TEXTO PARA DISCUSSÃO

ISSN 0103-9466

478

Does manufacturing still matter?
The revival of industrial policy and manufacturing´s contribution to development in high and middle-income countries

Antonio Carlos Diegues / Qiuyi Yang /
José Eduardo Roselino / Marcos José Barbieri Ferreira
Renato Garcia

Junho 2025

UNICAMP
Instituto de Economia

Does manufacturing still matter?
The revival of industrial policy and manufacturing’s contribution to development in high and middle-income countries [1]

Antonio Carlos Diegues [2]
Qiuyi Yang [3]
José Eduardo Roselino [4]
Marcos José Barbieri Ferreira [5]
Renato Garcia [6]

Abstract

This paper aims to analyze manufacturing´s contribution to development in high-income (HIC) and middle-income countries (MIC) from 2000 to 2019, by econometrically testing the inverted-U curve hypothesis of Rowthorn (1994), Palma (2005), and Rodrik (2016). The original contribution of the analysis presented in this paper is to test the validity of this relationship for MIC and HIC by examining not the share of manufacturing in GDP (measured by value added), but the contribution of the manufacturing sector to development measured by the structural decomposition of productivity and wage growth. The paper´s main findings are: (i) the results do not indicate a decline in the contribution of manufacturing to development among middle- and high-income countries (MIC and HIC) as they attain higher levels of per capita income. In fact, across nearly all econometric specifications, no evidence of an inverted U-shaped curve was observed between the manufacturing’s contribution to development and per capita income levels, (ii) for high- and medium-tech sectors in MIC, empirical evidence suggests that the manufacturing’s contribution to development increases as per capita income rises above US$8,000, (iii) the higher the tech-intensity, the more important the contribution of manufacturing to development in HIC and MIC. These findings further underscore the central role of industrial and innovation policies as essential components in fostering sustainable growth trajectories, taking into account the heterogeneity of sectors and countries, especially in the context of a techno-productive paradigm shift driven by the imperative to facilitate digital and green transitions.

Keywords: Industrial policy; Manufacturing and development; Structural change; Inverted-U curve; High-income countries; Middle-income countries.

JEL Code: L52; L16; O14; O47.

Data availability statement: The data that support the findings of this study are available in Unido – Indstat 2 2022 – at https://stat.unido.org/database/INDSTAT.

---

(1) All authors are designated as co-first authors.

(2) Associate Professor / Deputy Coordinator for the Undergraduate Program / Coordinator of the Center for Industrial Economics and Technology – Institute of Economics, University of Campinas (Unicamp), Campinas, SP, Brazil. E-mail: diegues@unicamp.br. ORCID: https://orcid.org/0000-0002-4124-666X.

(3) Assistant Professor, Assistant Director of Financial Research Center Fudan Development Institute (FDDI), Fudan University, China. E-mail: yangqiuyi@fudan.edu.cn.

(4) Associate Professor at the Federal University of São Carlos (UFSCar), São Carlos, SP, Brazil. E-mail: jeroselino@ufscar.br. ORCID: https://orcid.org/0000-0001-8066-8024.

(5) Professor at the School of Applied Sciences (Unicamp), Campinas, SP, Brazil. E-mail: marcos.barbieri@fca.unicamp.br. ORCID: https://orcid.org/0000-0001-5792-2231.

(6) Associate Professor at the Institute of Economics (Unicamp), Campinas, SP, Brazil. E-mail: rcgarcia@unicamp.br. ORCID: https://orcid.org/0000-0001-9739-1658.

Resumo

A indústria ainda importa? O renascimento da política industrial e a contribuição da manufatura para o desenvolvimento em países de renda alta e média.

Este artigo tem como objetivo analisar a contribuição da indústria para o desenvolvimento em países de alta renda (PAR) e de renda média (PRM) entre 2000 e 2019, por meio de testes econométricos da hipótese da curva em U invertida de Rowthorn (1994), Palma (2005) e Rodrik (2016). A contribuição original desta análise está em testar a validade dessa relação para PRM e PAR, não examinando a participação da indústria no PIB (medida pelo valor adicionado), mas a contribuição do setor manufatureiro para o desenvolvimento, medida pela decomposição estrutural do crescimento da produtividade e dos salários. As principais conclusões do artigo são: (i) os resultados não indicam um declínio na contribuição da indústria para o desenvolvimento nos países de renda média e alta (PRM e PAR) à medida que alcançam níveis mais elevados de renda per capita. Na verdade, em quase todas as especificações econométricas, não foi encontrada evidência de uma curva em U invertida entre a contribuição da indústria para o desenvolvimento e os níveis de renda per capita; (ii) para os setores de média e alta tecnologia em PRM, as evidências empíricas sugerem que a contribuição da indústria para o desenvolvimento aumenta quando a renda per capita ultrapassa US$ 8.000; (iii) quanto maior a intensidade tecnológica, mais relevante é a contribuição da indústria para o desenvolvimento em PAR e PRM. Esses resultados reforçam ainda mais o papel central das políticas industriais e de inovação como componentes essenciais para promover trajetórias de crescimento sustentável, levando em consideração a heterogeneidade dos setores e países, especialmente no contexto de uma mudança de paradigma tecno-produtivo impulsionada pela necessidade de facilitar as transições digital e verde.

Palavras-chave: Política Industrial; Indústria e Desenvolvimento; Mudança Estrutural; Curva em U invertida; Países de alta renda; Países de renda média.

Section 1. Introduction

The link between changes in productive structures and development has been a central focus in economic literature since List’s (1841) National Systems of Political Economy. This perspective argues that varying productive configurations drive distinct productivity growth patterns and thus shape different modes of international integration (Fagerberg, 1987; Cimoli; Dosi; Stiglitz, 2009; Dosi; Riccio; Virgillito, 2021; 2022; Lee; Malerba, 2017; Hausmann; Hwang; Rodrik, 2007).

Schumpeter (1942) similarly highlighted economic development as driven by creative destruction, which reconfigures productive structures and creates disruptions through the internalization of innovation within capitalist competition. The evolutionary literature links this dynamic to development by promoting Schumpeterian efficiency (Dosi, 1988; Pavitt; Soette, 1990), facilitating structural change towards sectors with higher technological dynamism.

However, evolutionary theory posits that such structural changes do not arise spontaneously. Instead, they depend on innovation policies and national institutional arrangements that promote innovative learning (Dosi, 1982; 1988; Pavitt; Soette, 1990; Nelson; Nelson, 2002). These elements, which align with List’s (1841) ideas, illustrate that national innovation systems play a crucial role (Lundvall, 1992; Nelson, 1993; Freeman, 1995; Malerba; Nelson, 2011).

Based on these foundations, this paper examines the relationship between productive structure and development. Following Schumpeter’s (1942) perspective, development is defined as a process that involves surplus generation, reinvestment, and technological advancement, leading to structural shifts toward high-productivity, high-wage sectors, characterized by creative destruction and reduced socio-regional inequalities (Furtado, 1964).

Dosi (1988) suggests that Kaldor's (1966, 1967) insights enhance development analysis by linking intra-sectoral productivity dynamics with diffusion throughout the productive structure via linkage effects. Kaldor argued that manufacturing plays a central role in development due to its position as a primary site of technical progress, its economies of scale, and its ability to spread productivity gains across sectors.

Based on this perspective, both evolutionary and developmental literature underscore manufacturing's critical role in sustainable growth (Cimoli; Dosi; Stiglitz, 2009; Dosi; Riccio; Virgillito, 2021). Empirical studies using structural decomposition techniques (e.g., Mcmillan; Rodrik, 2011; Haraguchi, 2015; OECD, 1987) show that development correlates with structural changes toward sectors with greater technological complexity, productivity, and wages.

Initially, this structural change would take the form of an increase in the share of manufacturing value-added in GDP and total employment, as suggested by the stylized interpretation of the stages of development presented in the seminal work of Kuznets and Murphy (1966).

Subsequently, at certain levels of per capita income, the share of manufacturing sector in both GDP and total employment would decline, forming an inverted-U curve in the analysis of this relationship. In other words, for countries in the early stages of development, there would be an increase in the importance of manufacturing in their economies. After a certain level of per capita income, this importance would gradually decline as a transition to services would be expected (Rowthorn, 1995; Rowthorn; Ramaswamy, 1997; 1999).

However, the literature on deindustrialization since the 1970s has shown that this inflection in the inverted-U curve did not necessarily occur as a result of natural deindustrialization processes. In other words, these processes would have been accelerated by the set of transformations stemming from the consolidation of global value chains and the consequent shift of productive activities to middle-income countries (MIC), mainly in Asia (Tregenna, 2009, 2016; Andreoni; Tregenna, 2019; Andreoni; Chang, 2019; Chang; Andreoni, 2020; Dosi; Riccio; Virgilitto, 2021). And they would be reinforced by the inability of industrial and innovation policies to restore manufacturing's contribution to development (in high-income countries) and also to avoid premature deindustrialization processes (in MIC) (Chang; Andreoni, 2020; Andreoni; Tregenna, 2020; Botta; Yajima; Porcile, 2023).

In this sense, this paper aims to measure and analyze the contribution of manufacturing to development for high-income countries (HIC) and middle-income countries (MIC) between 2000 and 2019. In empirical terms, the aim is to test the validity of the inverted-U curve hypothesis as expressed by Rowthorn (1994), Palma (2005) and Rodrik (2016). Complementing Dosi, Riccio and Virgillito (2021), this paper empirically measures the evolution of the contribution of manufacturing to development in the context of deindustrialization processes in the international economy. To do this, the paper combines two empirical strategies: the analysis of productivity and wage growth towards shift-share techniques, and the econometric test of this decomposition to verify the validity of the inverted-U curve.

Here, manufacturing's contribution to development is defined empirically as its ability to drive productivity and wage growth within manufacturing sectors through structural shifts toward more technologically complex activities. The analysis focuses on the sectoral composition of manufacturing industries, according to tech-intensity.

The recent international literature on productive structure and development extensively analyzes the definitions and causes of deindustrialization, as well as the changes in international organization of industries. Nonetheless, the literature still lacks empirical efforts to measure how these phenomena affect productive structure´s contribution to economic development.

In other words, *the literature gap* is that although it identifies patterns that relate the behavior of industrialization and deindustrialization movements to the per capita income levels of HIC and MIC, there is no similar effort to identify, analyze, and measure the relationship between transformations in the capacity of manufacturing to contribute to development and the per capita income of countries. This capacity to contribute to long-term development would be the fundamental pillar that justifies the extensive literature on recent transformations in global productive structure, as well as the widespread revival of industrial and innovation policies (Edler; Fagerberg, 2017; Aiginger; Rodrik, 2020; Chang; Andreoni, 2020; Mazzucato; Kattel; Ryan-Collins, 2020; Mazzucato; Rodrik, 2023; Dosi et al., 2023; Juhász; Lane; Rodrik, 2023; Diegues et al., 2023).

Thus, the contribution of the paper is based on the empirical re-evaluation of the inverted U-shaped curve analysis estimated in Rowthorn’s seminal papers which relates the share of manufacturing in GDP to the level of per capita income (Rowthorn, 1995; Rowthorn and Ramaswamy, 1997; 1999). According to this curve, initially, there is an increase in the manufacturing’s share of GDP as per capita income rises. After a certain point, this trend reverses.

The original contribution of the analysis presented in this paper is to test the validity of this relationship for MIC and HIC by examining not the share of manufacturing in GDP (measured by value added), but the contribution of the manufacturing sector to development measured by the structural decomposition of productivity and wage growth. Thus, in line with the literature presented, the growth of industrial productivity and wages would be two variables that would explain the contribution of manufacturing to development.

The hypothesis are: (i) there are heterogeneities in the behavior of this curve according to the technological intensities of the sectors, (ii) this pattern of sectoral heterogeneity is different between HIC and MIC, and iii) as Dosi, Riccio and Virgillito, (2021) and despite the literature that show a stylized relationship in the form of an inverted-U curve when analyzing the share of manufacturing in GDP and the level of per capita income at the national level (Rowthorn, 1994; Palma, 2005 and Rodrik, 2016), when analyzing different sectors according to technological intensities, this relationship does not necessarily hold. This finding can be observed especially when measuring the manufacturing’s ability to increase the economy’s productivity and wages.

This paper is organized into five sections. Section 2 reviews the literature on the relationship between productive structure and development. Section 3 details the methodology and econometric strategy employed. Section 4 presents the empirical findings. Section 5 discusses the evolving challenges and changes in industrial policy amid a renewed focus on manufacturing’s role in development. The concluding section summarizes the findings and their implications.

