel, 2020).

[3] In Equation (2), since the dependent variable is measured at the sector level (manufacturing) while key explanatory variables (digitalisation and GVC participation) are at the country level, so we do not expect reverse causality running from the dependent variable to the explanatory variables.

Table 1
Summary statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
SC (%)	1398.00	0.29	3.06	−38.40	17.83
Internet penetration (%)	1230.00	18.16	23.52	0.00	96.02
GVC participation index	1342.00	0.48	0.51	0.23	18.81
HCI	1398.00	2.17	0.60	1.03	4.15
Mobile penetration (%)	1397.00	45.84	50.91	0.00	269.93
GCF % of GDP	1239.00	23.26	6.48	9.98	48.40
Manufacturing employment share (%)	1398.00	10.92	5.73	0.88	31.08
Agri. employment share (%)	1398.00	39.38	25.20	0.06	89.78
FDI inflow % GDP	1364.00	3.40	5.06	−6.90	58.52
Forward Linkages (%)	1342.00	0.28	0.49	0.09	17.81
Backward Linkages	1342.00	0.20	0.13	0.00	1.00
Log (GDP per capita)	1252.00	7.90	1.32	5.21	11.02
Country LP	1398.00	14.89	17.62	0.68	88.42
REER	1321.00	106.42	22.57	51.09	297.28

Note: GCF refers to gross capital formation, GDP refers to gross domestic product, and HCI refers to Human Capital Index.
Source: Authors, cross-country panel (1990–2018).

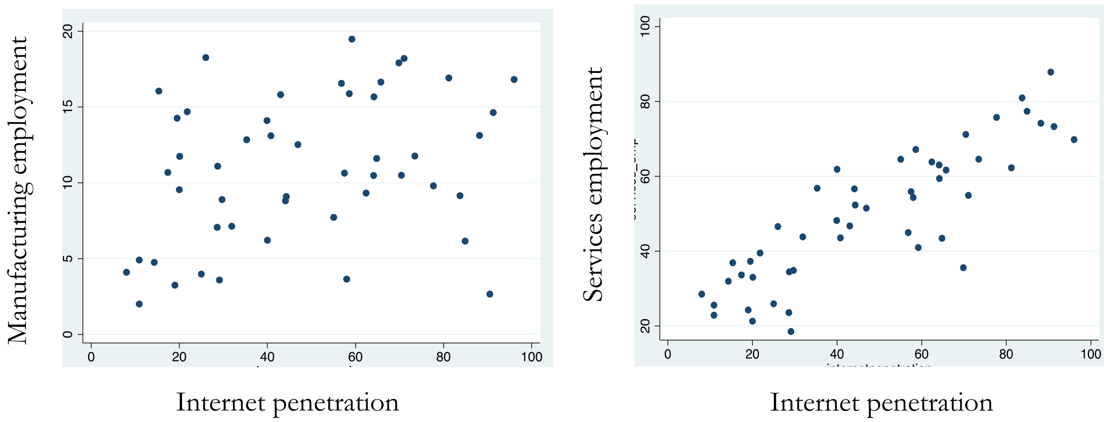

Fig. 1. Manufacturing (left) and services (right) employment shares, 2018.
Source: Authors' illustration.

