



## Deindustrialization and the limits of industry's contribution to development in Latin America and Africa: Revisiting the inverted-U curve hypothesis

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**Abstract:** Drawing on an understanding of development as a process of accumulation and investment associated with technological progress and structural transformation, this article examines the contribution of industry to development in Latin American and African countries between 2000 and 2019. It seeks to reassess the validity of the inverted U-shaped relationship, as estimated in the works of Rowthorn (1995), Palma (2005), and Rodrik (2016), which relates the contribution of industry to growth in GDP per capita, from an innovative perspective. The originality of the analysis lies in testing this relationship based on the structural decomposition of labor productivity and average wages, treated as indicators of industry's contribution to development. To this end, the contribution of industrial sectors is examined according to their technological intensity, using shift-share techniques. In a second step, econometric tests are conducted to assess the empirical validity of the inverted U-shaped relationship, in dialogue with Rodrik (2016) and Tregenna and Andreoni (2020). The results indicate that: (i) structural change dynamics were stagnant or declining in both regions; (ii) there was an increasing relative participation of low-technology-intensity sectors at the expense of more technologically sophisticated sectors; (iii) both regions exhibited growth in static structural change alongside a decline in dynamic structural change; and (iv) evidence of an inverted U-shaped relationship was found in both regions, illustrating the declining contribution of industry to development over the period.

**Keywords:** Industry and development; Structural change; Deindustrialization; Latin America; Africa.

**JEL Codes:** L16; O14; O47.

**Área Temática:** Indústria, produtividade e competitividade

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## **Desindustrialização e os limites da contribuição da indústria ao desenvolvimento na América Latina e África: revisitando a hipótese da curva em U-invertido**

**Resumo:** A partir da compreensão do desenvolvimento como processo de acumulação e investimento associado ao progresso tecnológico e à transformação estrutural, este artigo analisa a contribuição da indústria para o desenvolvimento dos países da América Latina e África entre 2000 e 2019. Busca-se re-avaliar a validade da curva em U-invertido, estimada nos trabalhos de Rowthorn (1995), Palma (2005) e Rodrik (2016), que relaciona a contribuição da indústria ao crescimento do PIB per capita, a partir de uma abordagem inovadora. A originalidade da análise reside em testar essa relação com base na decomposição estrutural da produtividade do trabalho e da remuneração média dos trabalhadores, considerados como indicadores da contribuição da indústria ao desenvolvimento. Para tanto, examina-se a contribuição dos setores industriais segundo sua intensidade tecnológica, por meio de técnicas de *shift-share*. Em um segundo momento, são realizados testes econométricos para avaliar a validade empírica da relação em U-invertido, em diálogo com Rodrik (2016) e Tregenna e Andreoni (2020). Os resultados indicam que: (i) os movimentos de mudança estrutural foram estagnantes ou declinantes em ambas as regiões; (ii) identificou-se uma maior participação relativa dos setores de baixa intensidade tecnológica em detrimento dos setores de maior sofisticação tecnológica; (iii) ambas as regiões apresentaram crescimento da mudança estrutural estática em paralelo ao declínio da mudança estrutural dinâmica; (iv) encontrou-se evidências da curva em U-invertido em ambas as regiões, o que ilustra o declínio da contribuição da indústria para o desenvolvimento do período.

**Palavras-chave:** Indústria e desenvolvimento; Mudança estrutural; Desindustrialização; América Latina; África.

## 1. Introduction

The understanding of economic development as a process of accumulation, investment, and structural transformation toward higher-productivity activities has historically assigned a central role to manufacturing in the literature on growth and development (McMillan & Rodrik, 2011). From the early perception of Hamilton (1791) and List (1841) of a mutual determination between industrialization and development, to the classical development economists of the mid-twentieth century, industrialization has been viewed as both an instrument and a manifestation of national progress (Rosenstein-Rodan, 1943; Hirschman, 1958; Furtado, 1964).

Building on this tradition, manufacturing is regarded as the sector most capable of driving economic development, as it embodies the sophistication of the productive structure. Its main contributions operate through three channels: (i) fostering productivity growth across sectors, (ii) generating employment with above-average wages, and (iii) enhancing the productive and technological content of national exports. In line with this perspective, this article aims to analyze the contribution of manufacturing to economic development by examining one of these three traditional channels. Specifically, it focuses on assessing the manufacturing's capacity to promote productivity growth through the reconfiguration of the productive structure toward higher-productivity and higher wages activities, as in Mcmillan & Rodrik (2011); de Vries et al. (2015); Rodrik (2016) and Dosi et al. (2021).

While this theoretical consensus remains widely acknowledged, recent decades have witnessed renewed concern about deindustrialization and its implications for long-term growth. A growing literature has examined the causes and definitions of industrial decline in both advanced and developing economies (Tregenna, 2009; Andreoni & Chang, 2019; Rodrik, 2016), as well as the relationship between deindustrialization and per capita income (Felipe, Mehta & Rhee, 2018). However, these debates have largely focused on explaining why deindustrialization occurs rather than assessing how such structural transformations affect the developmental role of manufacturing; especially when it comes to non-industrialized economies in the global south, such as Latin America and Africa.

Since the late 1990s, Latin America and Africa have experienced declining industrial shares and increasing specialization in lower value-added segments, accompanied by weak or regressive contributions of productivity, employment, and industrial wages to overall growth (Palma, 2019; Rodrik, 2016; Tregenna & Andreoni, 2020; Nguimkeu & Zeufack, 2024). In a context of profound transformations in the global industrial landscape and renewed debates on industrial policy, understanding how changes in industrial structure condition per capita income growth has become especially pressing for regions that have not fully consolidated their industrial base. Therefore, this paper addresses this gap by providing empirical evidence on how deindustrialization shapes manufacturing's capacity to sustain productivity growth.

Against this background, the study revisits the classical relationship between industrialization and development proposed by Rowthorn (1995) and Rowthorn & Ramaswamy (1997, 1999). Their well-known inverted U-shaped curve relates the share of industry's employment in GDP to per capita income, suggesting that manufacturing employment expands during early development and declines once higher income levels are reached, as expenditure increases towards services. Yet this framework captures only the quantitative dimension of industrialization, overlooking how structural change qualitatively contributes to development.

To this end, this study evaluates the contribution of manufacturing to development in Latin America and Africa through a structural decomposition of productivity and wage growth. The choice of these variables is justified by the expectation that, in a virtuous process of structural transformation, employment shifts toward sectors with productivity and wages above the economy-wide average. Using shift-share techniques (McMillan & Rodrik, 2011; Timmer & de Vries, 2009; de Vries et al., 2015), the analysis estimates how changes in productivity and wages have shaped overall economic

performance through three structural change components: intrasectoral, intersectoral, and dynamic effects. The decomposition follows the technological classification of manufacturing proposed by the OECD (1987), allowing for a distinction between sectors of high, medium, and low technological intensity.

Subsequently, a stacked panel data econometric test with fixed effects is conducted to estimate the relationship between the growth of the structural decomposition components of productivity and average wages and per capita income growth from 2000 to 2019, following Rodrik (2016), Tregenna and Andreoni (2019), and Dosi et al. (2021). This approach enables a detailed examination of variations in industrial productivity and average wages in light of the three structural decomposition components, segmented by sectoral technological intensity.

Building on Andreoni & Tregenna (2019) and Tregenna & Andreoni (2020) we seek to demonstrate that technological heterogeneity across manufacturing sub-sectors produces differentiated patterns of industrialization and deindustrialization, challenging the traditional inverted-U hypothesis. Thus, the paper extends the inverted U-shaped curve framework through the structural decomposition of productivity and wages by providing quantitative evidence on how industrial structure and technological composition condition the developmental impact of manufacturing in two regions that are not yet fully industrialized and that, in recent decades, have suffered the effects of deindustrialization in a more accelerated manner (Palma, 2019; Nguimkeu; Zeufack, 2024).

By pursuing this approach, the paper contributes to three interrelated debates. First, it offers a new empirical perspective on the industry–development nexus, moving beyond traditional analyses of manufacturing’s share of GDP to a disaggregated assessment based on the structural decomposition of productivity. Second, it highlights the heterogeneous nature of structural change, emphasizing that the developmental contribution of manufacturing varies according to technological intensity and income level.

The paper is organized as follows. Section 2 reviews the literature on the relationship between industry and development, emphasizing debates on deindustrialization, structural change and the foundations of the inverted-U curve. Section 3 details the methodological shift-share and econometric approach and data. Section 4 presents the results, followed by the concluding remarks.

## **2. Literature Review: Industry and development**

Manufacturing has long been contemplated as the backbone of economic growth, with industrialization as a pivotal prerequisite for enabling structural changes compatible with higher complex stages of development. Earlier debates emphasized the coordination failures and complementarities involved in industrialization (Rosenstein-Rodan, 1943; Hirschman, 1958), while later approaches integrated innovation and technological learning as key dimensions of industrial dynamics (Schumpeter, 1934; Dosi, 1988). More recent contributions have focused on the challenges of deindustrialization and premature deindustrialization (Tregenna, 2009; Andreoni & Chang, 2019; Rodrik, 2016; Andreoni & Tregenna, 2018; Özçelik & Özmen, 2023), seeking to explain how globalization, technological change, and shifts in global value chains affect the role of manufacturing in developing and advanced economies alike.

A central argument about manufacturing’s contribution to development is synthesized in what is conventionally called Kaldor’s laws (Kaldor, 1966; 1967). This idea is grounded on the greater value added and productivity present in industrial activities, given their dynamic increasing returns to scale and the transmission of gains from technical progress towards other economic sectors. Additionally, manufacturing goods present greater income elasticity of demand compared to non-manufactured goods, which contributes to alleviating external restrictions on a country’s balance of payments (Thirlwall, 1979). This association, in turn, contributes to more robust catching-up pathways.

