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

Antônio Carlos Diegues[1,*], Qiuyi Yang[2], José Eduardo Roselino[3], Marcos José Barbieri Ferreira[4] and Renato Garcia[5]

[1]Center for Industrial Economics and Technology Institute of Economics, University of Campinas (UNICAMP), Campinas, Brazil. e-mail: diegues@unicamp.br, [2]Financial Research Center Fudan Development Institute (FDDI), Fudan University, Shanghai, China. e-mail: yangqiuyi@fudan.edu.cn, [3]Federal University of São Carlos—UFSCar, São Carlos, Brazil. e-mail: jeroselino@ufscar.br, [4]School of Applied Sciences—UNICAMP, Limeira, Brazil. e-mail: marcos.barbieri@fca.unicamp.br and [5]Institute of Economics—UNICAMP, Campinas, Brazil. e-mail: rcgarcia@unicamp.br

*Main author for correspondence.

†All authors are designated as co-first authors.

This paper aims to analyze manufacturing's contribution to development in high-income (HIC) and middle-income countries (MIC) from 2000 to 2019, revisiting the link between manufacturing and economic development by testing the inverted-U curve hypothesis (Rowthorn (1994); Palma (2005, *Beyond Reforms: Structural Dynamics and Macroeconomic Vulnerability*); Rodrik (2016, *Journal of Economic Growth*, 21, 1–33)) from an intra-manufacturing perspective. 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 (MICs and HICs) 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) in MIC, the empirical evidence reveals a broadly consistent pattern whereby rising per capita income is associated with an increasing contribution of manufacturing to development, whether measured in terms of productivity growth or wage growth, and (iii) For HIC, 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. Regarding the wage variable, there is an almost generalized tendency for its contribution to development to decline as per capita income rises, except within the structural change component for high-technology sectors. Although counterintuitive, this pattern may reflect intensified international competition—mainly via global value chains—pushing down manufacturing costs in high-income economies. These findings challenge the notion of "natural" deindustrialization and highlight the persistent relevance of manufacturing, especially in technologically intensive sectors. They underscore the need for industrial and innovation policies tailored to sectoral heterogeneity and national contexts, particularly in light of digital and green transitions that are reshaping global production systems.

JEL Classification: L52, L16, O14, O47

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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; Hausmann *et al*., 2007; Cimoli *et al*., 2009; Lee and Malerba, 2017; Dosi *et al*., 2021, 2022). Drawing on this background, the paper builds upon Rowthorn's (1995) seminal framework and the recent contribution of Dosi *et al*. (2021), who highlight the importance of distinguishing manufacturing sub-sectors by technological intensity when evaluating their role in development. 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), facilitating structural change toward sectors with higher technological dynamism.

In the evolutionary view, such structural changes are not spontaneous, since they emerge from deliberate innovation policies and national institutional arrangements that nurture learning and capability building (Dosi, 1982, 1988; Pavitt and Soette, 1990; Nelson and Nelson, 2002). In line with List's (1841) insights, these conditions underscore the pivotal role of national innovation systems in shaping long-term development trajectories (Lundvall, 1992; Nelson, 1993; Freeman, 1995; Malerba and Nelson, 2011). Based on these foundations, this paper examines the relationship between productive structure and development from an intra-manufacturing perspective, focusing on how the composition of manufacturing industries by technological intensity shapes their capacity to contribute to development, rather than on manufacturing's aggregate share in the economy. 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).

Building on Kaldor's (1966, 1967) insights, Dosi (1988) underscores how intrasectoral productivity dynamics can diffuse across the economy through linkage effects. In this view, manufacturing holds a pivotal role in development as a key locus of technical progress, economies of scale, and the transmission of productivity gains to other sectors. Based on this perspective, both evolutionary and developmental literature underscore manufacturing's critical role in sustainable growth (Cimoli *et al*., 2009; Dosi *et al*., 2021). Empirical studies using structural decomposition techniques (e.g., OECD, 1987; Mcmillan and Rodrik, 2011; Haraguchi, 2015) show that development correlates with structural changes toward sectors with greater technological complexity, productivity, and wages.