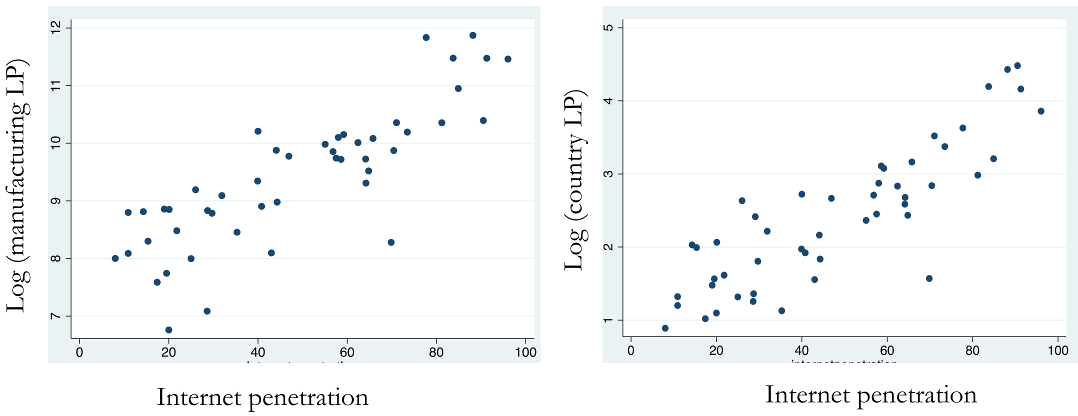

Fig. 2. Manufacturing LP (left) and country LP (right), 2018.
Source: Authors' illustration.

Furthermore, using disaggregated data on the type of GVC linkages, it is noted that backward linkages (BL) (measured by FVA share in exports) have a negative and significant impact on SC, while forward linkages (FL) have a positive and significant impact. 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

Table 2
Dependent variable: economy-wide annual SC.

VARIABLES	Model 1	Model 2	Model 3	Model 4
L.log LP	−0.410	−0.576	−0.584	−0.591
	(0.525)	(0.529)	(0.526)	(0.529)
Log (internet pen)	0.129*	0.133*	0.126*	0.137*
	(0.0651)	(0.0687)	(0.0684)	(0.0759)
L.FDI % of GDP	−3.00e-06	0.00335	0.00364	0.00399
	(0.0117)	(0.0105)	(0.0104)	(0.0109)
L.BL		−2.201	−3.519**	−3.385**
		(1.653)	(1.442)	(1.439)
L.FL			0.230***	0.227***
			(0.0640)	(0.0631)
L.HCI				0.471
				(0.635)
Constant	2.114	2.840*	2.989**	2.204*
	(1.380)	(1.484)	(1.447)	(1.300)
Time FE	yes	yes	yes	yes
SE	Cluster robust	Cluster robust	Cluster robust	Cluster robust
Observations	1202	1156	1156	1156
Number of countries	49	47	47	47

Notes: LP refers to labour productivity measured at the country level. HCI refers to human capital index, FL refers to forward linkages, BL refers to foreign value-added share of gross exports, FDI refers to foreign direct investment. The standard errors are robust, clustered on countries. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Source: Authors, cross-country panel (1990–2018).

somewhat surprising. Some scholars argue that technology transfer and domestic technology development do not occur automatically in GVCs (Korwatanasakul and Intarakumnerd, 2021; Pietrobelli and Rabellotti, 2011). 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

Table 3
Robustness checks- Dependent variable: economy-wide SC.

VARIABLES	Model 5	Mode 6	Model 7	Model 8	Model 9
L.log LP	−0.743**	−0.642	−1.228	−0.653	−0.591
	(0.362)	(0.531)	(0.900)	(0.540)	(0.529)
L.FDI % of GDP	0.00246	0.00421	0.00700	0.00238	0.00399
	(0.0131)	(0.0109)	(0.0121)	(0.0122)	(0.0109)
L.FL	0.0958	0.235***	0.233***		0.227***
	(0.0627)	(0.0626)	(0.0624)		(0.0631)
L.BL	−0.589	−3.467**	−3.540**		−3.385**
	(1.513)	(1.441)	(1.457)		(1.439)
L.HCI	0.679	0.155	−0.353	0.347	0.471
	(0.519)	(0.703)	(0.612)	(0.755)	(0.635)
Log (internet pen)	0.180**	0.171**		0.175**	0.137*
	(0.0722)	(0.0770)		(0.0794)	(0.0759)
L.GCF % of GDP	−0.0190				
	(0.0161)				
L. Agri employment sh.		0.0336*	0.0237	0.0306*	
		(0.0172)	(0.0277)	(0.0166)	
L.REER		0.000405	6.83e-05	0.00190	
		(0.00414)	(0.00436)	(0.00429)	
Log (mob penetration)			0.177**		
			(0.0873)		
L.GVC participation index				0.0934***	
				(0.0227)	
Constant	2.455*	1.486	3.791	0.543	2.204*
	(1.461)	(1.518)	(2.550)	(1.480)	(1.300)
Time FE	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes
Observations	1080	1116	1152	1116	1156
Number of countries	46	46	46	46	47