Nevertheless, this paper aligns with the strand of literature that maintains the enduring centrality of manufacturing for development, as it provides the technological and organizational foundations that foster complementarities, learning, and innovation across sectors (Andreoni & Chang, 2019). From this perspective, manufacturing remains pivotal to understanding productivity dynamics, particularly in middle-income economies where deindustrialization constrains the diffusion of technological progress and weakens the bases of structural transformation. Or, as Dosi et al. (2021, p.

183): “indeed, the development of a manufacturing sector has happened to be a necessary condition for catching- up (...) the manufacturing sector is an engine of growth also because it generates positive spillover effects for the economy as a whole”.

On that note, deindustrialisation is an anticipated phenomenon to detrimentally affect sustained growth possibilities, as pointed out in Rowthorn’s seminal works (Rowthorn, 1995; Rowthorn & Ramaswamy, 1997; 1999). From this standpoint, an inverted U-shaped curve of industrialization and deindustrialisation is estimated, which stresses the industry’s share in total employment relative to per capita income levels. Accordingly, as per capita income grows over time, there is a corresponding rise in industrial employment, coupled with a simultaneous decline in the share of agricultural employment. At a crucial turning point, which Rowthorn (1995) estimated to be US\$ 12,000, industrial labor stabilizes and this trend reverses, marked by an upswing in employment within the services sector even though productivity does not necessarily accelerate, indicative of the onset of deindustrialisation.

In developed economies, deindustrialisation tends to emerge at relatively high levels of per capita income and is considered a “natural” process. This pattern reflects the sector’s own technological maturity, as rapid productivity growth in manufacturing raises real incomes, shifts demand toward services, and gradually reduces industry’s share in GDP without implying an absolute decline in industrial value added (Rowthorn & Ramaswamy, 1999). In this sense, manufacturing simultaneously drives aggregate growth and shrinks as a proportion of the economy, an outcome consistent with early industrializing economies.

Conversely, as for developing economies, the decline of manufacturing in terms of employment and value added occurs before the formation of a diverse, productive, and innovation-diffusing industrial sector—that is, at much lower levels of per capita income than in advanced economies (Palma, 2005). This, in turn, perversely diminishes the industrial sector’s capacity to foster development (Tregenna & Andreoni, 2020).

From this perspective, the literature on deindustrialisation highlights its elevated degree of complexity. Studies based on empirical evidence show that per-capita income levels at the turning point of the inverted-U curve tend to be noticeably lower in developing countries compared to advanced ones. Palma (2008) reveals that the turning point of the employment share has shifted significantly over time, exposing sustained levels of manufacturing decline at various income levels, irrespective of whether countries have reached the theoretical peak. Between the 1980s and 1990s, the turning point moved respectively from \$21,000 to just over \$10,000, signaling that deindustrialisation first affected advanced countries in the 1980s and later middle-income economies in the 1990s. Nonetheless, by the 2000s this reversal had become so pronounced that no country had surpassed the turning point.

Drawing on similar analysis, Rodrik (2016) observes that, across various indicators and for groups of forty-two countries, the inverted-U relationship has been steadily declining over recent decades, especially among premature deindustrializers, at very low income levels. Among late industrializers, Asian economies were the least affected by deindustrialisation, while Latin American countries were the most severely hit. In contrast, industrialized countries have lost significant shares of employment, mostly in low-skilled jobs, although they have managed to retain important shares of manufacturing output.

Felipe, Mehta & Rhee (2018) explore the key relationship between the inverted-U curve and manufacturing employment through 1970–2010. They find that while output has little predictive power for a country’s wealth prospects, manufacturing employment plays a decisive role. All sampled wealthy countries experienced an industrial employment share above 18% since 1970, whereas developing economies were unable to reach such levels, given the structural characteristics of their late development process. These dynamics reinforce the pattern of premature deindustrialisation, which has become increasingly evident at lower levels of employment and output in the 2010s.

Alternatively, Özçelik & Özmen (2023) examine the relationship between manufacturing value added and real per capita GDP and find that the peak has shifted downwards and closer to the origin of the inverted-U curve. Their results indicate that peak manufacturing value added and real GDP per capita are much higher in advanced economies, 27% and US\$9,015, respectively, while in developing

and emerging economies they reach only 19.3% and US\$1,225, revealing striking premature deindustrialisation in the latter, with the notable exception of East Asia.

In a different and innovative perspective, Tregenna & Andreoni (2020) highlight the heterogeneity of deindustrialisation experiences at the sub-sectoral level, emphasizing potential instances of premature deindustrialisation based on the inverted-U pattern. Their findings show that the higher the technological intensity of manufacturing, the less concave the curve becomes, sometimes even assuming a convex shape—particularly in advanced high-tech sub-sectors.

In this context, Tregenna & Andreoni (2020) uncover that Asian economies, including South Korea, Thailand, and China, exhibit a higher proportion of technologically intensive products in their GDP, contributing to their successful convergence. Conversely, several industrialized economies, such as the UK, Spain, and Canada, struggle to sustain manufacturing's contribution to growth. On the flipside, Latin American and African countries faced a persistent case of premature deindustrialisation. Hence, Tregenna & Andreoni (2020) conclude that distinct technological intensities generate heterogeneous patterns of both industrialization and deindustrialization.

### 3. Methodology

In order to comprehend the limits of international industry's contribution to development, the methodological proposed by this study is based on the structural decomposition of productivity and wages, through shift-share techniques, as in OECD (1987), McMillan & Rodrik (2011), and De Vries et al. (2015). For the purpose of this study, the overall decomposition analysis is based on data from UNIDO INDSTAT Revision 3, at the 2-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC), which provides disaggregated data on the manufacturing sector. This analysis is supplemented with GDP (Parity Power Purchase) per capita in current US\$, obtained from World Bank's DataBank.

Table 1 - Latin American and African countries sample, share in world and regional manufacturing value added, employment and productivity statistics (%) (2019)

| Countries            | Manufacturing value added (% of GDP) | Manufacturing employment (% of national employment) | Share in world manufacturing value added (%) | Share in world manufacturing employment (%) | Average annual productivity growth (%), 2000–2018 |
|----------------------|--------------------------------------|-----------------------------------------------------|----------------------------------------------|---------------------------------------------|---------------------------------------------------|
| <b>Latin America</b> |                                      |                                                     |                                              |                                             |                                                   |
| Bolivia              | 10,50%                               | 11,20%                                              | 0,03%                                        | 0,05%                                       | 1,90%                                             |
| Brazil               | 10,30%                               | 11,60%                                              | 1,68%                                        | 3,37%                                       | 0,89%                                             |
| Chile                | 11,10%                               | 9,80%                                               | 0,20%                                        | 0,22%                                       | 1,37%                                             |
| Colombia             | 11,80%                               | 11,70%                                              | 0,22%                                        | 0,34%                                       | 1,55%                                             |
| Costa Rica           | 11,80%                               | 10,10%                                              | 0,06%                                        | 0,06%                                       | 1,92%                                             |
| Ecuador              | 14,40%                               | 10%                                                 | 0,04%                                        | 0,10%                                       | 1,06%                                             |
| Mexico               | 17,10%                               | 16,90%                                              | 1,27%                                        | 2,12%                                       | 0,17%                                             |
| Paraguay             | 19,40%                               | 10,40%                                              | 0,02%                                        | 0,06%                                       | 0,83%                                             |
| Uruguai              | 10,80%                               | 10,30%                                              | 0,03%                                        | 0,04%                                       | 1,76%                                             |
| <b>Medium</b>        | <b>13,02%</b>                        | <b>11,33%</b>                                       | <b>0,39%</b>                                 | <b>0,71%</b>                                | <b>1,27%</b>                                      |
| <b>Africa</b>        |                                      |                                                     |                                              |                                             |                                                   |
| Egypt                | 15,30%                               | 13%                                                 | 0,76%                                        | 1,91%                                       | 1,38%                                             |
| Ghana                | 11,50%                               | 11,50%                                              | 0,08%                                        | 0,13%                                       | 2,10%                                             |
| Kenya                | 9,10%                                | 7,00%                                               | 0,06%                                        | 0,17%                                       | 1,30%                                             |
| Mauritius            | 11,70%                               | 13%                                                 | 0,01%                                        | 0,03%                                       | 3,06%                                             |
| Morocco              | 15%                                  | 11,00%                                              | 0,13%                                        | 0,42%                                       | 1,21%                                             |
| Senegal              | 16,10%                               | 13,00%                                              | 0,01%                                        | 0,03%                                       | 1,37%                                             |

|               |               |               |              |              |              |
|---------------|---------------|---------------|--------------|--------------|--------------|
| South Africa  | 12,20%        | 9,50%         | 0,37%        | 0,57%        | 1,40%        |
| Tanzania      | 8,30%         | 3,00%         | 0,03%        | 0,07%        | 2,72%        |
| Tunisia       | 12,70%        | 18,20%        | 0,04%        | 0,26%        | 1,86%        |
| <b>Medium</b> | <b>12,43%</b> | <b>11,02%</b> | <b>0,17%</b> | <b>0,40%</b> | <b>1,82%</b> |

Source: authors, according to UNIDO – INDSTAT Revision 3; UNIDO – SDG 9 Monitoring; Dieppe et al. (2020) —

World Bank

As shown in Table 1, the sample comprises data from 18 economies, evenly split between Latin America and Africa. The sampled selection was determined by data availability in the referenced databases. Taken together, the industrial sectors in the sample account for an average of only 0.56% of global manufacturing value added and 1.11% of global manufacturing employment. At the national level, manufacturing represents, on average, 13.02% of total value added and 11.33% of total employment in the Latin American sample, while in the African sample it accounts for 12.43% of value added and 11.02% of employment. These figures underscore the relatively weak performance of manufacturing in both regions and provide a clear justification for examining the industry's contribution to development over the past two decades, particularly in economies where industrialization remains incomplete and increasingly constrained by processes of premature deindustrialization.