According to this interpretation of manufacturing as a driver of technical progress and productivity spillovers, the traditional development literature depicts structural change as an initial increase in the share of manufacturing value added in Gross Domestic Product (GDP) and total employment, followed at certain income levels by a decline, forming an inverted-U curve (Rowthorn, 1995; Rowthorn and Ramaswamy, 1997, 1999). In this view, manufacturing's importance rises in the early stages of development but gradually diminishes beyond a certain income threshold as economies transition toward services.

However, the literature on deindustrialization since the 1970s shows that this inflection in the inverted-U curve has not always resulted from "natural" processes of structural change. Instead, it has been driven by the consolidation of global value chains and the relocation of production to middle-income countries (MICs), mainly in Asia (Tregenna, 2009, 2016; Andreoni and Chang, 2019; Andreoni and Tregenna, 2019; Chang and Andreoni, 2020; Dosi *et al*., 2021). In high-income countries (HICs), industrial and innovation policies have struggled to restore manufacturing's contribution to development, since in MIC, they have often failed to prevent premature shifts away from manufacturing (Andreoni and Tregenna, 2020; Chang and Andreoni, 2020; Botta *et al*., 2023). In this paper, "deindustrialization" is therefore discussed not in terms of manufacturing's aggregate share of GDP, but as changes in the sector's internal composition and its ability to drive productivity and wage growth.

In this sense, this paper aims to measure and analyze the contribution of manufacturing to development for HICs and MICs between 2000 and 2019. In empirical terms, the aim is to

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test the validity of the inverted-U curve hypothesis as expressed by Rowthorn (1994), Palma (2005) and Rodrik (2016). Complementing Dosi *et al.* (2021), this paper empirically measures how the capacity of manufacturing to contribute to development has evolved by focusing on intrasectoral dynamics. Two empirical strategies are combined: (i) a shift-share decomposition of productivity and wage growth; and (ii) econometric tests of this decomposition to assess the inverted-U relationship.

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.

While literature extensively analyzes the definitions and causes of deindustrialization, as well as changes in the global organization of industries, there is still a lack of empirical research measuring how these transformations affect manufacturing's internal capacity to contribute to economic development. This capacity—rather than aggregate size—constitutes a fundamental pillar of the recent revival of industrial and innovation policies (Edler and Fagerberg, 2017; Aiginger and Rodrik, 2020; Chang and Andreoni, 2020; Mazzucato *et al*., 2020; Diegues *et al*., 2023; Dosi *et al*., 2023; Juhász *et al*., 2023; Mazzucato and Rodrik, 2023).

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.

Thus, the *contribution of the paper* lies in an empirical re-evaluation of the inverted-U-shaped curve, as originally proposed by Rowthorn, but applied to intra-manufacturing measures of productivity and wage growth, building on seminal papers that relate the share of manufacturing in GDP to the level of per capita income (Rowthorn, 1995; Rowthorn and Ramaswamy, 1997, 1999). The guiding propositions are: (i) the shape of the curve varies by technological intensity; (ii) this sectoral heterogeneity differs between HIC and MIC; and (iii) as suggested by Dosi *et al.* (2021), the inverted-U relationship observed in aggregate measures does not necessarily hold when focusing on different manufacturing sectors by technological intensity—particularly when measuring their ability to increase productivity and wages. 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.

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 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.