Notes: LP refers to labour productivity and is measured at the country level. HCI refers to human capital index, GCF % GDP refers to gross capital formation as a share in GDP, FL refers to forward linkages, BL refers to backward linkages, FDI refers to foreign direct investment. REER refers to the real effective exchange rate. Standard errors are robust, clustered on countries except in Model 9. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Source: Authors, cross-country panel (1990–2018).

been found for Vietnam (Korwatanasakul and Hue, 2022) and Turkey (Altun et al., 2022; Nasser Dine, 2022). We find no significant impact of FDI on structural transformation, also corroborated by Mensah et al. (2016) and Gui-Diby and Renard (2015).

4.2. Robustness checks

In Table 3, we check the robustness of the above results to ensure that they are not biased toward specific model specifications or measurement methods. We confirm that the baseline results in Model 4 are robust to the following:

- The addition of control variables, such as gross capital formation as a share of GDP (Model 5) and agricultural share in total employment and real effective exchange rate (Model 6).
- The use of an alternative indicator to measure digitalisation, substituting internet penetration (the percentage of population that has access to internet) with mobile penetration, measured as the number of mobile cellular subscriptions per 100 people (Model 7).
- The use of an alternative measure of GVC linkages, substituting BLs and FLs with an aggregate economy-wide measure of GVC participation (Model 8)
- The use of standard errors that not clustered on countries (Model 9)

4.3. Endogeneity checks

The literature suggests a potentially bidirectional relationship between digitalisation and SC. While digitalisation can drive structural change, economies with a larger modern services or manufacturing base and better infrastructure are more likely to adopt digital technologies quickly (McMillan et al., 2014). Moreover, unobservable variables, such as the institutional strength, can simultaneously affect both structural change and digitalisation leading to simultaneity bias. To control for potential endogeneity bias, we employ the FE-IV estimator, which instruments potentially endogenous variables (internet penetration) with an external instrument that is correlated with the endogenous variables and affects SC only through its effect on internet penetration. Further, all other explanatory variables, are presented using lagged values which further reduces potential endogeneity arising from other variables.

Table 4 presents different model specifications FE-IV estimations, where country-level internet penetration rate is instrumented by the regional average rate of internet penetration, expected to be correlated to a country's internet penetration rate but not SC (other

Table 4
Dependent variable: Economy-wide SC.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	FE-IV	*FE-IV*	*FE-IV*	*FE-IV*	*FE-IV*	*FE-IV*
L.log (LP)	−0.530	−0.559	−0.485	−0.514	−0.414	−0.408
	(0.421)	(0.417)	(0.411)	(0.410)	(0.378)	(0.421)
Log (internet pen) _IV	0.217*	0.204*	0.273**	0.258**	0.341***	0.329**
	(0.123)	(0.119)	(0.121)	(0.116)	(0.131)	(0.157)
L.FDI inflow % GDP	−0.00409	−0.00254	−0.00069	0.000505	−0.00130	−0.00059
	(0.0151)	(0.0151)	(0.0161)	(0.0158)	(0.0156)	(0.0159)
L.HCI	1.011**	0.851**	0.764	0.633	0.567	0.534
	(0.498)	(0.402)	(0.471)	(0.395)	(0.471)	(0.496)
L. GVC participation	0.084***		0.074***		0.067***	0.060**
	(0.0216)		(0.0227)		(0.0234)	(0.0245)
L.GCF % of GDP			−2.444**	−2.295*	−2.513**	−2.705**
			(1.226)	(1.198)	(1.243)	(1.259)
L.FL		0.191***		0.172***		
		(0.0559)		(0.0547)		
L. BL		−2.596*		−2.368*		
		(1.354)		(1.322)		
L.Agri_emp share					0.0383**	0.0374*
					(0.0185)	(0.0198)
L. Δ REER						−0.00585
						(0.00614)
Time FE	yes	yes	yes	yes	yes	yes
Observations	1062	1062	1062	1062	1062	1036
Number of countries	47	47	47	47	47	46
P value K	0.00	0.00	0.00	0.00	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