Subsequently, the value-added dataset was calculated in local currencies and posteriorly deflated through World Bank's Consumer's Price Index for each country, with 2019 as the base year.

In line with Tregenna & Andreoni (2020) manufacturing is disaggregated into 23 sub-sectors, at the 2-digit level of ISIC Rev. 3 and grouped by the technological intensity as proposed by Galindo-Rueda & Verger (2016) and UNIDO (2010), as Box 1.

Box 1 - Sub-sectoral technological classification

| ISIC Revision 3,<br>2 digits - Section D | Activity description                           | Technology<br>intensity |
|------------------------------------------|------------------------------------------------|-------------------------|
| 15                                       | Food and beverages                             | Low                     |
| 16                                       | Tobacco products                               | Low                     |
| 17                                       | Textiles                                       | Low                     |
| 18                                       | Wearing apparel, fur                           | Low                     |
| 19                                       | Leather, leather products and footwear         | Low                     |
| 20                                       | Wood products (excl. furniture)                | Low                     |
| 21                                       | Paper and paper products                       | Low                     |
| 23                                       | Coke, refined petroleum products, nuclear fuel | Medium                  |
| 24                                       | Chemicals and chemical products                | High                    |
| 25                                       | Rubber and plastic products                    | Medium                  |
| 26                                       | Non-metallic mineral products                  | Medium                  |
| 27                                       | Basic metals                                   | Medium                  |
| 28                                       | Fabricated metal products                      | Medium                  |
| 29                                       | Machinery and equipment n.e.c.                 | High                    |
| 30                                       | Office, accounting and computing machinery     | High                    |
| 31                                       | Electrical machinery and apparatus             | High                    |
| 32                                       | Radio, television and communication equipment  | High                    |
| 33                                       | Medical, precision and optical instruments     | High                    |
| 34                                       | Motor vehicles, trailers, semitrailers         | High                    |
| 35                                       | Other transport equipment                      | High                    |
| 36                                       | Furniture; manufacturing n.e.c.                | Low                     |
| 37                                       | Recycling                                      | Low                     |

|          |                            |
|----------|----------------------------|
| <b>D</b> | <b>Total Manufacturing</b> |
|----------|----------------------------|

Source: authors, according to Tregenna & Andreoni (2020); Galindo-Rueda e Verger (2016); UNIDO (2010)

Labor productivity was thus measured as the ratio of value added to the number of employees in industrial sectors, while average wages were calculated as the ratio of total wages to employment in each industrial sector, classified by technological intensity. In addition, GDP at constant Parity Purchase Power in US dollars was measured by the simple average between 2000 to 2019.

### 3.1 The shift-share techniques

The shift-share method is a descriptive analytical tool that decomposes the shift in an aggregate into a structural component, thereby assessing shifts in the composition of the aggregate and shifts within the individual units that constitute the aggregate. Consequently, it is intimately related to the variance analysis (FAGERBERG, 2000). It allows for the comprehension of the effects of employment reallocation on productivity and wages through three different components, revealing whether changes stem from sectoral productivity and wages variation (intrasectoral, or within effect), from shifts in employment to sectors with differing levels (intersectoral, or between effect), or even through fluctuations in aggregate productivity growth rates. Additionally, by adopting a novel approach by De Vries, Timmer & De Vries (2015), it is also possible to analyze productivity and wages through a dynamic standpoint, where the change in these variables and the change in the relative share of employment is captured across all sectors of the economy.

From this perspective, in a virtuous process of structural change, all components are expected to be positive, i.e., associated with the reconfiguration of the productive structure towards activities that increase productivity and are compatible with higher-wages activities.

Formally, the applied model is derived as follows:

$T$  =  $\Sigma$  of all sectors  $i$  ;

$S_i$  = participation of sector  $i$  in the total number of employed population;

$L_i$  = employed population;

$fy$  = final period;

$by$  = initial period;

$Q_i$  = value added;

$LP$  = labor productivity.

$t$  = time

First, for shift-share purposes, the weighting of the growth of each industrial subsector  $i$  in the total employed population of the subsector was calculated. The purpose of this step is to break down sectoral contributions in relation to the total employment weighting (which in this case is equal to 1).

$$S_i = \frac{L_i}{\Sigma L_i} \quad (1)$$

Next, labor productivity was measured by the ratio between the value added of industrial transformation and the employed population:

$$LP_i = \frac{Q_i}{L_i} \quad (2)$$

$$LP_T = \frac{Q_T}{L_T} = \frac{\sum_i Q_i}{\sum_i L_i} = \sum_i \left( \frac{Q_i}{L_i} \frac{L_i}{L} \right) = \sum_i LP_i S_i \quad (3)$$

By differentiating Equation (2) in time (from  $t-k$  to  $t$ , where  $t > k$ ), we obtain

$$LP_t - LP_{t-k} = \Delta LP_t = \sum_i LPP_{i,t} S_{i,t} - \sum_i LP_{i,t-k} S_{i,t-k} \quad (4)$$

The level of productivity for the years of analysis (2000, 2010 and 2019) was calculated taking into account the final and initial analysis periods.

As in De Vries, Timmer & De Vries (2015), productivity growth (4) was decomposed in Equation (3) components, as follows:

$$\Delta(LP_T) = \frac{LP_{T,fy} - LP_{T,by}}{LP_{T,by}} = I + II + III \quad (5)$$

Or, as in the growth-rate form, where:

$$\frac{\sum_{i=1}^n LP_{T,by} (S_{i,fy} - S_{i,by})}{LP_{T,by}} \quad (6)$$

**I**

Equation (6) represents the first term by the right side of Equation (5), term I, and it accounts for the intersectoral, or static, component of the structural transformation. This component stands for the contribution to productivity growth from changes in the allocation of labor between the differing industrial segments. Therefore, it is assumed that in a progressive development process, the relative share of employment shifts from low productivity sectors to those with above-average productivity rates, raising the overall labor productivity of the economy and making this component positive in the process (MCMILLAN; RODRIK, 2011).

$$\frac{\sum_{i=1}^n (LP_{i,fy} - LP_{i,by}) (S_{i,fy} - S_{i,by})}{LP_{T,by}} \quad (7)$$

**II**

Term II, the dynamic component of structural transformation is represented by Equation (7). It essentially captures the interaction between the change in labor productivity and the change in the relative share of employment across all sectors of the economy. This component is basically the internal product of productivity levels at the end of the analysis period and represents the change in the share of employment across sectors.

$$\frac{\sum_{i=1}^n (LP_{i,fy} - LP_{i,by}) S_{i,by}}{LP_{T,by}} \quad (8)$$

**III**

As for Term III, represented by Equation (8), it stands for the intrasectoral component of the structural transformation and captures the productivity growth within the different industrial segments, mainly through improvements in innovation, scale, or other internal variables to each sector. Similarly, if the change in this component is productive, regardless of the sector's share of total employment in

the economy, based on an analysis of the share of employment in each sector at the beginning of the analysis period, then the contribution of this component to structural change is also expected to be positive (MCMILLAN; RODRIK, 2011).

Only the decomposition of labor productivity is illustrated here, however, the same steps presented were replicated identically to the decomposition of average wages. The expected results follow the same logic: a virtuous development trajectory is associated with positive performance of the variable, in which employment is reallocated to sectors with higher average wages. To this end, the labor productivity variable was simply replaced by the ratio between total manufacturing wages and the total number of manufacturing's employed population.

### 3.2 Econometric model

Subsequently, pooled panel data regressions with fixed effects for countries and decades are performed to estimate the relationship between the growth of structural decomposition of productivity and average wages (obtained from the previous shift-share exercise) and the growth of per capita income between 2000 and 2019, following Rodrik (2016), Tregenna & Andreoni (2020), and Dosi et al. (2021). The tests thus provide a detailed examination of variations in industrial labor productivity and average wages across the three components of structural decomposition, segmented by sectoral technological intensity. Additionally, the estimations are used to assess the validity of the inverted-U curve in Latin American countries, as in:

$$Y_{jit} = \alpha_i + \beta_1 \ln(PIBPC)_{i,t} + \beta_2 \ln(PIBPC)_{i,t}^2 + \beta_3 \ln(POP)_{i,t} + \beta_4 \ln(POP)_{i,t}^2 + \sum_{i=1}^N \gamma_i C_i + \epsilon_{j,i,t} \quad (9)$$

Based on Equation (9),  $Y_{jit}$  represents total productivity/wage growth decomposed through shift-share techniques into static, dynamic, and intrasectoral components, segmented by technological intensity (high, medium, low). The model includes  $\ln(PIBPC)_{i,t}$ , its squared term,  $\ln(POP)_{i,t}$ , and its squared term as explanatory variables. Country ( $i$ ) and decade fixed effects are included, with  $\alpha_i$  as the intercept and  $\epsilon_{j,i,t}$  as the idiosyncratic error term. Coefficients  $\beta_1$ - $\beta_4$  are estimated using robust standard errors (HC1) to correct for potential heteroskedasticity and ensure reliable statistical inference.

It is worth mentioning that this study examines more than productivity and wage variation in manufacturing. It examines this variation by analyzing the three effects of the shiftshare decomposition model presented earlier. By doing so, the econometric model decomposes the results of structural change in productivity and average wages in Latin America (2000–2010; 2010–2019) into five model specifications: 1 - total static and dynamic components; 2 - intrasectoral; 3 - static; 4 - dynamic, and 5 - total effects of all three components.