Section 2: Literature review

2.1 Manufacturing’s contribution to development and the inverted U-curve

Historically, economic literature has highlighted manufacturing’s critical role in driving the development of the nations (List, 1841). Schumpeter (1942) expanded this view by linking development to creative destruction, where production moves toward high-tech activities.

Schumpeter argued that integrating innovation within capitalist competition drives productivity, especially in manufacturing. Studies by Cefis and Marsili (2005) support that such dynamics create firms and sectoral asymmetries, boosting innovation's role in competitive advantage in high-tech industries.

Building on this tradition, development literature empirically supports manufacturing's centrality to growth. Kaldor (1966; 1967) noted that manufacturing drives growth through economies of scale, technical progress, cross-sector linkages, and export potential, which help address external constraints faced by developing economies (Dosi; Riccio; Virgillito, 2022). Rodrik (2016) argued that a virtuous development path involves structural transformation, where labor shifts from low-productivity sectors to those with greater technological sophistication and wages. Initially, this process involves industrializing agrarian economies, followed by a shift to services as income levels rise, leading to a "natural" deindustrialization once certain income thresholds are reached.

Empirical studies by Rowthorn (1994), Palma (2005), and Rodrik (2016) show an inverted-U curve linking manufacturing's GDP share to per capita income. A similar trend is seen in manufacturing employment, indicating that even on a virtuous path, manufacturing's relative importance declines after reaching a certain income threshold, termed natural deindustrialization.

Recent literature, however, highlights limitations in these traditional interpretations (Dosi; Riccio; Virgillito, 2021; Andreoni; Tregenna, 2019; 2020; Chang; Andreoni, 2020). First, new studies reveal high variation in deindustrialization patterns. Evidence shows that since the 2000s, the inverted-U curve has flattened, with deindustrialization occurring at lower manufacturing shares in GDP, employment, and income, indicating premature deindustrialization (Botta, Yajima, and Porcile, 2023). This trend, associated with the technological middle-income trap, hinders MIC from advancing to more sophisticated production and sustaining growth (Dosi; Riccio; Virgillito, 2022).

Secondly, recent analyses of the inverted-U by technological intensity reveal distinct trends. Andreoni and Tregenna (2019) found that while low-tech sectors may follow the inverted-U, high-tech sectors tend to maintain or increase their GDP and employment shares with rising income. In high-tech sectors, the inverted-U is often replaced by an exponential curve, especially in technologically complex industries.

Building on these insights, this paper aims to empirically re-evaluate the inverted-U hypothesis by assessing manufacturing's role in development across income levels in HIC and MIC. This study goes beyond traditional measures of manufacturing's share in GDP and employment to examine links between industrial productivity, wage growth, and per capita income, using productivity and wage growth as proxies for evaluating manufacturing's contribution to development.

2.2 The revival of industrial and policy

The second decade of the 21st century marked a gradual return to industrial and innovation policies, driven by a combination of factors. The 2008 financial crisis revived the debate on industrial policy and development, but the most significant catalyst was the shift in the techno-productive paradigm introduced by Industry 4.0 technologies (robotics, AI, machine learning, data analytics, and 3D printing).

These paradigm shifts and the rise of new Asian economies, particularly China, prompted developed countries, especially the U.S., to re-engage with industrial and innovation policies aimed at maintaining technological leadership through protective measures and advancing the technological frontier (Diegues; Roselino, 2023). U.S. policies since 2017 have emphasized trade protections, safeguarding strategic firms, and restricting critical technology transfers, while also increasing incentives and subsidies for local industries. With the 2020 administration change, U.S. policy became even more aggressive, targeting substantial subsidies to the semiconductor, energy, and infrastructure sectors (House, 2021; Hufbauer; Jung, 2021).

Notably, not only the U.S., but also other developed and emerging economies, have reintroduced industrial and innovation policies. In 2020, the European Commission launched the "New Industrial Strategy," which aims to boost the digital economy, advance energy sustainability, and counter Chinese influence (Tagliapietra; Veugelers, 2023). In other words, the advancement of digitalization – broadening the role of intangible assets as determinants of competitiveness across economic sectors (Ciarli et al., 2021) – and the development of technologies associated with Industry 4.0 must be viewed within a broader geopolitical context. These technologies are not spontaneously generated or developed in a political or institutional vacuum. Instead, they emerge from an intensified Schumpeterian process of firm-level competition, which redefines competitiveness factors and creates new markets (Cefis, 2023).

In this context, the widespread return to industrial and innovation policies has normalized their use. Today, the question is no longer about whether to implement industrial policies but rather about how to design and execute them (Aiginger; Rodrik, 2020). The specific goals and capacities of states to implement these policies vary considerably across nations, resulting in diverse approaches and outcomes (Juhász et al., 2024).

According to an IMF report (Evenett et al., 2024), "strategic competitiveness is the dominant motive governments give for taking action." Yet, a range of recent events unrelated to competitiveness have required industrial and innovation policies. The COVID-19 pandemic demanded an unprecedented coordinated effort in vaccine development and production. It also caused severe disruptions to global supply chains. The Russo-Ukrainian conflict in 2022 underscored the need for robust local production of strategic defense products, leading many European countries to adopt policies aimed at strengthening their defense industrial bases (du Bois; Buts, 2024; Bellais, 2024). Additionally, the surge in extreme weather events has underscored the need for policies that support decarbonization and sustainable development (Anzolin; Lebdioui, 2021).

These complex challenges have necessitated industrial and innovation policies that address interdisciplinary, long-term, and socially relevant goals. Mission-oriented innovation policies (MOIP) have thus gained traction, focusing on social, environmental, and security challenges of the 21st century (Mazzucato, Kattel and Ryan-Collins, 2020 Boon and Edler, 2018; Diegues et al, 2023). Meanwhile, targeted sectoral policies are being reinforced to meet the competitive and geopolitical shifts (Evenett et al., 2024; Chang and Andreoni, 2020). Regardless of model or specific objectives, a clear resurgence in industrial and innovation policies is evident, especially among developed economies, reflecting the ongoing role of industry in driving economic dynamism and wealth creation.

Section 3. Data and methods

3.1 Data

This paper measures and analyzes manufacturing's contribution to development through a structural decomposition of productivity and wages using shift-share techniques, following methodologies established in prior studies by the OECD (1987), Timmer and De Vries (2009), McMillan and Rodrik (2011), Haraguchi (2015), and particularly De Vries, Timmer, and De Vries (2015). Data were sourced from the United Nations Industrial Development Organization (UNIDO) Industrial Statistics database, available at the 2-digit level of the International Classification of Industrial Standards (ISIC – INDSTAT2), which provides detailed information on the manufacturing sector. Additionally, GDP per capita data in current US dollars, adjusted for purchasing power parity (PPP), were obtained from the World Bank DataBank.

Table 1 indicates that the sample includes data from 40 economies, equally divided between HIC and MIC[7]. Country classifications reflect their income group as of the initial year analyzed, 2000. The sample comprises 15 European countries, 10 Asian, 3 each from North America, Latin America, and Africa, and 1 from Oceania. Together, these countries represent 97% of global manufacturing value added in 2019, with HIC contributing 51.1% and MIC 41.8%. Furthermore, the sample accounts for 98% of global manufacturing employment, with 21% from HIC and 57% from MIC. On average, manufacturing value added constitutes 16.05% of GDP in HIC and 16.64% in MIC, offering a representative sample of the global manufacturing sector.

Table 1
HIC and MIC sample, share in world manufacturing value added and employment,
manufacturing value added as proportion of GDP (%), 2019

	Share in world manufacturing value added (%)	**Share in world manufacturing employment (%)**	**Manufacturing value added as proportion of GDP (%)**
High Income Countries			
Australia	0,60%	0,84%	5,60%
Austria	0,60%	1,11%	17,50%
Belgium	0,60%	0,91%	12,30%
Canada	1,60%	0,84%	9,70%
Czechia	0,40%	1,63%	25,30%
Denmark	0,40%	0,81%	14,20%
France	2,30%	0,89%	10,40%
Germany	6,00%	1,19%	20,40%
Italy	2,30%	1,13%	14,90%
Japan	7,70%	1,06%	20,90%
Netherlands	0,70%	0,71%	11,10%
Poland	0,80%	1,41%	17%
Republic of Korea	3,90%	1,08%	26,40%
Singapore	0,60%	0,65%	19,20%
Spain	1,10%	0,90%	11%
Sweden	0,50%	0,81%	13,10%
Switzerland	1,00%	0,89%	19,20%
Taiwan	1,50%	1,57%	31,90%
United Kingdom	1,90%	0,79%	9,10%
United States of America	20,80%	0,86%	11,70%
Total – HIC	**55%**	**21%**	

(7) Due to data limitations, Argentina, Kazakhstan, and Ukraine – formerly among the top 20 MIC manufacturing sectors – were excluded from the sample.

Table 1 – Continuation

Middle Income Countries			
Brazil	1,79%	3,21%	10,30%
China	28,01%	34,76%	27,90%
Colombia	0,24%	0,33%	11,80%
Egypt	0,34%	0,91%	15,30%
India	1,64%	7,4%	14,50%
Indonesia	1,89%	2,9%	20,30%
Iran	0,44%	0,83%	13,90%
Malaysia	0,62%	1,04%	22,20%
Mexico	1,35%	2,02%	17,10%
Morocco	0,13%	0,39%	15%
Oman	0,13%	0,04%	9,50%
Pakistan	0,27%	1,16%	12,10%
Peru	0,24%	0,34%	12,80%
Philippines	0,22%	0,64%	19,40%
Romania	0,19%	0,54%	19%
Russia	1,78%	3,15%	13,20%
South Africa	0,34%	0,54%	12,20%
Thailand	0,74%	1,89%	25,80%
Türkiye	0,70%	1,76%	16,30%
Viet Nam	0,71%	3,51%	24,20%
Total - MIC	**42%**	**67%**	
Total	**97%**	**97%**	

Source: Authors, based on World Bank classification of countries in the first yearof the period – DataBank and UNIDO – SDG 9 Monitoring.

The value-added data were calculated in local currencies and subsequently deflated using the World Bank’s Consumer Price Index for each country (2019 as the base year). Productivity was also calculated in local currencies to neutralize the effects of exchange rate fluctuations on the results, a significant consideration, particularly in MIC, as the paper analyzes productivity changes over a 20-year period. The manufacturing industry is disaggregated into 23 sectors at the 2-digit level of ISIC Rev. 3 and grouped by technological intensity, following the classifications proposed by UNIDO (2010) and Galindo-Rueda and Verger (2016) (Table 2).

Table 2
Sectoral technological classification

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

Source: Andreoni and Tregenna (2019), according to Galindo-Rueda and Verger (2016) and UNIDO (2010).

Thus, labor productivity was measured by the ratio of value added to the employed population in the industrial sectors, while GDP at current PPP USD was measured by the average between 2000 and 2019.

3.2 Shif-share techniques and structural decomposition

This paper uses the shift-share technique, which builds on the approaches of OECD (1987), Timmer and De Vries (2009), McMillan and Rodrik (2011), and Haraguchi (2015), to decompose productivity and wage changes. Using the methodology of De Vries, Timmer, and De Vries (2015), it identifies the contribution of sectoral productivity and wage changes through three components: intrasectoral changes, intersectoral shifts (static structural change), and dynamic structural change. In a virtuous structural transformation, all components should have positive effects, reflecting a shift in the structure of the economy toward sectors with higher productivity and wages.

The model for analyzing productivity change is formally derived as follows, with a similar approach applied to wage change. The only adjustment is to replace labor productivity with average wages as the observed variable.