Note: internet penetration is instrumented with average regional internet penetration and lagged internet penetration. Labour productivity is measured at the country level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. LP refers to labour productivity, IP refers to internet penetration, HCI refers to human capital index, GCF % GDP refers to gross capital formation as a share in GDP, FL refers to forward linkages, BL refer to backward linkages, and REER refers to real effective exchange rate. Agri_emp share refers to share of agriculture in total employment. Fisher and Im–Pesaran–Shin tests confirm that both SC and log of internet penetration variables are stationary.
Source: Authors, cross-country panel (1990–2018).

than through internet penetration). The results confirm that in the period 1990-2018, digitalisation has significantly increased economy-wide SC. We find that aggregate GVC participation, and specifically FL, increases SC while BL has a negative impact on SC.

For skills development, we note a positive and significant impact of HCI, albeit there is only weak evidence. According to 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 reduces structural change. As noted by Rohit (2023), investment in labour-saving physical capital in the early stages of development can lead to premature de-industrialisation, adversely affecting structural change (Rohit, 2023). As in McMillan and Rodrik (2011), countries with a higher agricultural share in employment experience faster structural changes.

Appendix Table A3 presents results using the system GMM estimator. Levels are instrumented with lagged values of the 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 negatively affects current period SC, supporting the convergence hypothesis. In the process of development, inter-sectoral gaps in productivity disappear, leading to structurally developed economies experiencing slower structural change (McMillan et al., 2014). System GMM results confirm that internet penetration has a positive and significant impact on SC, with estimates comparable to the FE regressions. Like the FE results, a positive impact is noted for FLs on SC, while BLs have a negative impact. These results hold even after accounting for both time and regional fixed effects.

4.4. Heterogeneity tests

Our literature review highlighted that the effect of digitalisation on SC can be heterogeneous. In this section, we check the heterogeneity of our results across income -levels of countries, their structural development journeys, and their integration into the global economy (Table 5).

In Model 1, we add an interaction of digitalisation with an income dummy which is equal to 1 for upper-middle and high-income countries in our sample, and 0 for other countries. We note that the positive effect of digitalisation on SC is significantly higher in low- and lower-middle-income economies than in upper-middle and high-income countries. The former set of economies has a lower initial

Table 5
Heterogeneous effects of digitalisation on economy-wide SC.

VARIABLES	Model 1 FE	Model 2 FE	Model 3 FE	Model 4 FE	Model 5 FE
L.log (LP)	−0.308	−0.393	−0.278		−1.036
	(0.496)	(0.532)	(0.472)		(0.715)
L.SC				−0.195*	
				(0.102)	
Internet penetration	0.00660	0.00603	0.0463**	0.0528**	
	(0.00966)	(0.00760)	(0.0198)	(0.0261)	
ST developing# internet pen			−0.0448***	−0.0520**	
			(0.0166)	(0.0210)	
ST developed # internet pen			−0.0499***	−0.0577**	
			(0.0171)	(0.0224)	
UMIC-HIC# internet pen	−0.0147**				
	(0.00556)				
L.log FL		0.527*			
		(0.273)			
L.logFL# internet pen		0.0105**			
		(0.00515)			
Mobile penetration					−0.00131
					(0.00621)
ST developing# mob pen					−0.00932*
					(0.00521)
ST developed# mob pen					−0.00846
					(0.00530)
L. HCI	0.297	0.143	0.206	0.0606	−0.473
	(0.549)	(0.492)	(0.498)	(0.636)	(0.641)
L.FDI % of GDP	−0.00343	0.00127	−0.00603	−0.00575	−0.00266
	(0.0125)	(0.0113)	(0.0130)	(0.0154)	(0.0243)
L.GCF % GDP	0.00215	0.659	0.147	0.373	0.400
	(1.345)	(1.373)	(1.442)	(1.828)	(2.085)
L.Agri employment sh.	0.0285**	0.0263	0.0330**	0.0402**	0.0228
	(0.0135)	(0.0224)	(0.0142)	(0.0170)	(0.0239)
Time FE	yes	yes	yes	yes	yes
Observations	1195	1149	1195	1194	1314
Number of countries	49	47	49	49	49