Additionally, the Lind and Mehlum (2010) test was employed to formally assess the presence of an inverted U-shaped relationship. This procedure evaluates whether the estimated linear and quadratic coefficients exhibit opposite signs, as required for an inverted-U pattern, and tests whether the slope of the relationship is positive at the lower bound and negative at the upper bound of the observed data range. Moreover, the test verifies whether the estimated turning point lies within the support of the data, rather than outside the sample range, thereby ensuring the statistical validity and economic interpretability of the estimated curvature. This approach provides a more stringent and reliable assessment of nonlinear relationships than conventional significance tests of quadratic terms alone.

## 4. Results: Industry's contribution to development in Latin America and Africa (2000-2019)

When it comes to the shift-share decomposition for the Latin American countries from 2000-2019, the very first observation worth mentioning is that productivity growth and structural change patterns contributed to reducing rather than enhancing economic growth, as shown in Table 2.

Labor productivity declined on average by 3.52% between 2000 and 2019, failing to operate as a driver of development over the period. The fastest-growing segment was low-tech manufacturing, with an average growth rate of approximately 3.1%. This evidence is consistent with the literature on premature deindustrialization in the region (Rodrik, McMillan, and Verduzco-Gallo, 2014; Paus, 2020), which associates productivity stagnation with a shift in productive dynamism toward activities that remain distant from the international technological frontier. The negative aggregate performance was largely driven by medium-technology sectors, which experienced a cumulative contraction of around 208% between 2000 and 2019, signaling a substantial loss of competitiveness and innovative capacity in sectors that have traditionally supported industrial convergence in developing economies.

Table 2 - Productivity and wages decomposition average results (%) - 2000 to 2019 - Latin America

| Productivity                          |                |        |        |        | GDP PPP per capita (2000 to 2019 average) (USD) |
|---------------------------------------|----------------|--------|--------|--------|-------------------------------------------------|
| Structural decomposition effects      | Tech intensity |        |        | Total  |                                                 |
|                                       | High           | Low    | Médium |        |                                                 |
|                                       |                |        |        |        |                                                 |
| Structural change (static component)  | 3,2%           | -3,9%  | 3,6%   | 2,84%  | 13.255,47                                       |
| Intra sectoral component              | -1,8%          | 6,9%   | -9,0%  | -3,82% |                                                 |
| Structural change (dynamic component) | -0,7%          | 0,1%   | -1,9%  | -2,54% |                                                 |
| Structural decomposition - Total      | 0,71%          | 3,10%  | -7,33% | -3,52% |                                                 |
| Wages                                 |                |        |        |        | GDP PPP per capita (2000 to 2019 average) (USD) |
| Structural decomposition effects      | Tech intensity |        |        | Total  |                                                 |
|                                       | High           | Low    | Médium |        |                                                 |
|                                       |                |        |        |        |                                                 |
| Structural change (static component)  | 3,5%           | -4,4%  | 2,5%   | 1,62%  | 13.255,47                                       |
| Intra sectoral component              | 3,0%           | 15,6%  | 2,5%   | 21,12% |                                                 |
| Structural change (dynamic component) | -0,4%          | 0,3%   | -0,8%  | -0,94% |                                                 |
| Structural decomposition - Total      | 6,17%          | 11,52% | 4,10%  | 21,80% |                                                 |

Source: authors, according to UNIDO - INDSTAT 2 and World Bank

The most severe productivity declines were observed in upper-middle-income economies, notably Ecuador (−42.2%), Paraguay (−32.7%), and Brazil (−15.6%). Brazil stands out as the only country exhibiting negative productivity contributions across all three components of the structural decomposition. Similar, though less pronounced, patterns of declining productivity were also observed in higher-income economies, such as Chile (−1.4%) and Uruguay (−7.2%).

Regarding the decomposition results, all nine Latin American countries displayed negative total structural change effects, particularly Ecuador, Paraguay, Mexico, and Brazil. Although the static component, considered in isolation, accounted for most of the measured structural transformation (approximately 2.84%), indicating an intersectoral reallocation of employment toward sectors with

higher initial productivity, its effect was largely offset when combined with the dynamic component. As a result, the overall contribution of structural change to productivity growth was limited to only 0.3%, providing no evidence of a virtuous process in which employment shifted toward activities with sustained above-average productivity levels.

Average wages increased by 21.8% over the period, with gains relatively evenly distributed across industrial sectors by technological intensity, though more pronounced in low-tech activities (11.5%), according to Table 2. Nevertheless, the 14.2% wage growth observed in high-tech segments underscores the relevance of occupations associated with higher technological complexity for the structural change process. At the country level, average wage growth exceeded the regional mean in Costa Rica (79.2%) and Ecuador (102.2%), followed by countries with growth close to the average, such as Brazil (26.2%), Chile (14.3%), and Uruguay (14.5%).

From a structural perspective, wage gains were predominantly driven by the intrasectoral component, indicating a reallocation of labor within sectors rather than across them. This pattern is consistent with the influence of sector-specific wage policies and is largely concentrated in lower-skilled activities, where earnings tend to converge toward the national minimum wage. Regarding the components of structural change, the static effect was positive, indicating that employment reallocation occurred toward medium- and high-technology sectors, those which offer higher wages.

Table 3 - Productivity and wages decomposition average results (%) - 2000 to 2019 - Africa

| Productivity                          |                |        |        |        | GDP PPP per capita (2000 to 2019 mean) (USD) |
|---------------------------------------|----------------|--------|--------|--------|----------------------------------------------|
| Structural decomposition effects      | Tech intensity |        |        | Total  |                                              |
|                                       | High           | Low    | Médium |        |                                              |
| Structural change (static component)  | 5,9%           | -5,8%  | 2,6%   | 2,57%  |                                              |
| Intra sectoral component              | 1,8%           | 19,4%  | 9,9%   | 31,13% |                                              |
| Structural change (dynamic component) | 0,7%           | 0,7%   | -4,1%  | -2,73% |                                              |
| Structural decomposition - Total      | 8,37%          | 14,16% | 8,44%  | 30,97% |                                              |
| Wages                                 |                |        |        |        |                                              |
| Structural decomposition effects      | Tech intensity |        |        | Total  |                                              |
|                                       | High           | Low    | Médium |        |                                              |
| Structural change (static component)  | 6,0%           | -5,7%  | 2,9%   | 3,27%  |                                              |
| Intra sectoral component              | 0,8%           | 7,4%   | 1,8%   | 9,96%  |                                              |
| Structural change (dynamic component) | -2,2%          | 0,5%   | -1,3%  | -2,99% |                                              |
| Structural decomposition - Total      | 4,65%          | 2,15%  | 3,45%  | 10,24% |                                              |

Source: authors, according to UNIDO - INDSTAT 2 and World Bank

When it comes to the African sampled countries, more intense productivity gains were observed in contrast to Latin America, with an increase of 30.97% between 2000 and 2019, as seen in

Table 3. This especially due to the performance of low-intensity sectors, which accounted for nearly two-thirds of productivity growth, expanded by an average of 45.7%, when compared with more modest increases in medium- and high-technology sectors, at approximately 27.3% and 27.0%, respectively.

The data highlight the relative importance of low-complexity and low-technology sectors in the productive structures of the African economies analyzed. Part of this outcome reflects favorable international terms of trade and the commodity price boom experienced by several countries in the sample. Accordingly, the decomposition results indicate a significant increase in productivity from the early 2000s onward, coinciding with what the international literature describes as the period of renewed African growth, or “Africa Rising”, particularly among Sub-Saharan economies that are exporters of oil and mineral commodities (Newman et al., 2016; Frankema and Waijenburg, 2018).

However, this does not appear to reflect a process of structural change driven by intersectoral and dynamic employment shifts toward more productive sectors, as 31.13% of the average total growth is attributed to intrasectoral dynamics. Even in the context of the region’s relatively strong economic growth over the period, there is little evidence of a decoupling of African productive structures from historically regressive patterns of specialization embedded in the unequal and hierarchical international division of labor.

This interpretation is reinforced by the decomposition results, which show that the combined static and dynamic components of structural change contributed negatively to productivity growth (−0.16%), indicating that employment reallocation failed to generate efficiency gains across sectors. Within this framework, the best-performing cases are economies that display more successful convergence trajectories, notably Egypt (137%), South Africa (55,82%) and Mauritius (47,49%).

The distribution of wages in Africa did not exhibit the same virtuous trajectory, increasing by an average of only 10.24%, primarily due to the performance of high- and medium-tech sectors. In this case, similarly to productivity, the intrasectoral component accounts for the vast majority of wage gains, approximately 97.2% of the total decomposition, indicating that these gains are largely driven by wage dynamics within sectors.

In an additional attempt to evaluate manufacturing’s contribution to development in Latin America and Africa, this paper offers an empirical re-evaluation of the inverted-U-shaped curve, originally estimated in Rowthorn and Ramaswamy’s seminal studies, which links manufacturing’s GDP share to per capita income levels (Rowthorn and Ramaswamy, 1997, 1999). By using Rodrik’s (2016) model as a guideline, it applies Andreoni and Tregenna’s (2019) sectoral analysis approach to examine the relationship between per capita income and manufacturing’s role in development in Latin America and Africa.

The fixed effects panel estimation of productivity for Latin America reveals that most models show statistically significant structural decomposition components, suggesting a direct association with GDP per capita growth, as seen in Table 4. The only exception is Model 1, which aggregates the static and dynamic components and does not yield significant coefficients. Although significant, the negative signs of the estimated coefficients imply that the contribution of productivity growth to development, captured by the decomposition components; declines and eventually becomes negative beyond a certain level of average per capita income.