$T \ = \Sigma$ 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, the paper measures the share of the respective manufacturing sector i in the total number of the employed population in manufacturing:

$$\boldsymbol{S_i} = \frac{\boldsymbol{L_i}}{\boldsymbol{\Sigma\, L_i}} \tag{1}$$

Next, labor productivity is measured by the ratio between the value added and the employees:

$$\boldsymbol{LP_i} = \frac{\boldsymbol{Q_i}}{\boldsymbol{L_i}} \tag{2}$$

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

Differentiating equation 1 in time (from t-k to t, where t>k), we obtain

$$\boldsymbol{LP_t} - \boldsymbol{LP_{t-k}} = \Delta LP_t = \sum_i LPP_{i,t} S_{i,t} - \sum_i LP_{i,t-k} S_{i,t-k} \tag{4}$$

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

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

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

$$\boldsymbol{\frac{\Sigma_{i=1}^{n} LP_{T,by}\left(S_{i,fy} - S_{i,by}\right)}{LP_{T,by}}} \quad \textbf{(6)}$$

I

Equation (6) represents the intersectoral or static component of structural change (Term I). This component captures the contribution of labor reallocation across manufacturing sectors to overall productivity growth. In a development trajectory, employment gradually shifts from low-productivity sectors to those with above-average productivity. This shift increases aggregate labor productivity, thus making the component positive within the development process (McMillan and Rodrik, 2011).

$$\boldsymbol{\frac{\Sigma_{i=1}^{n} \left(LP_{i,fy} - LP_{i,by}\right)\left(S_{i,fy} - S_{i,by}\right)}{LP_{T,by}}} \quad \textbf{(7)}$$

II

Term II, the dynamic component of structural change, is represented by Equation (7) and captures the interaction between changes in labor productivity and shifts in the relative employment shares across all sectors of the economy. This component is essentially the product of productivity levels at the end of the analysis period and the sectoral changes in employment shares. In a virtuous structural transformation process, employment shares are expected to correlate positively with resource reallocation toward industries experiencing rapid productivity growth.

$$\boldsymbol{\frac{\Sigma_{i=1}^{n} \left(LP_{i,fy} - LP_{i,by}\right) S_{i,by}}{LP_{T,by}}} \quad \textbf{(8)}$$

III

Term III (Equation 8), denotes the intra-sectoral component of structural transformation, capturing productivity growth within individual industrial segments primarily through advancements in innovation, scale, or other sector-specific factors. A positive variation in this component is thus anticipated to contribute positively to structural transformation (McMillan and Rodrik, 2011).

3.3 OLS Regression with Robust Standard Errors

This section details the econometric methodology implemented to explore the potential inverse U-shaped relationship between manufacturing productivity and wage growth, as postulated by Rodrik (2016) and Dosi, Riccio and Virgillito (2021), in HIC and MIC. The regression model (9) examines the relationship between manufacturing productivity and wage growth across sectors of varying technological intensity, controlling for GDP per capita and population size:

$$Y_{ij} = \alpha + \beta_1 gdppc_i + \beta_2 (gdppc_i)^2 + \beta_3 pop_i + \epsilon_{ij} \tag{9}$$

Where:

Y_{ij} is the total manufacturing productivity / wage growth structural decomposition according to tech intensity (high tech, medium tech and low tech) and also according to the components of the shift share decomposition presented on previous section (static and dynamic structural changes, intrasectoral, and total structural changes),

j is the tech intensity category for country i.

$gdppc_i$ is natural logarithm of GDP per capita for country i,

$(gdppc_i)^2$ is the squared term of natural logarithm of GDP per capita,

pop_i is the logarithm of the population of country i,

α is the overall intercept,

β_1, β_2, β_3 are the coefficients to be estimated,

and ϵ_{ij} is the error term.

Robust standard errors are used to correct for potential heteroscedasticity, ensuring more reliable hypothesis tests and confidence intervals. To ensure reliable statistical inference, the paper adopts the HC1 type of robust standard error estimator, which provides better finite sample adjustments.

Section 4. Results

4.1 Descriptive statistics

4.1.1 High-income countries

Between 2000 and 2019, productivity in HIC grew by only 31.57%. However, high-tech sectors accounted for nearly two-thirds (65.64%) of these gains (Table 3), underscoring the concentration of economic dynamism within the most advanced technological sectors.

An analysis of HIC productivity growth (Table 3) shows that intra-sectoral components contributed almost entirely (93.84%) to overall productivity increases, while structural changes (static and dynamic) – the reallocation of industrial labor toward higher-productivity sectors – accounted for a modest 6.16%. This suggests that in HIC, where productive structures are consolidated in technologically intensive sectors, productivity growth primarily stemmed from within-sector advances through innovations, economies of scale, or other sector-specific factors (McMillan; Rodrik, 2011).

Table 3
Productivity structural decomposition effects – 2000 to 2019 – High Income Countries

Structural decomposition effects	**Tech intensity**			**Total**	**GDP PPP per-capita (median 2000 to 2019) (USD)**
	High	**Low**	**Medium**		
Structural change (static component)	3,7%	-3,6%	0,8%	1,2%	40522
Intra sectoral component	15,4%	8,7%	5,1%	29,7%	
Structural change (dynamic component)	1,6%	-1,1%	0,2%	0,78%	
Structural decompostion - Total	**20,75%**	**3,97%**	**6,07%**	**31,61%**	

Source: Source: authors, based on Indstat-Unido, World Bank and IMF.

Combining sectoral and structural dimensions, nearly half (48.74%) of HIC productivity growth during the early 21st century arose from intra-sectoral gains within high-tech segments, reinforcing pre-existing structural advantages. Yet, productivity analysis across countries reveals notable variation: while Poland (108.77%) more than doubled its productivity, other countries, such as Canada (-3.39%), Switzerland (-5.64%), and Australia (-12.01%), experienced declines. Notably, the United States had a growth rate of 31.41%, close to the HIC average.

Country-level sectoral distribution of productivity also varies. Most HIC saw productivity gains concentrated in high-tech segments. In absolute terms, Singapore and Taiwan led, with over 50% productivity growth in high-tech sectors during the period. Relatively, Western European countries (Spain, Italy, the Netherlands, Germany, and Austria), along with Japan, demonstrated significant high-tech growth. In contrast, countries like Australia, Switzerland, the United States, and Canada experienced high-tech productivity declines.

For most HIC (12 of 20), high-tech productivity gains occurred through intra-sectoral improvements, consolidating technological strengths within production structures. Spain and Austria, however, achieved high-tech productivity gains primarily through structural change towards more advanced segments. In the United States, Canada, and Australia, intra-sectoral productivity gains focused on medium-tech segments, indicating a regression in their productive structures.

Wage trends further illustrate deindustrialization's impact in HIC (Table 4). Between 2000 and 2019, wages grew by 27.22%, aligning with productivity growth (31.61%), with HIC's average income (GDP PPP per capita) at a high level of $40,522. Approximately 63.19% of wage growth occurred within high-tech segments, mirroring productivity distribution. Structural decomposition reveals that almost all wage gains (94.12%) were due to intra-sectoral enhancements, reinforcing HIC's structural advantages.

Country-specific wage growth, however, showed high variability. Eastern European countries Poland (97.62%) and the Czech Republic (80.78%) recorded wage growth well above average, while Japan (5.66%) and Canada (5.48%) saw minimal increases. Switzerland was unique in experiencing negative wage growth (-11.57%) during this period.

Sectoral analysis reveals wage increases concentrated in high-tech sectors across most HIC. Taiwan (167.59%), the Netherlands (109.57%), and Spain (108.60%) saw high-tech sectors exceed total wage growth, offsetting wage declines in other segments. In the United States and Australia, wage growth was balanced across all segments, while in Sweden and Canada, wage increases were centered in medium-tech segments (43.02% and 113.85%, respectively), reflecting the importance of medium- and low-tech sectors, often related to natural resources, in these economies.

Table 4
Wage structural decomposition effects – 2000 to 2019 – High Income Countries

Structural decomposition effects	**Tech intensity**			**Total**	**GDP PPP per-capita (median 2000 to 2019) (USD)**
	High	**Low**	**Medium**		
Structural change (static component)	3,8%	-3,4%	0,7%	1,2%	40522
Intra sectoral component	12,2%	7,4%	6,0%	25,6%	
Structural change (dynamic component)	1,2%	-1,0%	0,2%	0,45%	
Structural decompostion - Total	**17,20%**	**3,03%**	**6,99%**		

Source: Source: authors, based on Indstat-Unido, World Bank and IMF.

Poland stands out as the only HIC where low-tech segments drove wage growth (41.09%), indicating a less developed productive structure compared to other HIC.

In summary, productivity and wage gains in HIC have been concentrated in high-tech sectors, primarily resulting from intra-sectoral improvements. Despite ongoing deindustrialization, high-tech sectors remain the main drivers of the manufacturing sector in HIC, as supported by recent literature (Andreoni and Tregenna, 2019; Dosi, Riccio, and Virgillito, 2021; 2022).

4.1.2 Middle-income countries

As can be seen in Table 5, productivity gains in the MIC during the period were much more intense than those observed in the HIC, with an overall increase of 80.59%. Significant differences are also observed in terms of sectoral breakdown, with the medium and low-technology sectors explaining more than half of the productivity gains (58.22%).

These data reveal distinct dynamics between the two groups of national economies that certainly arise from the greater relative importance of the less sophisticated sectors in the productive structures of the MIC.

The most successful performance in terms of productivity gains during the period was in China, which achieved an overall increase of over 357%. It is worth noting that this performance was achieved through significant progress in productivity in the three groups of sectors, with the high and medium-tech group accounting for 72.23% of this performance.

Table 5
Productivity structural decomposition effects – 2000 to 2019 – Middle-Income Countries

Structural decomposition effects	Tech intensity			Total	GDP PPP per-capita (median 2000 to 2019) (USD)
	High	**Low**	**Medium**		
Structural change (static component)	6,3%	-5,3%	4,4%	5,5%	12.943
Intra sectoral component	20,3%	24,8%	25,1%	70,2%	
Structural change (dynamic component)	7,0%	-3,2%	1,1%	4,94%	
Structural decompostion – Total	**33,66%**	**16,26%**	**30,67%**	**80,59%**	

Source: authors, based on Indstat-Unido, World Bank and IMF.

As with the HIC, most of the productivity growth is explained by the intra-sectoral component, but in this group a more significant productivity gain is also observed due to structural change (static and dynamic). These data are consistent with the literature on economic development and highlight the more important role played by structural change in the catching-up process of MIC.

While the analysis of general trends yields valuable insights, significant heterogeneity within this group of national economies necessitates highlighting data from specific cases. The most successful performance in terms of productivity gains during the period was in China, which achieved an overall increase of over 357%. It is worth noting that this performance was achieved through significant progress in productivity in the three groups of sectors, with the high and medium technology sectors accounting for 41.07% of this performance.

In addition to China's leadership in productivity gains during the period, other cases should be mentioned in which variations exceeded 100%: Oman (329.99%), Russian Federation (243.12%), Indonesia (191.15%) and Egypt (137.09%).

On the other hand, the negative highlights with the worst performances refer to the Brazilian and Mexican cases, both of which showed an overall change in terms of productivity during the period of -15.61% and -15.19%, respectively. Brazilian industrial activity regressed in terms of productivity in all three groups of sectors, while in the Mexican case the regression in productivity was concentrated in the group of low-technology activities.

The Brazilian and Mexican cases are the most severe among the twenty economies analyzed as part of the MIC, but two other Latin American countries also showed negative performance (Colombia with -4.85% and Peru with -10.74%). In addition to these four Latin American countries, Iran (-0.71%) and Pakistan (-13.06%) also had an overall negative variation in productivity during the period.

There was a significant increase in wages in general terms in MIC, reaching a variation of 97.39% in the period, as can be seen in Table 6. This significant growth occurred at rates higher than those of productivity gains (80.59%), and is also largely explained by gains obtained by the intra-sectoral component. As was observed in the case of HIC, the sectoral breakdown shows that wage increases are concentrated in occupations linked to activities of greater technological complexity, however there are also significant gains in the other sectors.

Table 6
Wage structural decomposition effects – 2000 to 2019 – Middle-Income Countries

Structural decomposition effects	**Tech intensity**			**Total**	**GDP PPP per-capita (median 2000 to 2019) (USD)**
	High	**Low**	**Medium**		
Structural change (static component)	7,0%	-5,6%	3,8%	5,2%	12.943
Intra sectoral component	30,6%	41,1%	20,5%	92,2%	
Structural change (dynamic component)	5,9%	-6,1%	0,2%	0,01%	
Structural decompostion – Total	**43,47%**	**29,47%**	**24,45%**	**97,39%**	

Source: authors, based on Indstat-Unido, World Bank and IMF.

Once again, it is notable that there is significant heterogeneity in the behavior of this variable. Once again, China's performance stands out as the most positive, showing growth of 477.23%. The other countries that have a performance above the group's overall average are: Romania (454.94%), Russian Federation (228.02%), Oman (182.76%), Vietnam (161.40%) and Indonesia (100.88%).

Once again, the cases of Latin American economies stand out as those with the worst performance, and of the four cases in which salaries show negative variation, three are from this region: Peru (-18.23%), Colombia (-11.43%) and Mexico (-6,05%). The other economy that also showed negative variation was Morocco with -5.06%.

The wage variations in this group of countries show a close correlation between the performance of this variable and that of productivity, indicating that the two variables behave coherently as indicators of the economic development process. It should be considered, however, that the variation in wages also presents other determinants besides those directly related to the process of structural change, such as macroeconomic performance and unemployment levels, demographic factors, as well as institutional and political aspects.