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 *et al*., 2022). Rodrik (2016) argued that a

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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 (Andreoni and Tregenna, 2019, 2020; Chang and Andreoni, 2020; Dosi *et al*., 2021). 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 *et al*., 2023). This trend, associated with the technological middle-income trap, hinders MIC from advancing to more sophisticated production and sustaining growth (Dosi *et al*., 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 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 United States, to re-engage with industrial and innovation policies aimed at maintaining technological leadership through protective measures not only in the commercial sphere, but also safeguarding strategic companies and critical technologies, in addition to increasing incentives and subsidies for local companies to advance on the technological frontier (Diegues and Roselino, 2023). After the 2020 administration change, U.S. policy became even more aggressive, targeting substantial subsidies to the semiconductor, energy, and infrastructure sectors (House, 2021; Hufbauer and Jung, 2021).

Notably, not only the United States, 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 and Veugelers, 2023).

In this context, the widespread return to industrial and innovation policies has normalized their use (Aiginger and 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*., 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 et al., 2023).

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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 and coordinated effort in vaccine development and production. It also caused severe disruptions to global supply chains. The Russo-Ukrainian conflict, which began 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 (Bois and Buts, 2024; Bellais, 2024). Additionally, the surge in extreme weather events has underscored the need for policies that support decarbonization and sustainable development (Anzolin and Lebdioui, 2021).

These complex challenges have required industrial and innovation policies that address interdisciplinary, long-term, and socially relevant goals. In this context, mission-oriented innovation policies have thus gained traction, focusing on social, environmental, and security challenges of the 21st century (Mazzucato *et al*., 2020 Boon and Edler, 2018; Diegues *et al*., 2023). Meanwhile, targeted sectoral policies are being reinforced to meet the competitive and geopolitical shifts (Chang and Andreoni, 2020; Evenett *et al*., 2024).

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. This growing historical evidence questions the hypothesis presented in the inverted-U curve of Rowthorn (1994), Palma (2005), and Rodrik (2016), that the contribution of industry to development declines with increasing levels of per capita income.

Despite the process of international reallocation of industrial activity on a global scale that has occurred in recent decades (Yu *et al*., 2015), empirically, it is observed that the higher a country's per capita income, the greater the importance of industry and, consequently, of industrial and innovation policy for its development. According to Dosi *et al*. (2021), a higher per capita income reflects a more balanced and diversified industrial composition, such that the most dynamic and technologically sophisticated sectors continue to increase their share of employment and value added in more developed countries.

Evidence confirms the importance of industry in HIC, which seek to maintain technological leadership by implementing industrial policies that address new technological and geopolitical challenges. Specialization in complex products and the pursuit of technological frontiers allow for a high degree of appropriability and the maintenance of barriers to entry. The aim is to combat growing competition from manufacturing activities in the East, particularly China. In short, there is a shift in the nature of industrial policy.

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 *et al*. (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.[1] Country classifications reflect their income group as of the initial year analyzed,

[1] Due to data limitations, Argentina, Kazakhstan, and Ukraine—formerly among the top 20 MIC manufacturing sectors—were excluded from the sample. Also due to the unavailability of disaggregated sector-level data, certain sectors in specific countries had to be removed from the U-curve estimations. In cases where data for a given year were missing and a proximate year (within a 3-year range) was available, the substitute value was used to ensure continuity and feasibility of the analysis. Detailed information on sectoral exclusions and year substitutions is provided in the appendix (Figures A1 and A2). Due to the lack of disaggregated sector-level data for the United Kingdom, the U-curve estimations for this country were restricted to the years 2000, 2005, and 2010. The 2010 results were calculated using data from 2007, which were employed as a substitute owing to the unavailability of data for this year.

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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%**	
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 year of the period—DataBank and UNIDO—SDG 9 Monitoring.

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.

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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)	Nonmetallic 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).

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).