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. SC = structural change, LP = labour productivity, FL = forward linkages, IP = internet penetration, ST developed = structurally developed countries, ST developing = structurally developing countries, HCI = human capital index, HIC = high-income country, UMIC = upper middle-income country.
Source: Authors, cross-country panel (1990–2018).

digital technological base and a larger share of the workforce involved in low-productivity agricultural and informal activities. Therefore, the same level of digitalisation can deliver larger SC gains in these economies compared to others.

In Model 2, we add an interaction term between digitalisation and forward linkages (FLs). We note that the effect of internet penetration on SC is stronger in countries with FLs in GVCs. Countries with higher FLs (usually measured by the domestic value-added in other countries' exports) tend to be more exposed to foreign markets and consumers, international technology standards, and higher quality requirements and production practices, which can lead to knowledge spillovers. FLs not only improve SC via enhanced competition, learning, and specialisation effects but, as our results show, also amplify the effect of digitalisation on SC.

In Model 3, we add an interaction term for digitalisation and the structural development level of countries. Using Sen's (2019) approach, we divide the countries in our sample into three categories of structural development based on the latest year of the panel 2018. Structurally underdeveloped economies are those in which the agricultural share of employment is the highest. Structurally developing economies are those in which the services sector accounts for the largest share of employment, followed by agriculture, while in structurally developed economies, the share of the manufacturing sector in employment is higher that of agriculture. In our sample, 19 countries are identified as structurally underdeveloped, the majority of which are developing 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 developed 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.

As per Models 3 and 4, the effect of digitalisation, as measured by internet penetration, on SC is higher in structurally underdeveloped economies than for structurally developing and developed economies. Using mobile penetration as an alternative measure (Model 5), we confirm a higher effect of digitalisation on structurally underdeveloped economies than for structurally developing economies.

4.5. *Benchmark results for manufacturing employment share*

Table 6 presents the results of Equation (2), with manufacturing employment share as the dependent variable. Models 1–4 run FE regressions while Models 5-7 run FE regressions using instrumental variables for internet penetration. Similar to Kruse et al. (2022), across the models, GDP per capita has a positive and significant impact on the manufacturing employment share, while its squared

Table 6
Dependent variable: manufacturing employment share.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	FE	*FE*	*FE*	*FE*	*FE-IV*	*FE-IV*	*FE-IV*
Internet penetration	−0.0782***	−0.0753***	−0.0762***	−0.0596***	−0.0430***	−0.0626***	−0.0413*
	(0.0226)	(0.0217)	(0.0220)	(0.0220)	(0.0103)	(0.0236)	(0.0247)
Log (population)	−0.912	−2.454	−2.886	1.238	0.493	1.178	−2.461
	(3.403)	(3.472)	(3.594)	(3.315)	(3.000)	(3.204)	(4.752)
Population_sq	0.328	0.432	0.455	0.412	0.467	0.410	0.188
	(0.432)	(0.437)	(0.440)	(0.443)	(0.388)	(0.434)	(0.601)
Log (GDPC)	16.76***	15.99***	15.72***	15.62**	17.23***	14.90***	30.16***
	(5.046)	(5.180)	(5.230)	(5.871)	(5.814)	(5.694)	(7.539)
GDPC_sq	−1.158***	−1.107***	−1.096***	−1.012***	−1.120***	−0.970***	−1.931***
	(0.352)	(0.359)	(0.363)	(0.361)	(0.363)	(0.354)	(0.499)
L. GVC participation		−0.0361		−0.0297	−0.0674***	−0.0279	−0.0507***
		(0.0253)		(0.0192)	(0.0247)	(0.0185)	(0.0194)
L.FL			0.0892				
			(0.124)				
L.BL			−3.079				
			(3.074)				
HCI				0.243	−0.154	0.257	0.254
				(1.443)	(1.257)	(1.416)	(1.569)
FDI inflow, % GDP				−0.162***	−0.169***	−0.162***	−0.0141
				(0.0220)	(0.0225)	(0.0214)	(0.0332)
GCF, % GDP				0.0604	0.0772**	0.0596	
				(0.0443)	(0.0382)	(0.0437)	
L. log (real wage)							0.241
							(0.935)
Year FE	yes	yes	yes	yes	no	yes	yes
Observations	1280	1181	1181	1111	1105	1105	701
Number of countries	45	43	43	42	42	42	37