4.3 Econometric models

To evaluate manufacturing's contribution to development in HIC and MIC, this paper offers an empirical re-evaluation of the inverted U-shaped curve, originally estimated in Rowthorn's seminal studies, which links manufacturing's GDP share to per capita income levels (Rowthorn, 1995; Rowthorn and Ramaswamy, 1997; 1999). According to this curve, manufacturing's share of GDP initially increases with rising per capita income, but after a threshold, this trend reverses.

This analysis adopts the empirical framework of Rodrik (2016), later extended by Andreoni and Tregenna (2019), which examines the relationship between manufacturing's GDP share and a country's per capita income. Rodrik's (2016) econometric model relates the manufacturing value-added share in GDP (MVA%) and the manufacturing employment share (EMP%) to per capita income (GDP/CAP), with adjustments for population size. The findings reveal a U-shaped curve between manufacturing's GDP share and per capita income, as well as between manufacturing employment share and per capita income.

Andreoni and Tregenna (2019) advanced this model by uncovering sectoral heterogeneity in deindustrialization patterns, identifying cases of premature deindustrialization through variations in the U-shaped curve. They observed that higher technological intensity within manufacturing is associated with reduced concavity in the curve, evolving into a monotonically increasing or convex pattern, especially in high-tech sectors.

Their study highlights that Asian economies like South Korea, Thailand, and China, with greater shares of technology-intensive sectors, have achieved convergence, while industrialized economies such as the United Kingdom, Spain, and Canada have struggled to sustain manufacturing's role in growth. In Latin America, premature deindustrialization remains a pressing issue. Andreoni and Tregenna (2019) suggest that the U-curve hypothesis requires refinement to account for sector-specific technological intensity differences across economies.

This paper addresses this gap by analyzing the limits of manufacturing´s contribution to development, offering an additional perspective on the U-shaped curve model. Using Rodrik's (2016) model as a baseline, 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 MIC and HIC. Unlike previous studies, this paper investigates the structural decomposition of productivity and average wages in manufacturing relative to per capita income.

Thus, it is important to emphasize that the paper examines more than productivity and wage variation in manufacturing. It examines this variation by analyzing the three effects of the shift-share decomposition model presented earlier.

To emphasize this, in the econometric models, the paper further decomposes the productivity and wage variation in manufacturing for MIC and HIC countries into three models:

i. In model 1 Y_{ij} captures static and dynamic structural changes,

ii. In model 2 Y_{ij} measures intrasectoral structural change,

iii. In Model 3 Y_{ij} represents the total effects of all structural changes.

The regression outcomes of manufacturing productivity and wage growth in HIC and MIC are summarized in Table 7.1 to 7.4 and Figure 4.1 to 4.4. The robustness checks, without controlling for natural logarithm of population as well as controlling for natural logarithm of population and its squared term, are detailed in Appendix. From Figures A.1 to A.8, it can be observed that, regardless of whether the natural logarithm of population size and its quadratic term are controlled for, the overall trends remain consistent.

Table 7.1
Regression Results of manufacturing productivity growth according to shift-share structural decomposition for MIC

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-5.273**	-3.271***	1.520***	-4.557*	-2.726	-0.510	-9.753**	-6.001*	1.070
	(1.962)	(0.428)	(0.394)	(2.474)	(3.099)	(3.050)	(4.244)	(2.864)	(2.658)
$(gdppc_i)^2$	0.289**	0.180***	-0.0843***	0.262*	0.169	0.0418	0.547**	0.350**	-0.0457
	(0.105)	(0.0229)	(0.0212)	(0.132)	(0.166)	(0.164)	(0.227)	(0.154)	(0.143)
pop_i	-0.00562	-0.0264	-0.0130	0.128	0.194	0.171*	0.122	0.167	0.156*
	(0.0495)	(0.0318)	(0.0150)	(0.111)	(0.123)	(0.0936)	(0.157)	(0.106)	(0.0792)
Constant	24.19**	15.31***	-6.671***	17.50	7.360	-1.762	41.36*	22.70	-8.669
	(9.313)	(2.116)	(1.822)	(11.80)	(14.52)	(14.20)	(20.14)	(13.42)	(12.38)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.504	0.679	0.502	0.301	0.291	0.245	0.367	0.375	0.273

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7.2
Regression Results of manufacturing wage growth according to shift-share structural decomposition for MIC

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-1.283	-2.471***	2.534***	0.307	-1.292	-2.716	-0.940	-3.766**	-0.150
	(1.305)	(0.449)	(0.519)	(2.865)	(2.041)	(3.329)	(3.731)	(1.716)	(2.839)
$(gdppc_i)^2$	0.0727	0.135***	-0.139***	0.00885	0.0874	0.159	0.0795	0.223**	0.0174
	(0.0691)	(0.0240)	(0.0276)	(0.151)	(0.108)	(0.176)	(0.197)	(0.0907)	(0.150)
pop_i	0.0167	-0.0256	-0.00324	0.220	0.137	0.108	0.236	0.111	0.106
	(0.0530)	(0.0260)	(0.0243)	(0.161)	(0.116)	(0.164)	(0.211)	(0.0940)	(0.140)
Constant	5.444	11.74***	-11.52***	-7.322	2.144	9.944	-2.016	13.90*	-1.762
	(6.143)	(2.161)	(2.347)	(13.05)	(9.513)	(15.10)	(17.03)	(7.935)	(12.87)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.080	0.687	0.511	0.214	0.231	0.064	0.169	0.358	0.061

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7.3
Regression Results of manufacturing productivity growth according to shift-share structural decomposition for HIC

	Model 1			Model 2			Model 3		
	hightech	mediumtech	lowtech	hightech	mediumtech	Lowtech	hightech	mediumtech	lowtech
$gdppc_i$	-0.242	4.024***	-4.176**	-12.07**	-7.072**	-12.31***	-12.38*	-2.988	-16.21***
	(2.174)	(0.672)	(1.517)	(4.688)	(3.051)	(3.587)	(6.034)	(3.094)	(4.001)
$(gdppc_i)^2$	0.00701	-0.190***	0.202**	0.573**	0.325**	0.570***	0.583*	0.132	0.760***
	(0.102)	(0.0322)	(0.0715)	(0.225)	(0.145)	(0.171)	(0.287)	(0.148)	(0.189)
pop_i	-0.0220	-0.00601	0.0193	-0.0208	-0.00148	-0.0177	-0.0436	-0.00780	0.000729
	(0.0127)	(0.00678)	(0.0129)	(0.0287)	(0.0164)	(0.0305)	(0.0344)	(0.0228)	(0.0245)
Constant	2.203	-21.17***	21.19**	64.09**	38.48**	66.73***	66.67*	17.00	86.50***
	(11.51)	(3.429)	(7.989)	(24.43)	(15.94)	(18.47)	(31.69)	(16.02)	(20.99)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.182	0.425	0.320	0.242	0.572	0.579	0.231	0.348	0.624

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

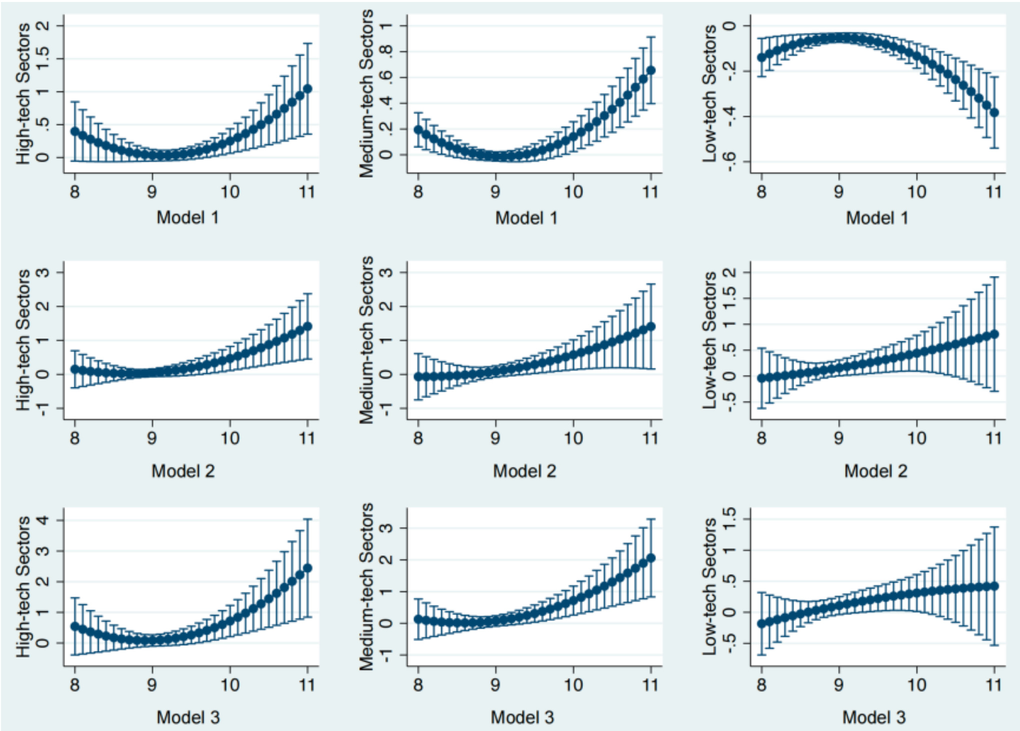
Table 7.4
Regression Results of manufacturing wage growth according to shift-share structural decomposition for HIC

	Model 1			Model 2			Model 3		
	hightech	mediumtech	lowtech	hightech	mediumtech	Lowtech	hightech	mediumtech	lowtech
$gdppc_i$	-0.480	4.229***	-3.086	-6.890**	-4.901***	-7.769***	-7.548	-0.697	-10.81***
	(2.435)	(0.659)	(1.826)	(2.802)	(0.710)	(1.519)	(4.708)	(1.225)	(2.709)
$(gdppc_i)^2$	0.0177	-0.201***	0.151*	0.315**	0.223***	0.354***	0.341	0.0228	0.502***
	(0.114)	(0.0317)	(0.0857)	(0.134)	(0.0342)	(0.0732)	(0.222)	(0.0591)	(0.127)
pop_i	-0.0135	-0.00478	0.0157	-0.0172	-0.0157*	-0.0153	-0.0306	-0.0215	0.00173
	(0.0130)	(0.00713)	(0.0128)	(0.0165)	(0.00896)	(0.0186)	(0.0230)	(0.0158)	(0.0146)
Constant	3.371	-22.15***	15.45	38.05**	27.25***	42.92***	42.37	5.256	58.11***
	(12.96)	(3.343)	(9.689)	(14.65)	(3.603)	(7.681)	(24.93)	(6.152)	(14.33)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.178	0.420	0.257	0.375	0.765	0.773	0.408	0.516	0.639

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

From Table 7.1 – 7.4, the following findings can be derived: First, structural change decomposition effects on per capita GDP are generally significant for both MIC and HIC, whether measured by productivity or wage. Second, for MIC, productivity and wage growth driven by static and dynamic changes (Model 1) are more significant than those driven by intrasectoral changes (Model 2), while HIC show more balanced effects across all decomposition components. Third, if we further examine the medium-tech column across all tables, it consistently shows a high level of significance. This suggests that, for both HIC and MIC, the medium-tech sector has a strong relationship between per capita income and manufacturing's contribution to development. It is a crucial and solid sector that cannot be overlooked.

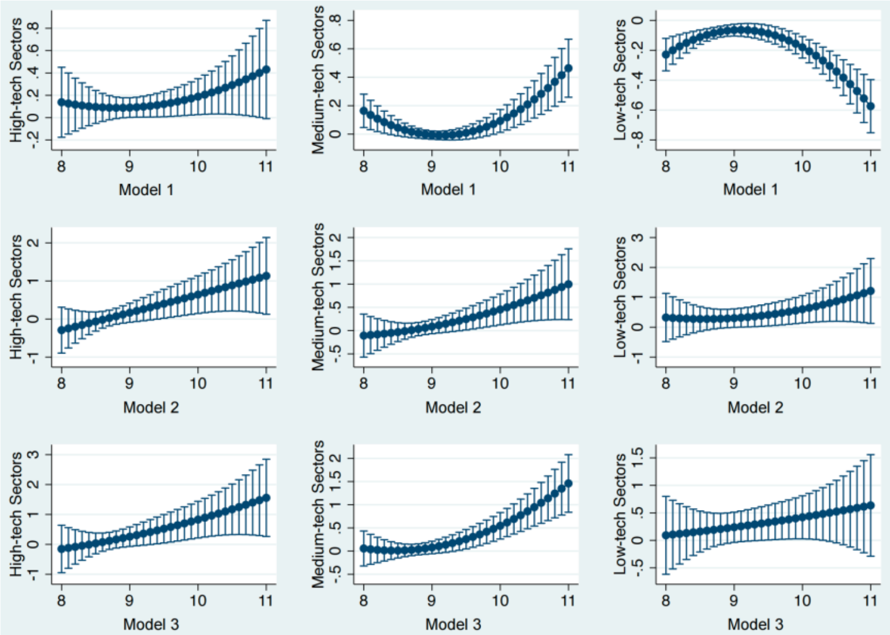
Figure 4.1
Econometric estimation of the relationship between productivity growth in the manufacturing sector according to the shift-share structural decomposition for the MIC



Source: Drawn by the authors using Stata 15.