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 Shift-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 *et al*. (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:

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

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

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

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

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

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

As in De Vries *et al*. (2015), productivity growth (4) was decomposed in three components, as follows:

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

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

$$\underbrace{\frac{\Sigma_{i=1}^{n} LP_{T,by} \left(S_{i,fy} - S_{i,by} \right)}{LP_{T,by}}}_{\text{I}} \tag{6}$$

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).

$$\underbrace{\frac{\Sigma_{i=1}^{n} \left(LP_{i,fy} - LP_{i,by} \right) \left(S_{i,fy} - S_{i,by} \right)}{LP_{T,by}}}_{\text{II}} \tag{7}$$

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.

$$\underbrace{\frac{\Sigma_{i=1}^{n} \left(LP_{i,fy} - LP_{i,by} \right) S_{i,by}}{LP_{T,by}}}_{\text{III}} \tag{8}$$

Term III (equation 8) denotes the intrasectoral 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).

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3.3 Fixed effects panel regression with country-clustered 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 *et al*. (2021), in HIC and MIC. To account for unobserved heterogeneity across sectors, countries, and years, the regression model (9) examines the relationship between manufacturing productivity and wage growth across sectors of varying technological intensity:

$$Y_{cst} = \beta_1 ln\left(gdppc_{ct}\right) + \beta_2\left[ln\left(gdppc_{ct}\right)\right]^2 + \beta_3 ln\left(pop_{ct}\right) + \beta_4\left[ln\left(pop_{ct}\right)\right]^2 + \beta_5 ln\left(gdppc_{ct}\right) \times ln\left(pop_{ct}\right) + \alpha_c + \gamma_s + \lambda_t + \varepsilon_{cst} \quad (9)$$

where,

Y_{cst} represents manufacturing productivity or salary 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) for sector s in country c at time t,

$ln\left(gdppc_{ct}\right)$ and its squared term capture the potentially nonlinear relationship between income and manufacturing outcomes, and $ln\left(pop_{cti}\right)$ controls for population size.

Country fixed effects (α_c), sector fixed effects (γ_s), and year fixed effects (λ_t) are included to control for unobserved heterogeneity. Standard errors are clustered at the country level. α is the overall intercept, β_1, β_2, β_3 are the coefficients to be estimated, and ϵ_{ij} is the error term.

Country-clustered standard errors are used to correct for potential heteroscedasticity and within-country correlation, ensuring more reliable hypothesis tests and confidence intervals. This approach accounts for the fact that observations within the same country may be correlated across time periods and sectors, while also addressing heteroscedasticity concerns. The clustering adjustment provides robust inference that is valid under arbitrary forms of heteroscedasticity and autocorrelation within countries.

4. Results

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

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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_{cst} captures static and dynamic structural changes,
ii. In Model 2, Y_{cst} measures intrasectoral structural change,
iii. In Model 3, Y_{cst} represents the total effects of all structural changes.

In the econometric analysis, the dependent variable is constructed from structural decompositions of the three principal industrial aggregates—high, medium, and low technology—and each is employed independently in the estimation.

The regression outcomes of manufacturing productivity and wage growth in HIC and MIC are summarized in Tables 3–6 and Figures 1–4. To further examine the presence and statistical significance of an inverted-U (or U-shaped) relationship between log GDP per capita and manufacturing productivity (or wage) growth, we apply the Lind-Mehlum (2010) *U*-test. Unlike standard significance tests for quadratic terms, the Lind-Mehlum test formally evaluates whether the relationship is strictly concave (inverted-U) or convex (U-shaped) within the observed data range, based on the sign of the slopes at the endpoints of the regressor's support. The last three rows of Tables 3–6 report the results of the *U*-test.

Tables 3–6 present the fixed effects regression results for manufacturing productivity and wage growth, decomposed by technology intensity (high-, medium-, low-tech) and by development group (MIC and HIC).

First, across all specifications, the decomposition effects of structural change on per capita GDP are generally significant for both MICs and HICs, whether measured using productivity growth or wage growth. This confirms that the reallocation and transformation of manufacturing activities play a critical role in economic upgrading at various stages of development.