In sectoral terms, the relationship between productivity growth and GDP per capita growth is statistically significant in low- and medium-technology sectors. The pattern is particularly robust in low-technology activities, underscoring the substantial role played by less technologically sophisticated sectors in shaping the productive structure of Latin American economies.

According to Table 5, estimation for wages in Latin America displays lower statistical significance compared to productivity (Models 1–4), suggesting that wage growth is more strongly associated with the total structural decomposition effects (Model 5) than with its individual components. Sectorally, high- and medium-technology activities exhibit negative coefficients in most specifications, indicating that, at initial stages, increases in GDP per capita are associated with declining average wages in these sectors. Consistently, these sectors also show the smallest contributions to wage decomposition under the shift–share methodology.

Figure 1 displays the predicted productivity and wages as a function of the natural logarithm of GDP (PPP) per capita. Evidence of an inverted-U relationship emerges only for productivity, according to the Lind and Mehlum (2010) test, Model 2 (intrasectoral effects) and Model 5 (total effects), both in medium-technology sectors. In line with Tregenna and Andreoni (2020) and Dosi et al. (2021), these findings suggest that, as economies reach higher income levels, the employment reallocation toward higher-productivity sectors weakens, indicating diminishing structural transformation gains at more advanced stages of development.

Regarding wages, no inverted-U evidence was found; in many cases, wages tend to rise and then decline as income levels increase, displaying a downward exponential relationship. This interpretation is further supported by the slope statistics of minimum and maximum per capita income values across the five models.

Table 4 – Fixed effects panel regression results: Manufacturing productivity growth and GDP per capita for Latin America

|                                  | Model 1   |           |          | Model 2   |            |           | Model 3  |            |          | Model 4    |           |          | Model 5   |           |           |
|----------------------------------|-----------|-----------|----------|-----------|------------|-----------|----------|------------|----------|------------|-----------|----------|-----------|-----------|-----------|
|                                  | High      | Medium    | Low      | High      | Medium     | Low       | High     | Medium     | Low      | High       | Medium    | Low      | High      | Medium    | Low       |
| $\ln(PIBPC)_{i,t}$               | -75.18    | -30.497   | 74.317   | -221.72** | 61.180     | -814.80** | -80.553  | -71.074*** | 30.009   | -22.803*** | 64.709*** | 77.831*  | -326.175  | 44.337*   | -706.08** |
|                                  | (-59.768) | (19.054)  | (42.851) | (64.33)   | (34.204)   | (246.676) | (64.634) | (15.725)   | (65.383) | (5.08)     | (15.894)  | (31.012) | (153.755) | (18.950)  | (248.948) |
| $\ln(PIBPC)_{i,t}^2$             | 1.6734    | 1.3633    | 7.4269   | 4.7927    | 44.99****  | 75.036**  | 2.1621   | 10.489**   | -8.083   | 3.3263*    | -7.891**  | -4.569   | 9.124     | 50.98**** | 62.186*   |
|                                  | (6.479)   | (2.514)   | (5.335)  | (9.087)   | (3.364)    | (29.068)  | (7.514)  | (4.215)    | (7.923)  | (1.612)    | (2.251)   | (3.41)   | (18.554)  | (1.184)   | (30.778)  |
| $\ln(POP)_{i,t}$                 | -43.72    | -208.71** | 202.396  | -373.54   | -467.75*   | -473.17   | -160.74  | -134.25**  | 283.90   | 15.628     | 46.077    | 34.208   | -513.74   | -627.86** | -147.85   |
|                                  | (270.39)  | (73.77)   | (144.21) | (303.69)  | (182.00)   | (775.41)  | (224.38) | (50.867)   | (221.23) | (13.230)   | (94.929)  | (92.176) | (697.59)  | (117.72)  | (788.21)  |
| $\ln(POP)_{i,t}^2$               | 140.41    | 69.977    | -182.158 | -327.100  | 1229.4**** | 1308.74   | 211.082  | 42.719     | -170.370 | -20.497    | 89.401    | -104.80  | -149.116  | 1362****  | 1027.86   |
|                                  | (169.50)  | (66.229)  | (155.78) | (213.111) | (94.09)    | (672.40)  | (254.61) | (155.33)   | (228.96) | (76.272)   | (94.985)  | (94.123) | (470.33)  | (41.511)  | (612.09)  |
| Slope at $\ln(PIBPC)_{i,t}$ min. | -55.49    | 16.45     | -53.75   | 223.7*    | 57.9***    | 47.9      | -43.26   | 113.9      | -109.3   | 32.5       | -64.8     | -0.96    | 206.0     | 63.0***   | 36.6      |
| Slope at $\ln(PIBPC)_{i,t}$ max. | -52.22    | 21.51     | -71.39   | 263.2*    | -63.6***   | 65.7      | -38.1    | 140.6      | -128.5   | 39.6       | -80.8     | -11.8    | 256.7     | -72.8***  | 51.3      |
| R <sup>2</sup>                   | 0.24      | 0.87      | 0.47     | 0.72      | 0.95       | 0.41      | 0.18     | 0.82       | 0.39     | 0.46       | 0.57      | 0.49     | 0.44      | 0.98      | 0.46      |

Source: author's, according to UNIDO-INDSTAT2 and World Bank. Note: Robust standard errors errors (HC1) in parenthesis. \* p < 0.1, \*\* p < 0.5, \*\*\* p < 0.01, \*\*\*\* p < 0.001.

Table 5 – Fixed effects panel regression results: Manufacturing wage growth and GDP per capita for Latin America

|                                   | Model 1   |           |           | Model 2   |           |           | Model 3  |           |          | Model 4  |          |          | Model 5   |            |           |
|-----------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|----------|-----------|----------|----------|----------|----------|-----------|------------|-----------|
|                                   | High      | Medium    | Low       | High      | Medium    | Low       | High     | Medium    | Low      | High     | Medium   | Low      | High      | Medium     | Low       |
| $\ln(PIBPC)_{i,t}$                | -94.552   | -47424**  | 81.256**  | 169.307   | -145.821  | -351.031  | -95.628  | 3.6151    | 55.712   | -39.269  | -44.606* | 58.823** | 35.717    | -173.66*** | -303.85** |
|                                   | (-50.540) | (13.651)  | (29.818)  | (162.457) | (123.190) | (215.062) | (73.435) | (26.498)  | (61.048) | (38.235) | (19.656) | (20.252) | (102.350) | (39.353)   | (113.804) |
| $\ln(PIBPC)_{i,t}^2$              | -52.386   | 1.8001    | -2.3550   | -52.550** | -3.5206*  | -48.569   | -137     | 5.8567    | -8.253   | 1.227    | 526      | -2.401   | -51236**  | -29774**   | -53.581   |
|                                   | (5.8752)  | (1.9353)  | (3.6703)  | (18.352)  | (16.145)  | (32.951)  | (8.594)  | (3.703)   | (7.534)  | (5.151)  | (2.566)  | (2.690)  | (13.342)  | (11.171)   | (28.358)  |
| $\ln(POP)_{i,t}$                  | 5.8752    | -180876** | 133.581   | 12590*    | 484.646   | 1321.53   | -96.869  | -190.157* | 222.36   | -69.842  | -24.666  | 89.606   | 1087.57** | 32394***   | 1343.39** |
|                                   | (185.82)  | (59.719)  | (108.16)  | (585.41)  | (410.53)  | (876.12)  | (260.33) | (-190.15) | (20.677) | (128.90) | (54.460) | (64.031) | (380.13)  | (122.46)   | (381.92)  |
| $\ln(POP)_{i,t}^2$                | 131.292   | 48.961    | 108.156   | -971.180  | -51.287   | -46.035   | 175.92   | 37.631    | -132.34  | 87.587   | 76.047   | -143.41* | -705.510  | 53.147     | -326.521  |
|                                   | (166.44)  | (49.335)  | (106.13)7 | (680.08)  | (517.39)  | (816.98)  | (276.96) | (91.904)  | (222.13) | (137.23) | (57.305) | (66.199) | (460.43)  | (511.45)   | (1008.0)  |
| Slope at $\ln(PIBPC)_{i,t}$ min   | -184.8*** | 14.72     | 40.64     | -736.9*** | -752.9*** | -1188.5** | -98.00   | 104.6***  | -86.61   | -18.09   | -35.53   | 17.41    | -847.8*** | -681.9***  | -1259.3** |
| Slope at $\ln(PIBPC)_{i,t}$ max.. | -197.3*** | 21.41     | 35.05     | -861.7*** | -836.5    | -1303.9   | -98.32   | 118.52*** | -106.2   | -15.17   | -34.28   | 11.71    | -969.5*** | -750.4***  | -1400**   |
| R <sup>2</sup>                    | 0.35      | 0.56      | 0.61      | 0.51      | 0.51      | 0.58      | 0.17     | 0.86      | 0.46     | 0.23     | 0.31     | 0.51     | 0.62      | 0.38       | 0.60      |

Source: author's, according to UNIDO-INDSTAT2 and World Bank. Note: Robust standard errors errors (HC1) in parenthesis. \* p < 0.1, \*\* p < 0.5, \*\*\* p < 0.01, \*\*\*\* p < 0.001.