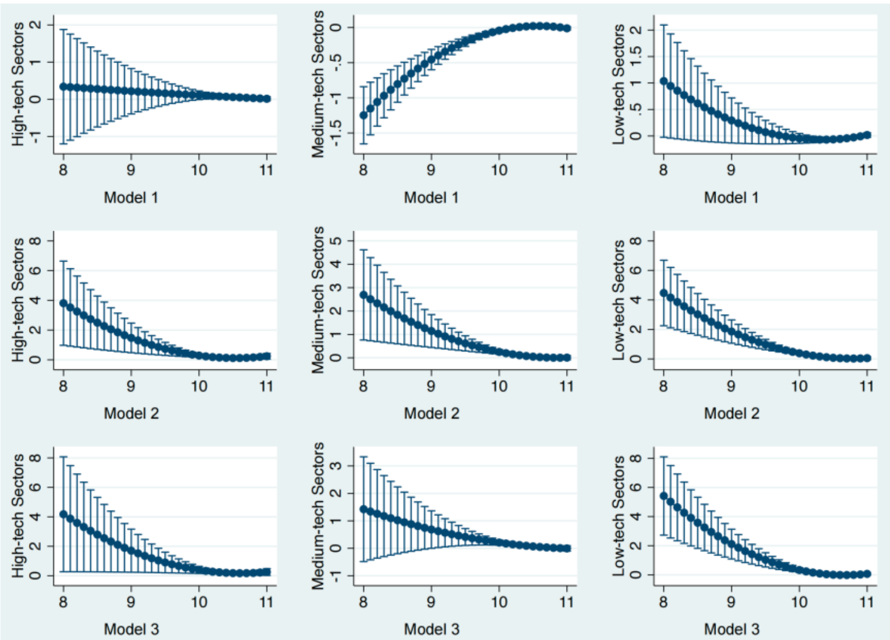
Notes: In accordance with Stata's default settings, ln(pop) is held constant at the mean value across all observations in the sample when drawing the figure. The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure 4.2
Econometric estimation of the relationship between wage growth in the manufacturing sector according to the shift-share structural decomposition for the MIC



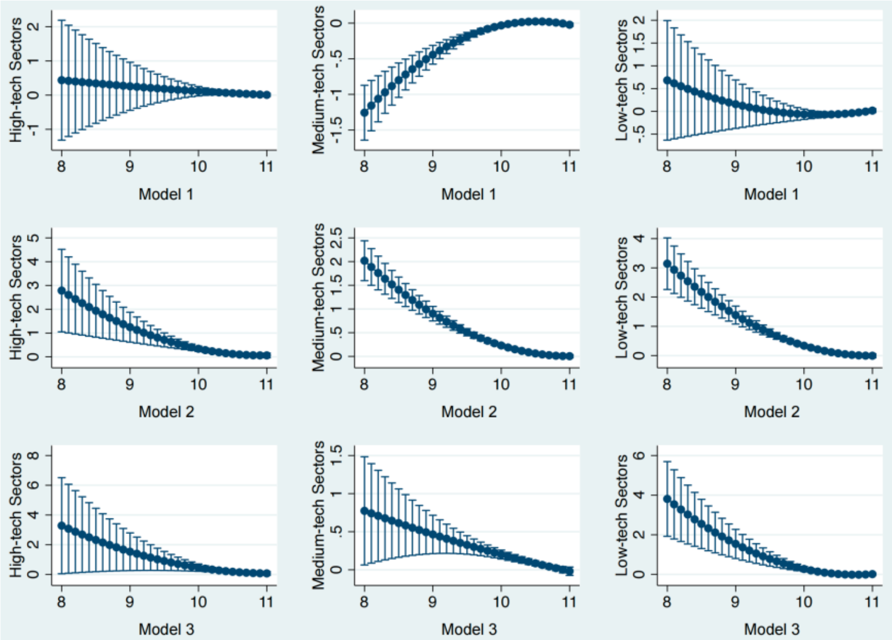
Source: Drawn by the authors using Stata 15.
Notes: In accordance with Stata's default settings, ln(pop) is held constant at the mean value across all observations in the sample when drawing the figure. The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure 4.3
Econometric estimation of the relationship between productivity growth in the manufacturing sector according to the shift-share structural decomposition for the HIC



Source: Drawn by the authors using Stata 15.
Notes: In accordance with Stata's default settings, ln(pop) is held constant at the mean value across all observations in the sample when drawing the figure. The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure 4.4
Econometric estimation of the relationship between wage growth in the manufacturing sector according to the shift-share structural decomposition for the HIC



Source: Drawn by the authors using Stata 15.
Notes: In accordance with Stata's default settings, ln(pop) is held constant at the mean value across all observations in the sample when drawing the figure. The horizontal axes in all nine subplots are GDP per capita (in logarithm).

The graphs presented in Figure 4.1 to 4.4 illustrate the predictive margins with 95% confidence intervals for the relationship between GDP per capita and manufacturing productivity and wage growth for MIC and for HIC respectively. In each figure, the structural change decomposition effects are arranged by rows (Model 1-3), while the different levels of technology intensity are arranged by columns.

Figures 4.1 to 4.4 do not show a consistent inverted U-shaped relationship between the contribution of manufacturing to development and GDP per capita in all models. On the contrary, the contribution of manufacturing to development generally declines and then increases as GDP per capita rises, although there are some exceptions and less strictly U-shaped relationships.

First, in low-tech sectors of MIC and medium-tech sectors of HIC, as GDP per capita increases, the contribution of sectoral productivity and wage changes through intersectoral shifts (static and dynamic structural changes) exhibits an inverse U-shaped relationship, initially increasing and then decreasing.

Second, in MIC, the contribution of sectoral productivity and wage changes through intrasectoral shifts shows a relatively flat, monotonically increasing trend, particularly in low-tech sectors.

Third, for HIC, the contribution of manufacturing to development generally shows only the first half of a U-shape, indicating a monotonically decreasing trend as GDP per capita increases. This decline is more moderate in high-tech sectors.

5 Discussion and conclusions: new challenges and the changes in the nature of industrial policy

This paper examines the role of manufacturing in economic development and the implications of this diagnosis for structuring industrial and innovation policies, considering the profound transformations in global industrial production over recent decades.

The structural changes observed across different country groups – which define manufacturing's role in driving productivity gains and wage increases–reflect national trajectories shaped by domestic factors. However, these trajectories are also deeply influenced by external forces, notably the significant shifts in industrial activity, particularly in sectors dominated by large global corporations.

These shifts are multifaceted, combining determinants across various dimensions, from technological advancements (such as digitalization and the emergence of Industry 4.0) to value chain governance led by multinational corporations, and extending to geopolitical factors, such as the resurgence of techno-nationalist policies in developed economies in response to China's ascent.

Within this context, there has been a resurgence of techno-nationalist industrial policy initiatives among central economies, aiming to reestablish historical hierarchies of productive and technological superiority. This dynamic and uncertain global landscape presents complex challenges for MIC and also HIC. The diversity of development trajectories among these economies in recent decades illustrates, as Primi and Toselli (2020) argue, that economic advancement does not result automatically from passive integration into global value chains. Successful integration into global markets requires a combination of institutions, instruments, and national policy strategies that progressively build local firms' capabilities.

From this perspective, the paper's empirical findings identify several key patterns in manufacturing's contribution to development in HIC and MIC between 2000 and 2019, with the main patterns being:

i. Contrary to the prevailing literature, which interprets deindustrialization as a natural and positive outcome of economic development (Rowthorn, 1995; Rowthorn and Ramaswamy, 1997, 1999), the findings do not indicate a decline in the contribution of manufacturing to development among MIC and HIC as they attain higher levels of per capita income. In fact, across nearly all econometric specifications outlined in Section 4, as well as in the robustness tests provided in the Appendix, no evidence of an inverted U-shaped curve was observed between the manufacturing's contribution to development and per capita income levels (excepts in low-tech sectors for MIC).

ii. In the MIC, empirical findings show that productivity outcomes demonstrate the highest levels of coefficient significance (Model 1 focused on the effects of structural change). Despite some variability across other models, the behavioral pattern of the variables remains largely consistent. This consistency suggests a relationship in high- and medium-tech sectors characterized by a very subtle U-shaped curve at income levels between $4,000 and $8,000, which then shifts into a positive exponential curve as income levels exceed this range. Thus, paper´s empirical evidence points to an increase in the manufacturing's contribution to development as per capita income rises. Conversely, in low-tech sectors, the trend inverts: as income rises, their contribution to development diminishes, indicating a structural change within MIC toward more technologically intensive sectors. Notably, these productivity curve patterns closely mirror those observed in the relationship between wage growth and per capita income levels within MIC.

iii. Regarding the HIC, the main empirical findings show that, contrary to what can be inferred from the interpretations of normal or positive deindustrialization, no inverted-U curve is observed regarding the behavior of productivity or wages. In general, 8 of the 9 curves relating productivity growth to per capita income show very similar behavior: an initial decline in the rate of productivity growth as income rises from $20,000 to $35,000, followed by a virtual stability of this rate beyond this level. The main exception is the curve measuring productivity growth (for medium-tech sectors). Due to structural change, it shows an exponential growth trend as the level of per capita income rises. It is noticeable that the pattern of behavior of the curves with respect to wages is exactly the same as that observed in the analysis of productivity. The difference is that the decline in its growth rate is more intense. It is worth noting that in the HIC the component contributing most to wage growth is intra-sectoral, whereas in the MIC the variation in wages is explained more by the effects of structural change. Therefore, wage growth is driven more by intra-sectoral dynamics than by the reallocation of labor to more technologically intensive sectors, as expected especially for countries closer to the technological frontier

Empirical findings of these patterns of manufacturing's contribution to development highlight the importance of tailoring industrial policies to account for the diverse dynamics across sectors and countries.

These findings further underscore the central role of industrial and innovation policies as essential components in fostering sustainable growth trajectories. As the shift towards a techno-productive paradigm - driven by the need to facilitate digital and green transitions - has redefined the structure of manufacturing activities and their innovation dynamics, the paper argues for the need to reconceptualize industrial and innovation policies to meet the challenges of the transition.

In this evolving landscape, scholars are increasingly acknowledging the critical role of these policies in economic development, especially given the influence of new technologies and the importance of manufacturing (Edler and Fagerberg, 2017; Boon and Edler, 2018; Cefis et al., 2023; Ciarli et al., 2021; Diegues et al, 2023). New technologies, such as artificial intelligence, robotics, and additive manufacturing, has profoundly reshaped manufacturing and services. As a consequence, digitalization and automation in manufacturing open up new opportunities, especially through enabling greater mass customization and manufacturing efficiency, with important impacts on the transformation of global production chains (Gerreffi, 2019; Rodrik, 2018).

These technologies not only present fresh avenues for economic growth but also pose challenges that require targeted industrial policies. In particular, new technologies require policies that promote interactive learning and new productive capacity building in a comprehensive way, establishing a robust economic ecosystem that can support innovation while addressing social and sustainability goals.

Industrial and innovation policies, therefore, must create incentives to strengthen the competitiveness of domestic industries in a sustainable way. These challenges are particularly pronounced in MIC, where the risk of an increasing technological gap with HIC is more acute. In this context, policies must encourage the integration of digital technologies and the strengthening of local capacities.

For manufacturing to fully contribute to economic development, it is crucial that industrial and innovation policies actively promote learning within production practices. One key aspect of these policies involves the workforce qualification and retraining, preparing workers for the evolving new technological demands. This approach not only facilitates firms' adoption of new technologies but also strengthens economic resilience, reducing the risk of industry-specific or regional downturns. The increasing demand for customized products and services is a powerful driver of "learning by doing" and "learning by using", favoring the development of new products and technologies.

In MIC, this learning dynamic can promote the formation of clusters of firms, where local producers and suppliers benefit from geographical proximity to share knowledge and foster innovation. Sustainability is another essential focus for innovation policy. With technologies like IoT and big data, resource use can be optimized, waste reduced, and energy efficiency improved. Addressing sustainability requires that industrial and innovation policies incorporate responsible practices, offering incentives for clean technologies and establishing regulations for resource use.