Second, for MIC, the results indicate that productivity and wage growth driven by intersectoral (static and dynamic) structural change components (Model 1) are more strongly associated with development than those driven by intrasectoral changes (Model 2). In contrast, for HIC, the effects are more evenly distributed across all components, reflecting the more advanced and balanced nature of structural change in these economies.

Third, the medium-tech sector emerges as especially important in both MIC and HIC. In almost every table and across most model specifications, the coefficients for the medium-tech columns are highly significant, underscoring a robust relationship between medium-tech manufacturing and per capita income growth. This highlights medium-tech manufacturing as a core driver of structural transformation, bridging the development gap between low- and high-tech sectors.

What's more, for both MIC and HIC, and across most technology groups and decomposition models, the LM *P*-values are 0.00, indicating strong rejection of the null hypothesis that the relationship between log GDP per capita and manufacturing growth is linear. This robustly confirms the presence of statistically significant nonlinear (either inverted-U or U-shaped) patterns in the data.

The inverted-U relationships are observed in several models—particularly in the high-tech and medium-tech sectors for MIC (Table 3), where the lower bound slope is strongly positive and the upper bound slope is strongly negative, both highly significant. This implies that at lower levels of income, increases in GDP per capita are associated with rising manufacturing productivity/wage growth, but after a turning point, further income growth leads to diminishing or even negative manufacturing contributions.

The significant inverted-U shape in high- and medium-tech sectors for MIC highlights a key development challenge. At earlier stages of industrialization, productivity and wage gains from

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Table 3. Fixed effects panel regression results: Manufacturing productivity growth and GDP per capita with country-clustered standard errors for MIC

	High-tech sectors			Medium-tech sectors			Low-tech sectors		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$ln\,(gdppc_{ct})$	−23.80	28.51*	4.717	8.443	47.02	55.46	−39.01	76.55	37.55
	(19.58)	(16.09)	(24.89)	(13.75)	(38.10)	(44.54)	(39.88)	(63.61)	(26.91)
$[ln\,(gdppc_{ct})]^2$	0.0851	−0.281	−0.196	0.0935	−1.931	−1.837	1.242	−1.998	−0.755
	(0.788)	(0.841)	(1.199)	(0.678)	(1.837)	(2.153)	(1.422)	(2.290)	(1.002)
$ln\,(pop_{ct})$	28.13	33.75**	61.88***	−7.437	17.69	10.25	−34.02	73.88	39.86
	(18.89)	(14.83)	(20.09)	(14.84)	(33.92)	(42.45)	(38.87)	(61.58)	(27.38)
$[ln\,(pop_{ct})]^2$	−1.387**	−0.436	−1.823**	0.327	−0.730	−0.403	0.895	−1.744	−0.849
	(0.604)	(0.556)	(0.736)	(0.546)	(1.267)	(1.602)	(1.169)	(1.828)	(0.862)
$ln\,(gdppc_{ct}) \times ln\,(pop_{ct})$	1.308***	−1.403***	−0.0953	−0.542**	−0.922	−1.464	0.819	−2.038*	−1.219**
	(0.390)	(0.374)	(0.535)	(0.247)	(0.737)	(0.861)	(0.755)	(1.177)	(0.521)
Year									
2005–2010	0.721	−0.00827	0.713	0.366	0.480	0.846	0.0335	−0.462	−0.429
	(0.647)	(1.133)	(1.405)	(0.738)	(2.045)	(2.269)	(0.735)	(1.474)	(0.995)
2010–2015	0.825	0.0725	0.897	0.350	3.059	3.409	−1.728	2.104	0.376
	(1.111)	(1.747)	(2.317)	(1.323)	(3.724)	(4.352)	(2.475)	(4.039)	(2.017)
2015–2019	0.0101	1.149	1.159	−0.216	4.985	4.769	−0.477	0.249	−0.229
	(1.737)	(2.383)	(3.137)	(1.655)	(4.869)	(5.565)	(1.807)	(3.371)	(2.251)
Constant	−57.29	−472.6**	−529.9**	31.18	−193.1	−161.9	437.2	−957.3	−520.0
	(208.2)	(167.4)	(246.6)	(150.2)	(336.9)	(408.6)	(456.1)	(725.1)	(303.2)
Observations	452	452	452	396	396	396	692	692	692
R^2	0.085	0.093	0.025	0.028	0.055	0.054	0.010	0.024	0.041
Number of panel units	113	113	113	99	99	99	173	173	173
Slope at min.	−22.470***	24.124***	1.654	9.901*	16.904	26.805	−19.629	45.391	25.762**
Slope at max.	−21.955***	22.421***	0.466	10.467*	5.219	15.686	−12.110	33.300**	21.190***
L-M *P*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Country-clustered standard errors are in parentheses. Year dummies are included with 2000–2005 as the reference period. Observations refer to country-industry-year cells in the panel. Panel units represent unique country–industry pairs. ***$P < 0.01$. **$P < 0.05$. *$P < 0.1$.