Figure 1 - Predicted productivity and wages as function of the natural logarithm of GDP (PPP) per capita, sectors by technological intensity - Latin America (2000-2019)<sup>3</sup>

Figure 1a - Productivity

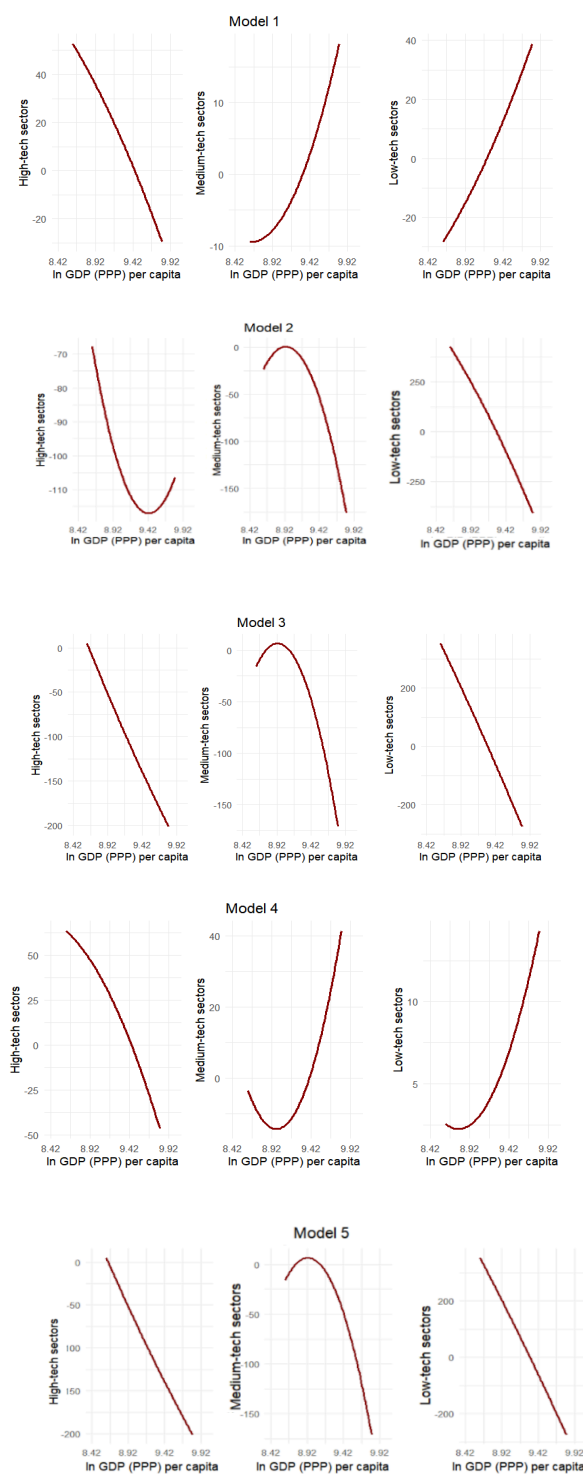
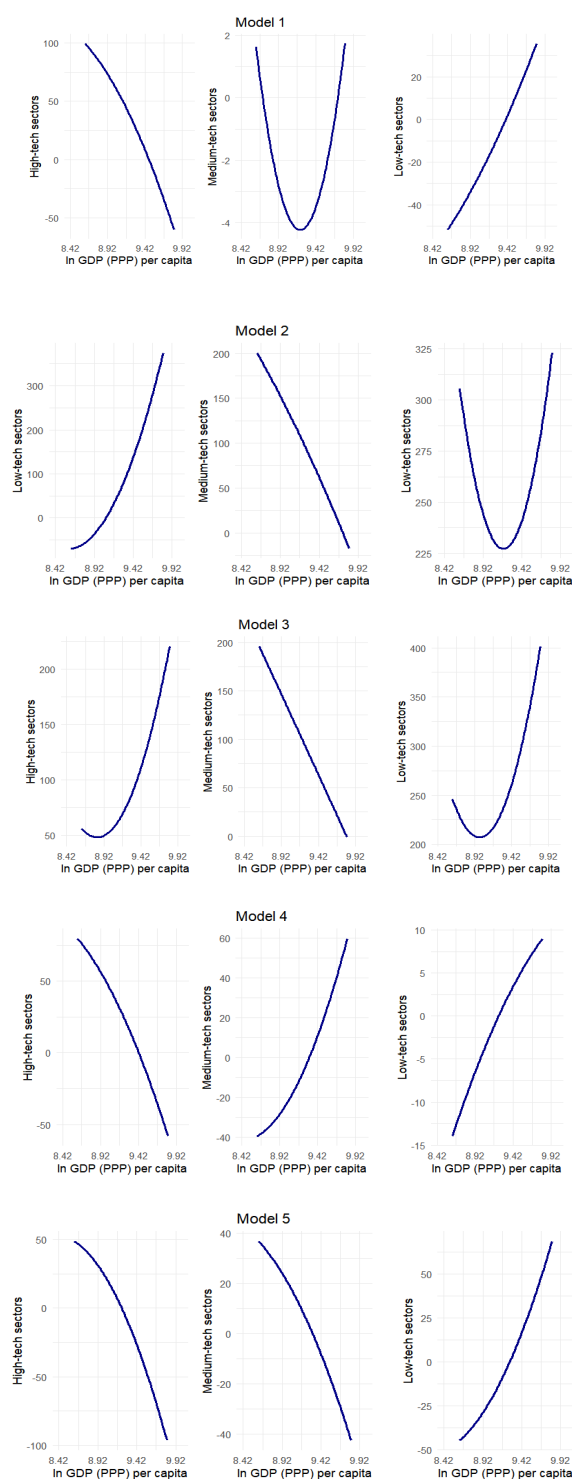


Figure 1b - Wages



Source: authors, according to UNIDO-INDSTAT2 and World Bank

<sup>3</sup> Model 1 (static and dynamic); Model 2 (intrasectoral); Model 3 (static); Model 4 (dynamic); Model 5 (total decomposition). In order to calculate the respective predicted productivity and wages values, the population logarithm variable and its quadratic term were fixed at their average values over all the observations.

When it comes to the estimation results for the sampled African countries, productivity reveals to be comparatively less statistically significant than those for Latin America (Table 6). Nevertheless, the static structural change component indicates a stronger contribution as per capita income rises (Model 3), as does the combined static and dynamic effect (Model 1). These findings point to a relatively virtuous pattern of structural transformation, associated with the reallocation of employment toward higher-productivity sectors. At the sectoral level, high- and medium-technology activities, when statistically significant, display positive coefficients in nearly all specifications, suggesting that income growth has effectively stimulated productivity gains in these sectors.

With regard to wages, although the models display lower statistical significance overall, their contribution to development appears to be linked primarily to the intrasectoral and static components, with larger gains in per capita income associated with low-technology sectors (Table 7). Specifically, the intrasectoral (Model 2) and static structural change (Model 3) components show comparatively stronger significance, whereas the dynamic component (Model 4) does not exhibit a statistically meaningful relationship with per capita income growth.

As for the analysis of Africa's industry contribution to development through the interpretation of the inverted-U curve, evidence for productivity was only confirmed in Model 1 for the high-technology sector, as validated by the Lind–Mehlum test (Figure 2). In all other models and sectoral specifications, although the predicted values plotted against the logarithm of per capita income suggest a possible inverted-U shape, the robustness test rejects this hypothesis. Hence, despite heterogeneous deindustrialization trajectories across countries, the industrial sector as a whole continues to function as a key vehicle for regional convergence.

A similar pattern emerges for wages. While the fitted values display an apparent inverted-U relationship, the robustness checks do not confirm its statistical validity. This result indicates that average wages have remained an important channel of development in Africa, particularly in low-technology sectors, which tend to exhibit a positive and increasingly steep relationship with per capita income.

Table 6 – Fixed effects panel regression results: Manufacturing productivity growth and GDP per capita for Africa

|                                 | Model 1               |                     |                      | Model 2             |                       |                     | Model 3                |                      |                       | Model 4             |                       |                     | Model 5             |                        |                     |
|---------------------------------|-----------------------|---------------------|----------------------|---------------------|-----------------------|---------------------|------------------------|----------------------|-----------------------|---------------------|-----------------------|---------------------|---------------------|------------------------|---------------------|
|                                 | High                  | Medium              | Low                  | High                | Medium                | Low                 | High                   | Medium               | Low                   | High                | Medium                | Low                 | High                | Medium                 | Low                 |
| $\ln(PIBPC)_{it}$               | 8.668***<br>(1.888)   | 15.844**<br>(6.002) | -11.43***<br>(2.173) | -2.958<br>(13.062)  | 67.012***<br>(17.226) | 4.134<br>(41.609)   | -3.828**<br>(3.963)    | 18.704**<br>(6.383)  | -14.26****<br>(2.085) | 12.520**<br>(4.746) | -5.991<br>(3.608)     | 1.905<br>(2.712)    | 5.463<br>(14.115)   | 100.28****<br>(14.895) | -7.499<br>(41.661)  |
| $\ln(PIBPC)_{it}^2$             | 411.64***<br>(89.896) | -309.44<br>(323.73) | -60.935<br>(146.42)  | 177.87<br>(531.96)  | 2841.0*<br>(1205.8)   | 991.96<br>(2226.8)  | 442.75**<br>(157.68)   | -325.43<br>(-325.43) | 1.400<br>(141.82)     | -31.155<br>(137.32) | 206.97**<br>(58.973)  | -7.170<br>(142.01)  | 619.42<br>(547.24)  | 1470.3<br>(1108.3)     | 927.09<br>(2135.9)  |
| $\ln(POP)_{it}$                 | 25.946<br>(78.405)    | 28.683<br>(205.55)  | 100.56<br>(110.38)   | -323.78<br>(304.03) | 1205.8<br>(1086.4)    | -2038.6<br>(2219.3) | -52.417<br>(125.71)    | 168.32<br>(168.32)   | -170.60<br>(100.81)   | 78.503<br>(130.03)  | -232.38**<br>(77.564) | 247.14*<br>(118.30) | -308.82<br>(376.92) | -422.40<br>(1196)      | -1939.4<br>(2146.4) |
| $\ln(POP)_{it}^2$               | -493.5****<br>(64.46) | 62.863<br>(238.87)  | 125.79<br>(82.340)   | 613.30<br>(730.75)  | 634.02<br>(1358.7)    | -272.73<br>(1763.1) | -395.41**<br>(-395.41) | 20.79<br>(262.39)    | 219.26*<br>(111.57)   | -98.428<br>(132.66) | 501.38***<br>(126.24) | 38.384<br>(173.74)  | 173.56<br>(835.61)  | -1834.6**<br>(693.53)  | -140.84<br>(1737.7) |
| Slope at $\ln(PIBPC)_{it}$ min. | 56.32***              | -42.12              | -84.3                | 42.1                | 24.4                  | 13.5                | -60.45**               | -44.2                | 4.86                  | -41.3               | 19.85                 | -85.56              | 61.17               | 20.18                  | 12.65               |
| Slope at $\ln(PIBPC)_{it}$ max. | -79.94***             | -59.87              | -11.93               | 59.8                | 34.6                  | 19.2                | 85.85**                | -62.9                | 12.89                 | -59.1               | 28.30                 | -12.16              | 86.83               | 28.62                  | 17.97               |
| R <sup>2</sup>                  | 0.77                  | 0.3                 | 0.59                 | 0.15                | 0.43                  | 0.44                | 0.52                   | 0.19                 | 0.30                  | 0.32                | 0.80                  | 0.49                | 0.17                | 0.40                   | 0.41                |