Moreover, the rapidly evolving nature of modern manufacturing demands flexible policies that can quickly respond to technological changes and adapt to shifting market requirements. Effective policies combines measures to expand manufacturing capabilities and strengthen local firms with strategies for knowledge development, such as workforce training and consulting services for small and medium enterprises. This approach not only reinforces local capabilities but also supports ongoing learning within sectoral industries.

In short, the role of industrial and innovation policies in a context of recognition of the role and importance of manufacturing is essential to promote inclusive and sustainable economic growth. Learning within production, the development of local capabilities, and sustainability are pillars of effective these policies. Successful policies must connect innovation to manufacturing capacities, encouraging government and private sector collaboration to strengthen the industrial ecosystem. With such alignment, industrial policies can become robust tools for building the dynamic capabilities needed for a modern economy.

References

AIGINGER, K.; RODRIK, D. Rebirth of industrial policy and an agenda for the twenty-first century. *Journal of Industry, Competition and Trade*, v. 20, p. 189-207, 2020.

ANDREONI, A.; CHANG, H.-J. The political economy of industrial policy: structural interdependencies, policy alignment and conflict management. *Structural Change and Economic Dynamics*, v. 48, p. 136-150, 2019.

ANDREONI, A.; TREGENNA, F. Beyond the inverted U: the changing nature and structural heterogeneity of premature de-industrialisation. In: INTERNATIONAL WORKSHOP: THE FUTURE OF INDUSTRIAL WORK: NEW PATHWAYS AND POLICIES OF STRUCTURAL TRANSFORMATION, Viena, 2019.

ANDREONI, A.; TREGENNA, F. Escaping the middle-income technology trap: a comparative analysis of industrial policies in China, Brazil and South Africa. *Structural Change and Economic Dynamics*, v. 54, p. 324-340, 2020.

ANZOLIN, G.; LEBDIOUI, A. Three dimensions of green industrial policy in the context of climate change and sustainable development. *The European Journal of Development Research*, v. 33, n. 2, p. 371-405, 2021.

BELLAIS, R. Market structures, competition and innovation: grounds for an alternative defence industrial policy. *Defence and Peace Economics*, v. 35, n. 4, p. 448-463, 2024.

BOIS, C. D.; BUTS, C. Introduction to the special issue 'Spend more and better'. *Defence and Peace Economics*, v. 35, n. 4, p. 401-403, 2024.

BOON, W.; EDLER, J. Demand, challenges, and innovation: making sense of new trends in innovation policy. *Science and Public Policy*, v. 45, n. 4, p. 435-447, 2018.

BOTTA, A.; YAJIMA, G. T.; PORCILE, G. Structural change, productive development, and capital flows: does financial "bonanza" cause premature deindustrialization? *Industrial and Corporate Change*, v. 32, n. 2, p. 433-473, 2023.

CEFIS, E.; LEONCINI, R.; MARENGO, L.; MONTRESOR, S. Firms and innovation in the new industrial paradigm of the digital transformation. *Industry and Innovation*, v. 30, n. 1, p. 1-16, 2023.

CEFIS, E.; MARSILI, O. A matter of life and death: innovation and firm survival. *Industrial and Corporate Change*, v. 14, n. 6, p. 1167-1192, 2005.

CHANG, H.; ANDREONI, A. Industrial policy in the 21st century. *Development and Change*, v. 51, n. 2, p. 324-351, 2020.

CIARLI, T. et al. Digital technologies, innovation, and skills: emerging trajectories and challenges. *Research Policy*, v. 50, n. 7, 104289, 2021.

CIMOLI, M.; DOSI, G.; STIGLITZ, J. E. *Industrial policy and development*: the political economy of capabilities accumulation. New York: Oxford, 2009. p. 113-137.

DE VRIES, G.; TIMMER, M.; DE VRIES, K. Structural transformation in Africa: static gains, dynamic losses. *The Journal of Development Studies*, v. 51, n. 6, p. 674-688, 2015.

DIEGUES, A. C.; ROSELINO, J. E. Industrial policy, techno-nationalism and Industry 4.0: China-USA technology war. *Brazilian Journal of Political Economy*, v. 43, p. 5-25, 2023.

DIEGUES, A. C. et al. The renewal of the debate on industrial policy: limitations and suggestion for a normative typology based on the dialogue between neo-schumpeterians and developmentalists. *Revista de Economia Contemporânea*, v. 27, e232723, 2023.

DOSI, G. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy*, v. 11, n. 3, p. 147-162, 1982.

DOSI, G. *Technical change and economic theory*. [S.l.]: [s.n.], 1988.

DOSI, G.; PAVITT, K.; SOETE, L. The economics of technical change and international trade. *LEM Book Series*, 1990.

DOSI, G.; RICCIO, F.; VIRGILLITO, M. E. Varieties of deindustrialization and patterns of diversification: why microchips are not potato chips. *Structural Change and Economic Dynamics*, v. 57, p. 182-202, 2021.

DOSI, G.; RICCIO, F.; VIRGILLITO, M. E. Specialize or diversify? And in what? Trade composition, quality of specialization, and persistent growth. *Industrial and Corporate Change*, v. 31, n. 2, p. 301-337, 2022.

DOSI, G. et al. Mission-oriented policies and the "entrepreneurial state" at work: an agent-based exploration. *Journal of Economic Dynamics and Control*, v. 151, 104650, 2023.

EDLER, J.; FAGERBERG, J. Innovation policy: what, why, and how. *Oxford Review of Economic Policy*, v. 33, n. 1, p. 2-23, 2017.

EVENETT, S. et al. The return of industrial policy in data. *The World Economy*, v. 47, n. 7, p. 2762-2788, 2024.

FAGERBERG, J. A technology gap approach to why growth rates differ. *Research Policy*, v. 16, n. 2-4, p. 87-99, 1987.

FREEMAN, C. The 'national system of innovation' in historical perspective. *Cambridge Journal of Economics*, v. 19, n. 1, p. 5-24, 1995.

FURTADO, C. *Development and underdevelopment*: a structural view of the problems of developed and underdeveloped countries. Berkeley: University of California Press, 1964.

GALINDO-RUEDA, F.; VERGER, F. OECD taxonomy of economic activities based on R&D intensity. *OECD Science, Technology and Industry Working Papers*, n. 4, Paris: OECD Publishing, 2016.

GEREFFI, G. Global value chains and international development policy: bringing firms, networks and policy-engaged scholarship back in. *Journal of International Business Policy*, v. 2, p. 195-210, 2019.

HARAGUCHI, N. Patterns of structural change and manufacturing development. In: ROUTLEDGE Handbook of Industry and Development. London: Routledge, 2015. p. 38-64.

HAUSMANN, R.; HWANG, J.; RODRIK, D. What you export matters. *Journal of Economic Growth*, v. 12, p. 1-25, 2007.

HOUSE, W. *Building resilient supply chains, revitalizing American manufacturing, and fostering broad-based growth*: 100-day reviews under Executive Order 14017. Washington, D.C.: The White House, 2021.

HUFBAUER, G. C.; JUNG, E. *Scoring 50 years of US industrial policy, 1970-2020*. Washington, D.C.: Peterson Institute for International Economics, 2021.

JUHÁSZ, R.; LANE, N.; RODRIK, D. The new economics of industrial policy. *Annual Review of Economics*, v. 16, 2023.

KALDOR, N. *Causes of the slow rate of economic growth of the United Kingdom*. Cambridge: Cambridge University Press, 1966.

KALDOR, N. Problems of industrialization in underdeveloped countries. In: STRATEGIC factors in economic development. Ithaca: Cornell University Press, 1967. p. 53-72.

KUZNETS, S.; MURPHY, J. T. *Modern economic growth*: rate, structure, and spread. New Haven: Yale University Press, 1966. v. 2.

LEE, K.; MALERBA, F. Catch-up cycles and changes in industrial leadership: windows of opportunity and responses of firms and countries in the evolution of sectoral systems. *Research Policy*, v. 46, n. 2, p. 338-351, 2017.

LIST, F. *Das nationale System der politischen Oekonomie*. Stuttgart/Tübingen: J. G. Cotta'scher Verlag, 1841.

LUNDVALL, B. A. *National systems of innovation: towards a theory of innovation and interactive learning*. London: Francis Printer, 1992.

MALERBA, F.; LEE, K. An evolutionary perspective on economic catch-up by latecomers. *Industrial and Corporate Change*, v. 30, n. 4, p. 986-1010, 2021.

MALERBA, F.; NELSON, R. Learning and catching up in different sectoral systems: evidence from six industries. *Industrial and Corporate Change*, v. 20, n. 6, p. 1645-1675, 2011.

MAZZUCATO, M.; KATTEL, R.; RYAN-COLLINS, J. Challenge-driven innovation policy: towards a new policy toolkit. *Journal of Industry, Competition and Trade*, v. 20, p. 421-437, 2020.

MAZZUCATO, M.; RODRIK, D. Industrial policy with conditionalities: a taxonomy and sample cases. *UCL Institute for Innovation and Public Purpose IIPP Working Paper Series*, v. 7, 2023.

MCMILLAN, M. S.; RODRIK, D. Globalization, structural change and productivity growth. *NBER Working Paper*, n. 17143, 2011.

NELSON, R. R. *National innovation systems*: a comparative analysis. Oxford: Oxford University Press, 1993.

NELSON, R. R.; NELSON, K. Technology, institutions, and innovation systems. *Research Policy*, v. 31, n. 2, p. 265-272, 2002.

OECD. *Structural adjustment and economic performance*. Paris; Washington, D.C.: OECD Publications and Information Centre, 1987.

PALMA, G. Four sources of de-industrialisation and a new concept of the Dutch Disease. *Beyond Reforms: Structural Dynamics and Macroeconomic Vulnerability*, v. 3, n. 5, p. 71-116, 2005.

PRIMI, A.; TOSELLI, M. A global perspective on industry 4.0 and development: new gaps or opportunities to leapfrog? *Journal of Economic Policy Reform*, v. 23, n. 4, p. 371-389, 2020.

RODRIK, D. Premature deindustrialization. *Journal of Economic Growth*, v. 21, p. 1-33, 2016.

RODRIK, D. New technologies, global value chains, and developing economies. *NBER Working Paper*, n. 25164, 2018.

ROWTHORN, B. *Korea at the cross-roads*. ESRC Centre for Business Research, University of Cambridge, 1995.

ROWTHORN, R.; RAMASWAMY, R. Growth, trade, and deindustrialization. *IMF Staff Papers*, v. 46, n. 1, p. 18-41, 1999.

ROWTHORN, R. E.; RAMASWAMY, R. Deindustrialization: causes and implications. *IMF Working Paper*, n. 97/42, 1997.

SCHUMPETER, J. A. *Capitalism, socialism, and democracy*. Urbana-Champaign: University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship, 1942.

TAGLIAPIETRA, S.; VEUGELERS, R. Industrial policy in Europe: past and future. *Sparking Europe's New Industrial Revolution*, p. 12, 2023.

TIMMER, M. P.; DE VRIES, G. J. Structural change and growth accelerations in Asia and Latin America: a new sectoral data set. *Cliometrica*, v. 3, p. 165-190, 2009.

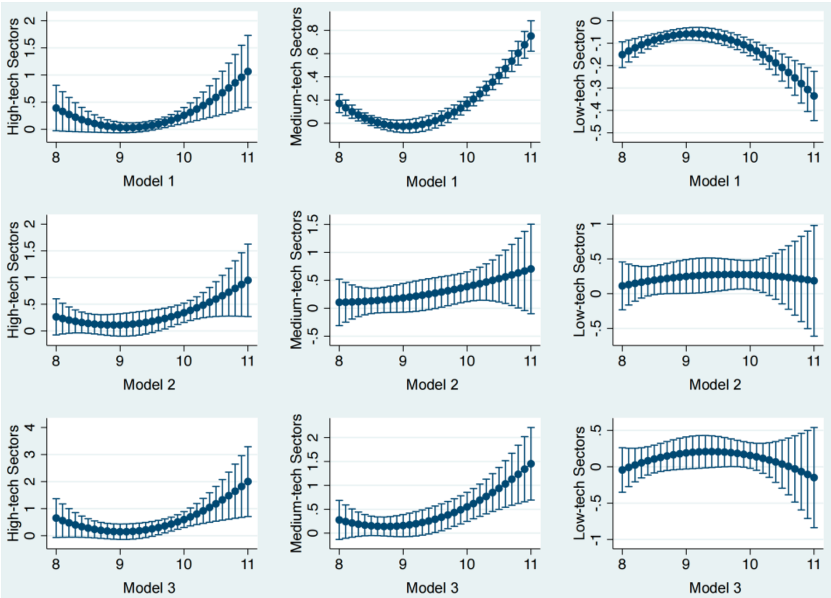
TREGENNA, F. Characterizing deindustrialisation: an analysis of changes in manufacturing employment and output internationally. *Cambridge Journal of Economics*, v. 33, n. 3, p. 433-466, 2009.