Note: Cluster-robust SE are used. The average regional internet penetration and lagged internet penetration are used as instruments. A constant is included in all models. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Results are also robust to the inclusion of l.log(real wage) as an explanatory variable instead of HCI, which are highly correlated with each other. HCI refers to human capital index, GCF % GDP refers to gross capital formation as a share in GDP, FL and BL refer to forward linkages and backward linkages, GDPC refers to GDP per capita.
Source: Authors, cross-country panel (1990–2018).

term has a significant negative impact. We also note a negative impact of GVC participation and inward FDI share on manufacturing employment share. The participation of developing countries in low value-added manufacturing GVCs and FDI concentrated in the primary sector, coupled with inadequate institutions, could be restricting SC. For SSA, Müller (2021) confirms the negative effect of FDI on industrialisation, with the effect amplified by a higher degree of ICT penetration.

In terms of digitalisation, we note that internet penetration has a significant and negative impact on manufacturing employment share. This implies that increasing internet reduces the share of manufacturing in the country's total employment or leads to digital de-industrialisation. One reason could be that manufacturing jobs are more routine-intensive and therefore, easier to automate with digital technologies (World Bank, 2016). Digitalisation 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 digitalisation across manufacturing value chains, further incentivising 'friend shoring' or 'near-shoring' by high-income countries. This could reinforce a 'technology bias' in favour of developed countries, limiting learning opportunities and upgrading capabilities for developing countries (Matthess and Kunkel, 2020). Third, digitalisation could reduce trade costs, which has a negative impact on manufacturing employment (Cravino and Sotelo, 2019).

Appendix Table A4 divides the sample into smaller subsamples based on income groups and regions. Even after removing the six high-income countries from our sample, we find that digitalisation 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 for 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 in SSA.

5. Conclusion, policy recommendations, and future research

Empirical evidence from our panel of 51 economies from 1990 to 2018 shows that while digitalisation has a positive and significant effect on annual economy-wide structural change, it has a negative impact on the share of manufacturing in total employment in developing countries. Furthermore, we find significant heterogeneity in the effects of digitalisation on SC depending on country contexts. Specifically, we find that the positive impact of digitalisation on SC is higher in low and lower-middle income countries than in upper-middle and high-income countries. In a similar vein, we find that the impact of digitalisation on SC is higher in structurally underdeveloped countries (agrarian economies) than structurally developing and developed economies.

Taken together, these findings suggest that digitalisation has the potential to accelerate structural change without industrialisation in developing countries. This is in line with Rodrik's (2018) argument that the dissemination of digital technologies, including through GVCs, destroys the comparative advantage of developing economies in labour-intensive manufacturing. In other words, digitalisation is likely contributing to 'premature de-industrialisation' (Rodrik, 2013) in developing countries. In agrarian economies, SC has already followed a different pathway, with workers moving directly from agriculture to non-business services (Sen, 2019). Our results increase concerns regarding digitalisation amplifying this pattern; digital technologies could lead to a leapfrogging of manufacturing activities but labour in agrarian economies is most likely to shift into traditional services, which are neither as tradable nor have the same productivity gains as manufacturing (Schlogl and Sumner, 2020). While digital platforms could potentially reduce barriers to entry for workers in developing countries into higher-skilled services tasks such as design, web development, translation, financial, legal and patent services, there are rising concerns regarding lack of decent and productive work (Cook and Rani, 2025).