Source: author's, according to UNIDO-INDSTAT2 and World Bank. Note: Robust standard errors errors (HC1) in parenthesis. \* p < 0.1, \*\* p < 0.5, \*\*\* p < 0.01, \*\*\*\* p < 0.001.

Table 7 – Fixed effects panel regression results: Manufacturing wage growth and GDP per capita for Africa

|                                 | Model 1                |                     |                      | Model 2             |                      |                        | Model 3                 |                     |                     | Model 4            |                     |                      | Model 5             |                     |                       |
|---------------------------------|------------------------|---------------------|----------------------|---------------------|----------------------|------------------------|-------------------------|---------------------|---------------------|--------------------|---------------------|----------------------|---------------------|---------------------|-----------------------|
|                                 | High                   | Medium              | Low                  | High                | Medium               | Low                    | High                    | Medium              | Low                 | High               | Medium              | Low                  | High                | Medium              | Low                   |
| $\ln(PIBPC)_{it}$               | 7.086**<br>(2.481)     | -8.051<br>(4.283)   | -0.620<br>(3.175)    | 12.096<br>(14.048)  | 27.679***<br>(7.777) | 230.46****<br>(30.652) | 4.371<br>(2.464)        | -11.70**<br>(3.701) | 7.105*<br>(3.301)   | 2.289<br>(3.469)   | 4.051<br>(2.502)    | -4.664***<br>(1.317) | 16.851<br>(15.674)  | 19.961*<br>(8.809)  | 232.5****<br>(28.941) |
| $\ln(PIBPC)_{it}^2$             | 573.65***<br>(161.25)  | -417.06<br>(273.32) | 235.57<br>(248.24)   | 263.42<br>(503.25)  | 907.70<br>(618.38)   | 1186.4<br>(1420.8)     | 445.68**<br>(132.42)    | -192.63<br>(204.06) | 14.007<br>(157.97)  | 163.31<br>(103.79) | -220.37<br>(127.61) | 55.27<br>(62.74)     | 984.53<br>(589.52)  | 493.70<br>(845.92)  | 1254.8<br>(1286.3)    |
| $\ln(POP)_{it}$                 | 101.65<br>(80.05)      | 112.78<br>(158.22)  | -376.62*<br>(182.33) | -193.30<br>(402.40) | -391.58<br>(444.57)  | -166.13<br>(1004.7)    | 48.52<br>(69.04)        | -25.870<br>(150.59) | -183.45<br>(143.42) | 39.167<br>(71.168) | 139.84<br>(130.64)  | -101.33*<br>(52.461) | -161.77<br>(474.35) | -275.44<br>(566.78) | -456.27<br>(914.18)   |
| $\ln(POP)_{it}^2$               | -655.0****<br>(103.49) | 172.00<br>(210.19)  | 685.02*<br>(329.54)  | -450.98<br>(812.69) | -472.97<br>(390.70)  | -1042.4<br>(1057.4)    | -476.91****<br>(78.981) | 128.49<br>(128.49)  | 210.20<br>(109.10)  | -93.15<br>(192.72) | 37.89<br>(79.61)    | 68.39<br>(59.027)    | -747.15<br>(618.40) | -307.47<br>(563.14) | -757.71<br>(926.37)   |
| Slope at $\ln(PIBPC)_{it}$ min. | 78.44***               | -57.06              | 95.71                | 56.64               | 12.42                | 16.44                  | 60.93***                | -26.43              | 19.8                | 1728               | -30.06              | 75.0                 | 13.46               | 67.65               | 17.37                 |
| Slope at $\ln(PIBPC)_{it}$ max. | 11.13***               | -80.99              | 13.58                | 80.39               | 17.63                | 23.24                  | 86.50***                | -37.48              | 27.8                | 24.52              | -42.71              | 10.67                | 19.11               | 95.97               | 24.57                 |
| R <sup>2</sup>                  | 0,68                   | 0,32                | 0,47                 | 0,14                | 0,23                 | 0,48                   | 0,57                    | 0,25                | 0,38                | 0,29               | 0,37                | 0,37                 | 0,32                | 0,1                 | 0,57                  |

Source: author's, according to UNIDO-INDSTAT2 and World Bank. Note: Robust standard errors errors (HC1) in parenthesis. \* p < 0.1, \*\* p < 0.5, \*\*\* p < 0.01, \*\*\*\* p < 0.001.

Figure 2 - Predicted productivity and wages as function of the natural logarithm of GDP (PPP) per capita, sectors by technological intensity - Africa (2000-2019)<sup>4</sup>

Figure 2a - Productivity

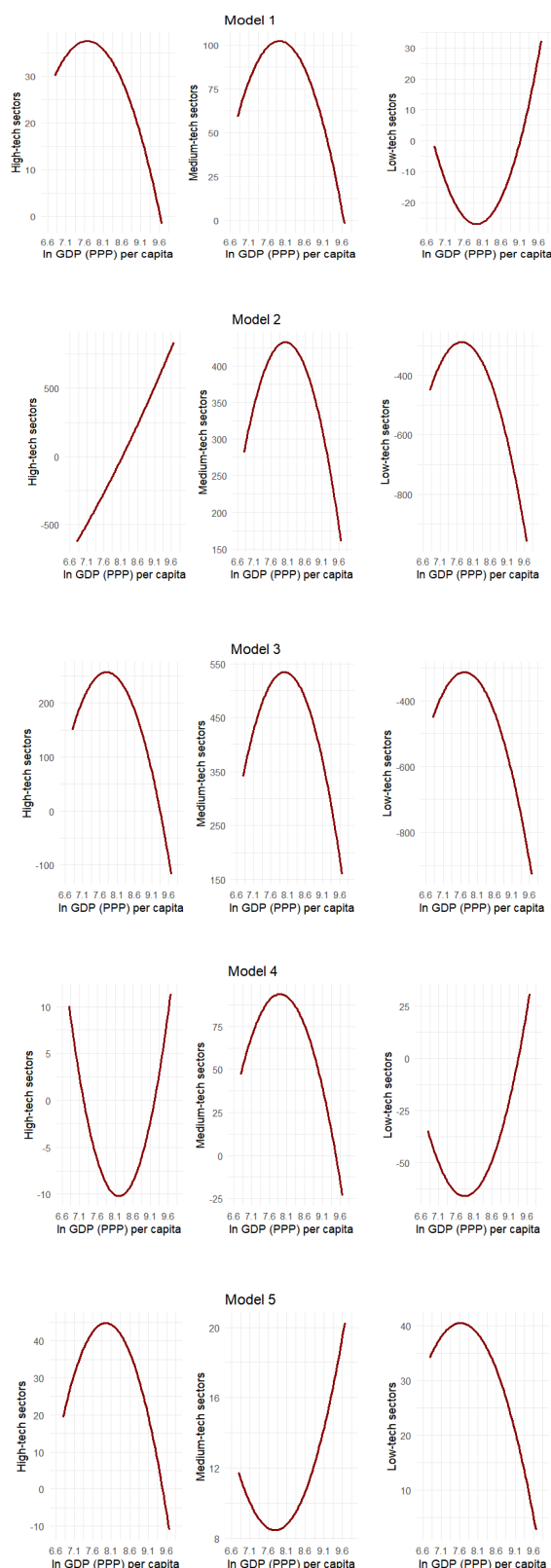
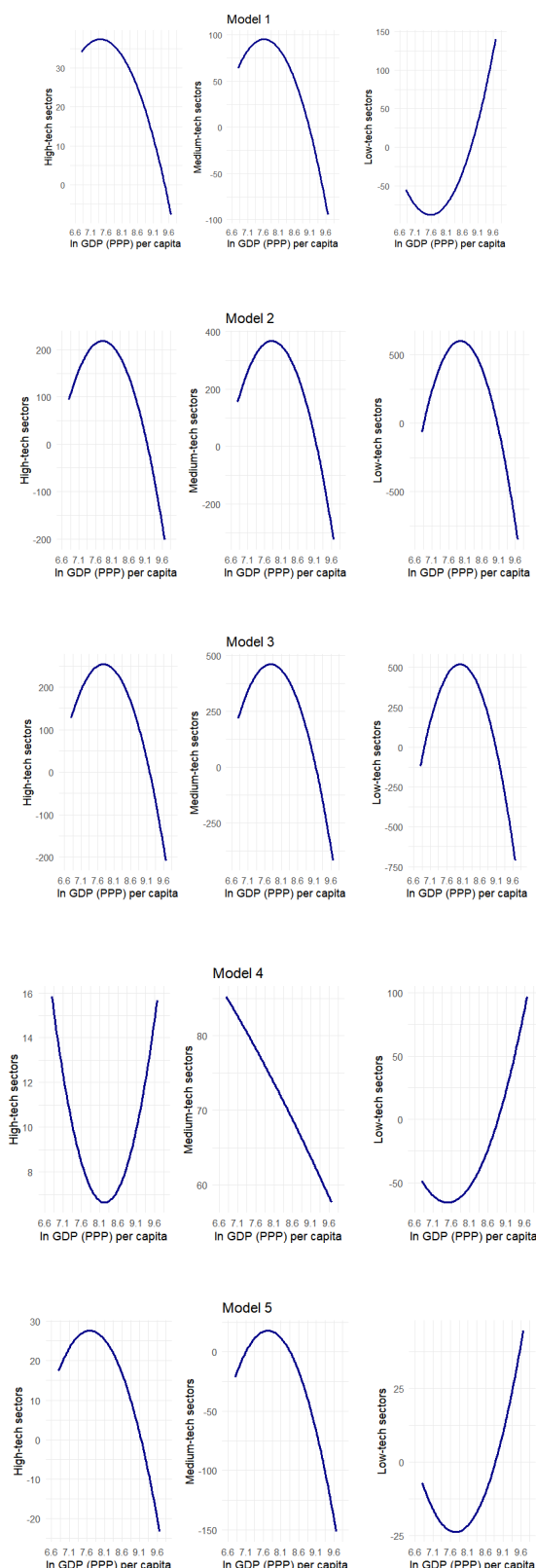