TREGENNA, F. Deindustrialization and premature deindustrialization. In: GHOSH, J.; KATTEL, R.; REINERT, E. (Org.). *Handbook of alternative theories of economic development*. Cheltenham, UK; Northampton, USA: Edward Elgar, 2016.

UNIDO. *Industrial statistics*: guidelines and methodology. Vienna: United Nations Industrial Development Organization, 2010.

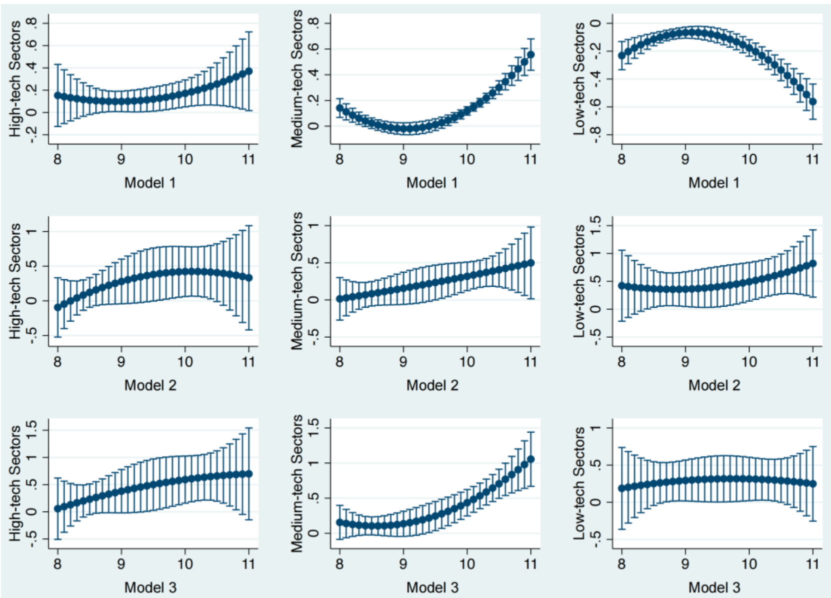
Appendix Figures

Figure A.1
Econometric estimation of the relationship between productivity growth in the manufacturing sector according to the shift-share structural decomposition for the MIC without controlling for natural logarithm of population



Source: Drawn by the authors using Stata 15.
Notes: The horizontal axes in all nine subplots are GDP per capita (in logarithm).

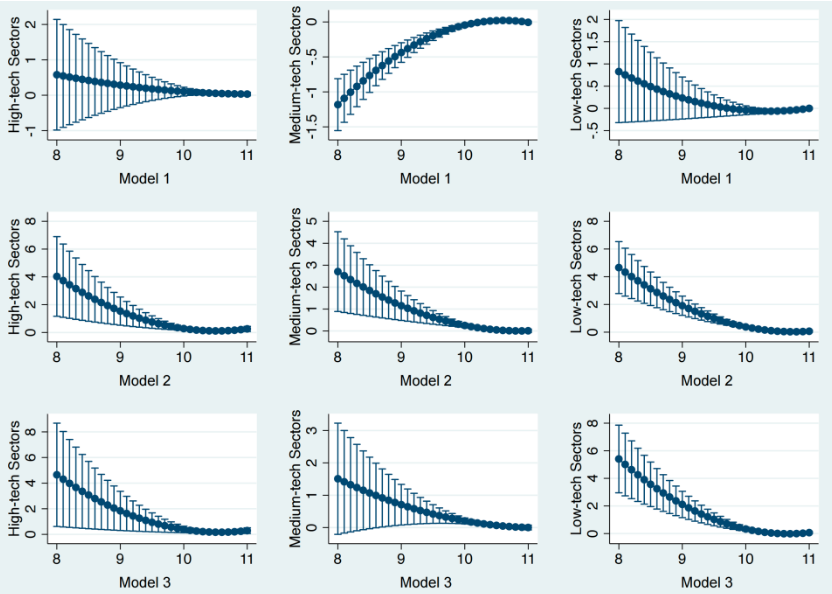
Figure A.2
Econometric estimation of the relationship between wage growth in the manufacturing sector according to the shift-share structural decomposition for the MIC without controlling for natural logarithm of population



Source: Drawn by the authors using Stata 15.
Notes: The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure A.3

Econometric estimation of the relationship between productivity growth in the manufacturing sector according to the shift-share structural decomposition for the HIC without controlling for natural logarithm of population

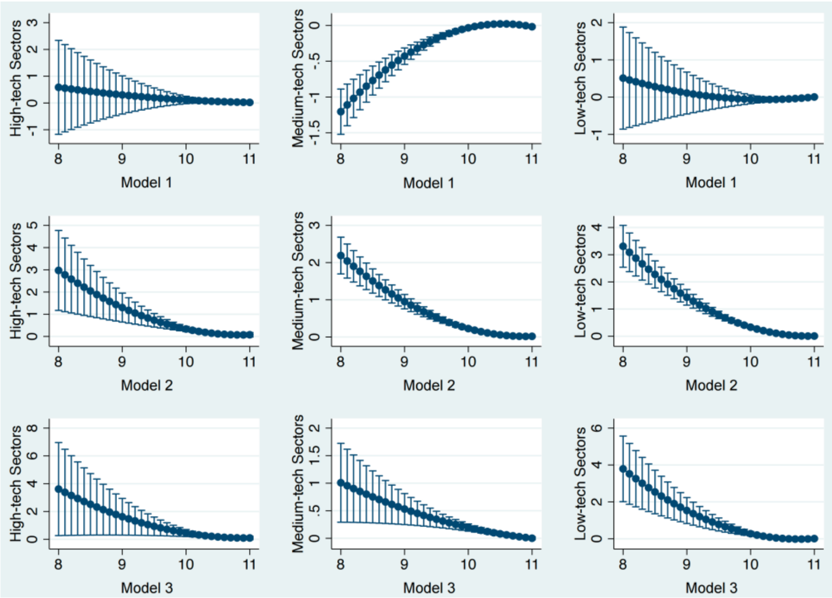


Source: Drawn by the authors using Stata 15.

Notes: The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure A.4

Econometric estimation of the relationship between wage growth in the manufacturing sector according to the shift-share structural decomposition for the HIC without controlling for natural logarithm of population

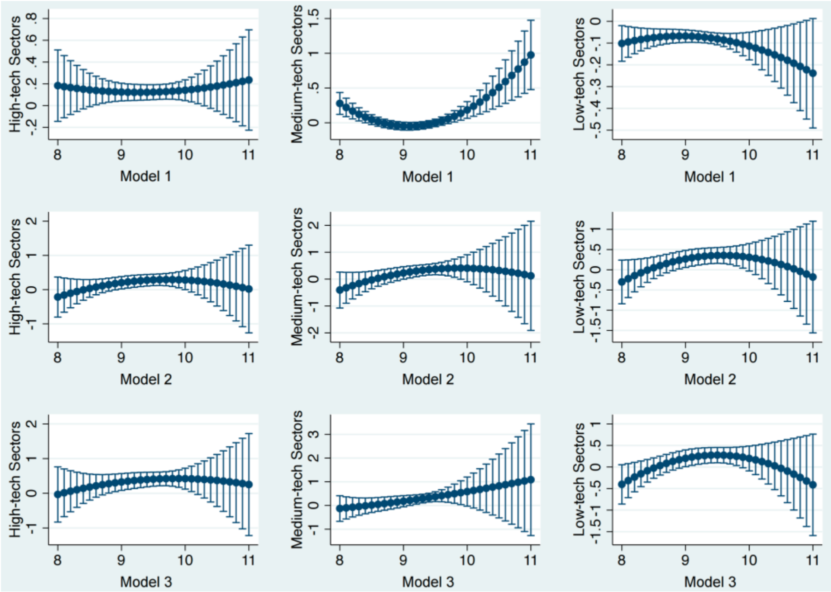


Source: Drawn by the authors using Stata 15.

Notes: The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure A.5

Econometric estimation of the relationship between productivity growth in the manufacturing sector according to the shift-share structural decomposition for the MIC controlling for natural logarithm of population and its squared term

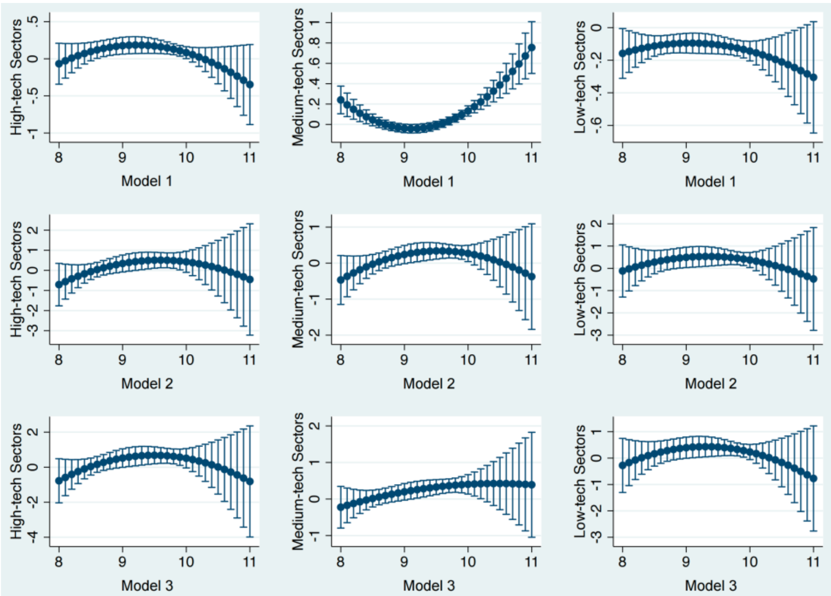


Source: Drawn by the authors using Stata 15.

Notes: In accordance with Stata's default settings, ln(pop) is held constant at the mean value across all observations in the sample when drawing the figure. The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure A.6

Econometric estimation of the relationship between wage growth in the manufacturing sector according to the shift-share structural decomposition for the MIC controlling for natural logarithm of population and its squared term

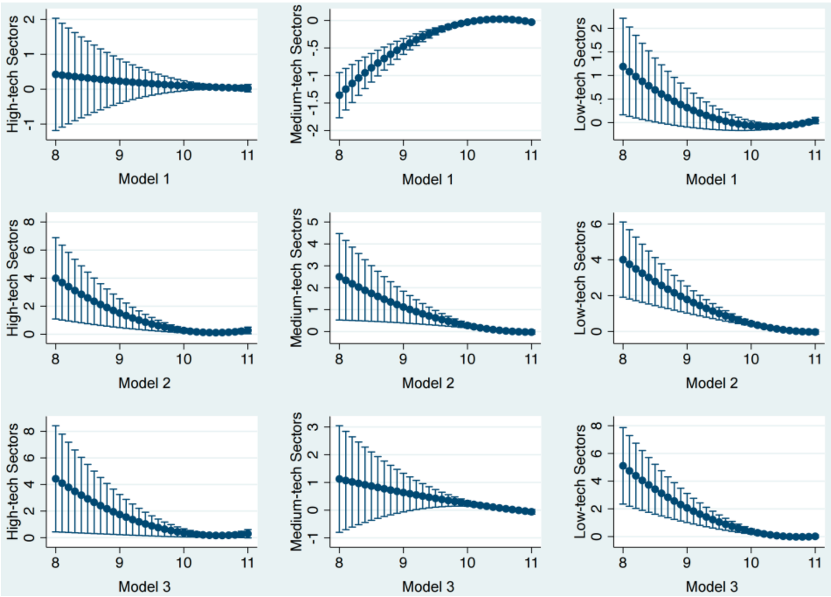


Source: Drawn by the authors using Stata 15.