Our findings underscore the importance of integrating digital policies, aimed at expansion of digital technologies, with appropriate "context-conscious and productive industrial policies" (Özçelik and Özmen, 2023) for large-scale employment generation in the digital economy. Policies to increase digital-led productivity gains need to be accompanied by improvements in domestic linkages between the domestic technology sector and manufacturing (Rodrik, 2018) and between highly productive firms and their domestic manufacturing suppliers. Further, education and skills-development policies need to target skill upgradation to equip the manufacturing labour force with new skills for the future.

Finally, our results show that GVC participation is an important driver of SC. When disaggregated based on the type of linkages, we find that forward linkages in GVCs can not only independently promote structural change but also amplify the gains from digitalisation. We find that the marginal effect of digitalisation on SC increases as countries become more integrated into the global economy though forward linkages. In contrast, we find that backward GVC linkages negatively affect SC.

These findings suggest that development strategies should move beyond generic digital adoption or export promotion and instead focus on aligning digital capabilities with upstream, value-added creating positions in global value chains. Policies that strengthen domestic intermediate production and digitally enabled services are likely to support sustained structural change rather than strategies centred on import-dependent assembly and processing trade. There is an urgent need to develop a coherent Digital Industrial Policy in developing countries, where digital policies (e.g., on the expansion of digital technologies) and trade policies (e.g. on increasing FL in GVCs) sit within the wider industrial policy to facilitate SC.

Our findings need to be contextualised and treated with caution. One caveat of our research is the use of internet penetration as a proxy for digitalisation. As data availability improves, different indicators of digitalisation, such as those on machine learning and artificial intelligence, can be used to check the robustness of our results. Further research is also needed on sector-wide SC to identify the specific sub-sectors of services towards which labour in developing countries is shifting.

CRediT authorship contribution statement

Karishma Banga: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Pankhury Harbansh:** Software, Methodology, Data curation. **Surendar Singh:** Writing – review & editing, Validation, Investigation, Conceptualization.

Data availability

Data will be made available on request.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors have not used any generative AI and AI-assisted technologies in the writing process.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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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_emp (% of total emp)	Manufacturing total employees/total employees	percentage
EORA	Backward linkages	Foreign value added embodied in country's exports as a share in gross exports	Share
EORA	Forward linkages	Domestic value added of a country, which is embodied in the exports of other countries as a share in gross exports	Share
EORA	GVC participation index	BL + FL	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
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	
FDI share	Foreign Direct Investment share	Inward FDI flows, share in GDP	Percentage
Bruegel dataset.	Annual changes in REER	Measure of currency overvaluation (or undervaluation). The REER data against 170 trading partners.	Percentage

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
Mean values, across income status

Country income level	Log (man_LP)	Structural change	Within-sector productivity growth	Man_ Employment share (%)	Internet pen. (%)
Low income	7.92	0.48	2.44	4.55	3.72
Lower-middle income	8.54	0.42	2.41	10.12	8.71
Upper-middle income	9.84	0.13	1.76	14.00	19.77
High income	10.79	0.02	1.99	14.96	43.41

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).

Table A3
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.BL	−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	1241	1241	1241	1241	1241
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).

Table A4
Dependent variable: manufacturing employment share

VARIABLES	Model 1	Model 2	Model 3	Model 4
	Low and middle income	*Low and middle income*	*South Asia*	*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)

(*continued on next page*)

Table A4 (*continued*)

VARIABLES	Model 1	Model 2	Model 3	Model 4
	Low and middle income	*Low and middle income*	*South Asia*	*SSA*
Time FE	yes	yes	yes	yes
Observations	947	324	132	346
R-squared	0.357	0.225	0.795	0.717
Number of countries	36	36	5	13

Note: ***p < 0.01, **p < 0.05, *p < 0.1.
Source: authors, cross-country panel (1990–2018).

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