Figure 2b - Wages



Source: authors, according to UNIDO-INDSTAT2 and World Bank

<sup>4</sup> Model 1 (static and dynamic); Model 2 (intrasectoral); Model 3 (static); Model 4 (dynamic); Model 5 (total decomposition). In order to calculate the respective predicted productivity and wages values, the population logarithm variable and its quadratic term were fixed at their average values over all the observations.

## 5. Concluding remarks

This study sought to reassess the role of manufacturing in the development trajectories of Latin America and Africa between 2000 to 2019, in a context marked by premature deindustrialization and increasing technological heterogeneity. While a vast literature has examined the industry–development nexus, important gaps remain regarding how changes in industrial structure affect the contribution of manufacturing to economic development in peripheral economies. Empirical efforts directly measuring how structural change in manufacturing conditions productivity, wages, and per capita income growth in Latin America and Africa are still limited. This gap becomes particularly salient in light of profound transformations in global industry over recent decades, which have intensified the heterogeneity of industrial contributions across regions that have not fully consolidated their industrial base.

Against this background, the paper assessed the contribution of manufacturing to development through a structural decomposition of productivity and wage growth, combined with panel estimations linking these components to per capita income growth between 2000 and 2019. Building on Andreoni and Tregenna (2019) and Tregenna and Andreoni (2020), manufacturing was disaggregated by sectoral technological intensity and by structural change components (intrasectoral, static, and dynamic structural change), moving beyond aggregate manufacturing shares in order to examine how industrial structure shapes developmental outcomes. In doing so, the study extended the traditional inverted-U framework (Rowthorn, 1995; Rowthorn & Ramaswamy, 1997, 1999) by demonstrating that technological heterogeneity across sub-sectors generates differentiated and region-specific patterns of industrialization and deindustrialization.

The main findings for Latin American countries are as follows:

- (i) Productivity growth and structural change patterns tended to *reduce*, rather than enhance, overall economic growth, with an average decline of  $-3.52\%$ . The highest average expansion occurred in low-technology sectors (around  $3.10\%$ ), indicating a concentration of gains in less sophisticated activities.
- (ii) Average wages increased by  $21.8\%$ , relatively evenly distributed across technological groups. Structurally, wage gains were predominantly associated with the intrasectoral component, suggesting labor reallocation and adjustments within sectors rather than across them.
- (iii) Static structural change accounted for the most robust share of productivity and wage gains. However, this pattern reveals limited capacity to sustain deeper structural transformation beyond certain income thresholds, as growth follows a cyclical pattern of expansion and contraction. This dynamic reflects premature deindustrialization in the region (Palma, 2005), linked to a low-growth trap and constrained dynamic capability building (Andreoni & Tregenna, 2019).
- (iv) Econometric tests provide evidence of an inverted-U relationship at the productivity level. Consistent with Tregenna and Andreoni (2020) and Dosi et al. (2021), employment reallocation toward higher-productivity sectors weakens as economies reach higher per capita income levels.

As for the African countries:

- (i) The sample countries display a comparatively more virtuous productivity trajectory, with average growth of nearly  $31\%$ , largely driven by low-technology sectors, which account for almost two-thirds of this expansion. However, this does not correspond to a structural transformation led by intersectoral or dynamic employment shifts, as  $31.13\%$  of total average growth is attributed to the intrasectoral component.
- (ii) Wage performance is more modest, with an average increase of  $10.24\%$ , mainly supported by high- and medium-technology sectors. As with productivity, wage gains are overwhelmingly explained by the intrasectoral component—approximately  $97.2\%$  of the total decomposition—indicating that improvements stem primarily from within-sector dynamics.
- (iii) Econometric and robustness tests do not confirm an inverted-U pattern. In line with Nguimkeu and Zeufack (2024), this suggests that, despite limited growth and heterogeneous deindustrialization experiences, African industry continues to function as an important channel for development.

Overall, the results indicate that structural change since the 2000s has been negative or stagnant in both Latin America and Africa. Although the African case appears more encouraging in light of its growth revival, low- and lower-middle-income countries exhibit signs of deindustrialization at relatively low levels of per capita income. Moreover, growth in the region has been driven

predominantly by intrasectoral gains rather than by intersectoral reallocation, suggesting that firm-level efficiency improvements were not accompanied by sufficient labor shifts toward more dynamic sectors. While this pattern contrasts with the view that intrasectoral gains dominate primarily in high-income economies (McMillan & Rodrik, 2011), it nonetheless reflects limited structural transformation.

In Latin America, despite higher income levels and a comparatively more mature industrial base, structural change during the period did not translate into a sustained upgrading toward technologically sophisticated sectors. Low-technology activities retained a significant relative weight, constraining broader productive transformation.

Across both regions, static structural change expanded while dynamic structural change declined. Although employment reallocation occurred toward sectors with above-average productivity and wages, particularly in high-technology activities, these sectors experienced stagnant or negative growth, weakening their relative performance and contributing to the decline of the dynamic component. Given that static gains were also modest, neither region exhibits a virtuous pattern of structural change dominance. These findings are consistent with De Vries, Timmer and De Vries (2015) and Mensah et al. (2023), in what follows a case of “static gains” versus “dynamic losses”.

In this context, successful convergence in productivity and average wages in Latin America and Africa requires the implementation of industrial policies capable of fostering sustained industrial contributions to development. This is particularly critical given ongoing transformations in the global techno-productive paradigm, marked by digitalization and the rise of Industry 4.0, the climate transition and the push for sustainable production. Effective integration of African and Latin American productive structures into global markets depends on a broad process of structural renewal, combining coordinated institutional action and policy instruments aimed at strengthening local knowledge generation and dynamic capabilities.

Such alignment is also essential for advancing Sustainable Development Goal 9 of the United Nations 2030 Agenda, which emphasizes technological development through R&D and innovation, particularly in developing economies. Although current trajectories in both regions diverge from this objective, well-designed innovation and industrial policies hold significant potential to build robust industrial ecosystems consistent with long-term economic modernization.

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Drawing on a structuralist understanding of development as a cumulative process driven by investment, technological progress, and structural transformation, this article examines the contribution of manufacturing to development in Latin American and African countries between 2000 and 2019. Over recent decades, both regions have experienced premature deindustrialization, increasing specialization in lower value-added activities, and weakening contributions of industrial productivity and wages to overall growth, raising concerns about the sustainability of their development trajectories. This study reassesses the inverted U-shaped relationship proposed by Rowthorn (1995), Palma (2005), and Rodrik (2016), which links industrialization to per capita income growth, from a novel perspective. Its originality lies in testing this relationship through the structural decomposition of labor productivity and average wages as indicators of industry's developmental contribution. Using shift-share techniques, manufacturing is disaggregated by technological intensity and by structural change components (intrasectoral, intersectoral/static, and dynamic structural change). In a second step, panel fixed-effects models evaluate the empirical validity of the inverted-U hypothesis, in dialogue with Rodrik (2016), Tregenna and Andreoni (2020) and Dosi, Riccio, Virgillito (2021). The findings indicate that structural change dynamics were stagnant or declining in both regions, accompanied by a rising relative weight of low-technology sectors. Static structural change expanded, while dynamic structural change weakened, suggesting limited intersectoral reallocation toward more productive activities. Econometric results provide partial evidence of an inverted-U pattern, revealing a declining contribution of manufacturing to development as income rises, though with important regional heterogeneity. The results underscore the need for renewed industrial policies capable of fostering technological upgrading and dynamic capabilities in the context of ongoing techno-productive transformations. Manufacturing remains a critical channel for structural transformation and catching-up in Latin America and Africa.