Notes: In accordance with Stata's default settings, ln(pop) is held constant at the mean value across all observations in the sample when drawing the figure. The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure A.7

Econometric estimation of the relationship between productivity growth in the manufacturing sector according to the shift-share structural decomposition for the HIC controlling for natural logarithm of population and its squared term

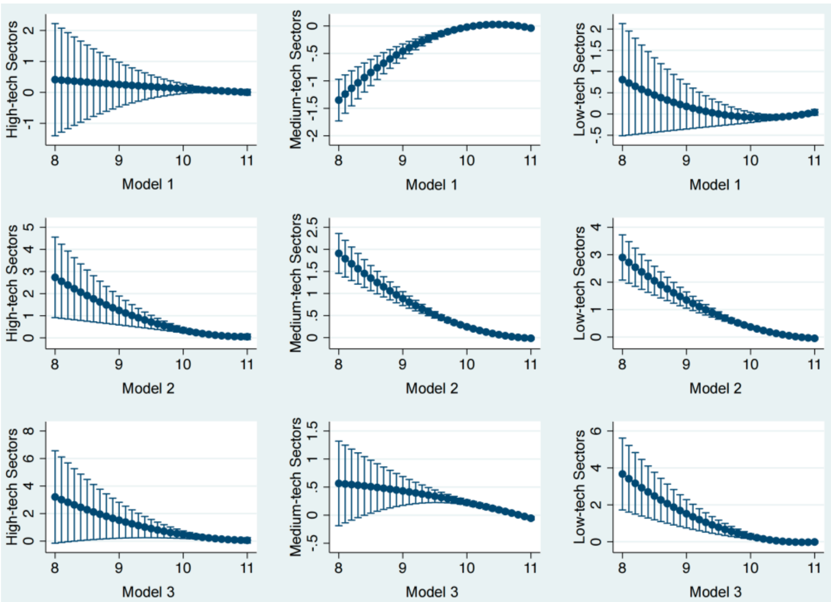


Source: Drawn by the authors using Stata 15.

Notes: In accordance with Stata's default settings, ln(pop) is held constant at the mean value across all observations in the sample when drawing the figure. The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Figure A.8

Econometric estimation of the relationship between wage growth in the manufacturing sector according to the shift-share structural decomposition for the HIC controlling for natural logarithm of population and its squared term



Source: Drawn by the authors using Stata 15.

Notes: In accordance with Stata's default settings, ln(pop) is held constant at the mean value across all observations in the sample when drawing the figure. The horizontal axes in all nine subplots are GDP per capita (in logarithm).

Appendix

Table A.1
Regression results of manufacturing productivity growth according to shift-share structural decomposition for MIC without controlling for natural logarithm of population

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-5.325**	-3.516***	1.400***	-3.371	-0.929	1.079	-8.624**	-4.453*	2.518
	(2.005)	(0.496)	(0.330)	(2.251)	(2.623)	(2.480)	(4.001)	(2.391)	(2.180)
$(gdppc_i)^2$	0.292**	0.195***	-0.0769***	0.189	0.0594	-0.0555	0.478**	0.255*	-0.134
	(0.108)	(0.0265)	(0.0177)	(0.121)	(0.141)	(0.135)	(0.216)	(0.128)	(0.118)
Constant	24.30**	15.80***	-6.429***	15.11	3.736	-4.966	39.08**	19.58*	-11.59
	(9.335)	(2.306)	(1.528)	(10.36)	(12.10)	(11.35)	(18.49)	(11.10)	(9.973)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.503	0.647	0.457	0.154	0.069	0.009	0.308	0.234	0.035

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2
Regression results of manufacturing wage growth according to shift-share structural decomposition for MIC without controlling for natural logarithm of population

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-1.128	-2.709***	2.504***	2.344	-0.0251	-1.718	1.243	-2.737	0.835
	(1.270)	(0.460)	(0.469)	(2.960)	(1.957)	(2.859)	(3.632)	(1.602)	(2.442)
$(gdppc_i)^2$	0.0632	0.150***	-0.138***	-0.116	0.00981	0.0974	-0.0542	0.160*	-0.0429
	(0.0672)	(0.0247)	(0.0246)	(0.158)	(0.105)	(0.150)	(0.193)	(0.0852)	(0.128)
Constant	5.131	12.22***	-11.46***	-11.43	-0.412	7.932	-6.421	11.82	-3.749
	(5.977)	(2.123)	(2.217)	(13.76)	(9.058)	(13.54)	(16.95)	(7.457)	(11.57)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.069	0.632	0.510	0.045	0.071	0.021	0.041	0.243	0.004

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3

Regression results of manufacturing productivity growth according to shift-share structural decomposition for HIC without controlling for natural logarithm of population

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-1.250	3.750***	-3.295**	-13.02**	-7.140**	-13.12***	-14.38**	-3.344	-16.18***
	(2.111)	(0.565)	(1.533)	(4.730)	(2.849)	(2.864)	(6.143)	(2.705)	(3.533)
$(gdppc_i)^2$	0.0562	-0.177***	0.159**	0.619**	0.328**	0.610***	0.680**	0.150	0.758***
	(0.0983)	(0.0268)	(0.0713)	(0.226)	(0.135)	(0.136)	(0.291)	(0.129)	(0.166)
Constant	6.980	-19.87***	17.02*	68.60**	38.81**	70.57***	76.13**	18.69	86.35***
	(11.33)	(2.982)	(8.238)	(24.69)	(14.98)	(15.12)	(32.39)	(14.22)	(18.80)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.069	0.391	0.192	0.223	0.572	0.559	0.175	0.340	0.624

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4

Regression results of manufacturing wage growth according to shift-share structural decomposition for HIC without controlling for natural logarithm of population

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-1.096	4.011***	-2.369	-7.676**	-5.617***	-8.468***	-8.949*	-1.679	-10.73***
	(2.365)	(0.504)	(1.836)	(2.924)	(0.725)	(1.186)	(4.835)	(1.047)	(2.497)
$(gdppc_i)^2$	0.0478	-0.190***	0.116	0.353**	0.258***	0.388***	0.409*	0.0707	0.499***
	(0.110)	(0.0240)	(0.0854)	(0.140)	(0.0342)	(0.0562)	(0.228)	(0.0494)	(0.117)
Constant	6.292	-21.11***	12.05	41.78**	30.64***	46.24***	49.01*	9.916*	57.74***
	(12.70)	(2.647)	(9.868)	(15.29)	(3.839)	(6.248)	(25.67)	(5.551)	(13.34)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.132	0.400	0.176	0.352	0.705	0.748	0.366	0.428	0.639

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5

Regression results of manufacturing productivity growth according to shift-share structural decomposition for MIC controlling for natural logarithm of population and its squared term

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-0.709	-5.081***	0.707	3.314	4.531	5.067	2.609	-0.514	5.775*
	(1.478)	(1.139)	(0.548)	(3.444)	(4.489)	(3.354)	(4.201)	(4.527)	(2.865)
$(gdppc_i)^2$	0.0382	0.280***	-0.0396	-0.170	-0.229	-0.265	-0.132	0.0484	-0.304*
	(0.0789)	(0.0628)	(0.0303)	(0.187)	(0.248)	(0.184)	(0.227)	(0.254)	(0.157)
pop_i	-2.038***	0.780	0.349	-3.378**	-3.039	-2.313*	-5.385***	-2.277	-1.940*
	(0.440)	(0.464)	(0.226)	(1.323)	(1.881)	(1.288)	(1.590)	(1.982)	(1.078)
$(pop_i)^2$	0.0541***	-0.0215	-0.00964	0.0934**	0.0861	0.0661*	0.147***	0.0651	0.0558*
	(0.0120)	(0.0124)	(0.00604)	(0.0359)	(0.0503)	(0.0345)	(0.0436)	(0.0520)	(0.0288)
Constant	22.49***	15.99***	-6.368***	14.57	4.653	-3.842	36.74**	20.66	-10.42
	(5.953)	(2.496)	(1.697)	(10.71)	(12.96)	(12.98)	(15.12)	(11.82)	(11.27)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.724	0.755	0.590	0.578	0.445	0.368	0.668	0.451	0.379

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6

Regression Results of manufacturing wage growth according to shift-share structural decomposition for MIC controlling for natural logarithm of population and its squared term

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	3.103*	-4.114***	1.017	9.244	6.435	6.809	12.43	2.265	7.789
	(1.714)	(0.768)	(1.017)	(7.723)	(4.465)	(7.219)	(9.146)	(4.015)	(6.241)
$(gdppc_i)^2$	-0.168*	0.226***	-0.0561	-0.482	-0.337	-0.365	-0.655	-0.108	-0.419
	(0.0926)	(0.0414)	(0.0551)	(0.421)	(0.242)	(0.390)	(0.497)	(0.219)	(0.337)
pop_i	-1.937***	0.706**	0.672*	-3.761	-3.305**	-4.135*	-5.719*	-2.575*	-3.430
	(0.532)	(0.298)	(0.335)	(2.592)	(1.494)	(2.297)	(3.024)	(1.356)	(1.975)
$(pop_i)^2$	0.0520***	-0.0195**	-0.0180*	0.106	0.0917**	0.113*	0.159*	0.0715*	0.0942*
	(0.0142)	(0.00820)	(0.00893)	(0.0685)	(0.0402)	(0.0612)	(0.0801)	(0.0360)	(0.0526)
Constant	3.808	12.35***	-10.95***	-10.66	-0.739	6.391	-7.003	11.65	-4.724
	(4.422)	(2.125)	(2.568)	(18.31)	(11.21)	(18.05)	(21.71)	(9.694)	(15.59)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.453	0.800	0.619	0.353	0.486	0.234	0.374	0.525	0.218

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7
Regression results of manufacturing productivity growth according to shift-share structural decomposition for HIC controlling for natural logarithm of population and its squared term

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-0.720	4.643***	-5.039***	-13.09**	-5.999*	-9.708**	-13.82**	-1.291	-14.45***
	(2.432)	(0.675)	(1.534)	(4.848)	(3.073)	(3.406)	(6.328)	(3.028)	(4.171)
$(gdppc_i)^2$	0.0310	-0.221***	0.245***	0.624**	0.271*	0.440**	0.655**	0.0472	0.671***
	(0.116)	(0.0323)	(0.0731)	(0.233)	(0.146)	(0.163)	(0.303)	(0.144)	(0.198)
pop_i	0.270	-0.384***	0.546	0.600	-0.657	-1.606**	0.836	-1.044**	-1.077
	(0.537)	(0.117)	(0.346)	(0.995)	(0.386)	(0.710)	(1.416)	(0.412)	(0.621)
$(pop_i)^2$	-0.00839	0.0109***	-0.0151	-0.0178	0.0188	0.0456**	-0.0253	0.0298**	0.0310*
	(0.0152)	(0.00330)	(0.00977)	(0.0285)	(0.0111)	(0.0202)	(0.0404)	(0.0118)	(0.0175)
Constant	2.049	-20.98***	20.92**	63.77**	38.83**	67.57***	66.21*	17.54	87.07***
	(11.94)	(3.284)	(7.681)	(25.19)	(15.80)	(15.70)	(32.76)	(15.34)	(20.20)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.200	0.543	0.407	0.257	0.626	0.727	0.252	0.480	0.694

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8
Regression results of manufacturing wage growth according to shift-share structural decomposition for HIC controlling for natural logarithm of population and its squared term

	Model 1			Model 2			Model 3		
	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Medium-Tech Sectors	Low-Tech Sectors
$gdppc_i$	-0.327	4.753***	-3.809*	-6.615**	-4.274***	-6.389***	-7.131	0.483	-10.03***
	(2.653)	(0.627)	(1.915)	(3.002)	(0.766)	(1.322)	(5.091)	(1.279)	(2.775)
$(gdppc_i)^2$	0.0101	-0.227***	0.187*	0.301*	0.191***	0.285***	0.320	-0.0363	0.463***
	(0.126)	(0.0300)	(0.0907)	(0.144)	(0.0369)	(0.0631)	(0.242)	(0.0614)	(0.131)
pop_i	-0.107	-0.325**	0.457	-0.185	-0.399*	-0.858**	-0.285	-0.742**	-0.475
	(0.474)	(0.135)	(0.358)	(0.474)	(0.201)	(0.303)	(0.823)	(0.276)	(0.376)
$(pop_i)^2$	0.00268	0.00919**	-0.0127	0.00484	0.0110*	0.0242**	0.00731	0.0207**	0.0137
	(0.0133)	(0.00382)	(0.0101)	(0.0134)	(0.00575)	(0.00882)	(0.0233)	(0.00791)	(0.0107)
Constant	3.420	-21.98***	15.22	38.14**	27.45***	43.36***	42.50	5.634	58.36***
	(13.35)	(3.085)	(9.721)	(15.14)	(3.725)	(6.599)	(25.71)	(5.879)	(14.61)
Observations	20	20	20	20	20	20	20	20	20
R-squared	0.180	0.499	0.315	0.377	0.797	0.842	0.411	0.605	0.661

Robust standard errors (HC1 type) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.