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Table 4. Fixed effects panel regression results: Manufacturing wage growth and GDP per capita with country-clustered standard errors for MIC

	High-tech sectors			Medium-tech sectors			Low-tech sectors		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
$ln\,(gdppc_{ct})$	8841	51,161	60,002	−4359	33,867	29,508	−2846	121,711	118,865
	(5,186)	(65,548)	(69,152)	(4,010)	(54,843)	(56,525)	(2,428)	(102,225)	(99,802)
$[ln\,(gdppc_{ct})]^2$	−223.3	−670.1	−893.3	282.0	−199.4	82.55	79.26	−3456	−3377
	(182.1)	(2323)	(2459)	(243.0)	(2029)	(2,201)	(73.56)	(3082)	(3009)
$ln\,(pop_{ct})$	6723	39,697	46,420	−3126	22,967	19,840	−2372	83,866	81,493
	(4544)	(56,042)	(59,312)	(3558)	(45,251)	(46,906)	(1925)	(82,111)	(80,190)
$[ln\,(pop_{ct})]^2$	−100.0	−164.0	−264.1	157.4	154.0	311.4	40.51	−1,283	−1,242
	(121.1)	(1474)	(1570)	(147.3)	(1235)	(1344)	(41.91)	(1795)	(1754)
$ln\,(gdppc_{ct}) \times ln\,(pop_{ct})$	−216.1*	−1664	−1880	−36.67	−1286	−1322	58.11	−2472	−2413
	(106.3)	(1270)	(1340)	(49.66)	(1022)	(1028)	(48.82)	(2052)	(2003)
Year									
2005 – 2010	−360.1	−4,057	−4,418	−152.8	−3,332	−3,484	144.6	−5,799	−5,654
	(216.7)	(3043)	(3244)	(154.2)	(2542)	(2600)	(119.2)	(4966)	(4848)
2010 – 2015	−612.9	−4,514	−5,127	−39.30	−3,688	−3,727	211.2	−8,231	−8,020
	(398.3)	(5156)	(5426)	(197.6)	(4297)	(4356)	(203.2)	(8458)	(8256)
2015 – 2019	−649.9	−7,828	−8,478	−488.8	−6,650	−7,139	251.4	−9,771	−9,519
	(412.8)	(5780)	(6163)	(451.6)	(4975)	(5245)	(210.1)	(8639)	(8432)
Constant	−115,004*	−800,121	−915,125	26,821	−546,362	−519,541	39,300	−1,507,109	−1,467,809
	(63,665)	(813,516)	(858,425)	(33,520)	(658,278)	(666,934)	(30,557)	(1,290,442)	(1,259,921)
Observations	452	452	452	396	396	396	700	700	700
R^2	0.009	0.055	0.053	0.027	0.057	0.055	0.004	0.079	0.080
Number of panel units	113	113	113	99	99	99	175	175	175
Slope at min.	5357.495**	40,707.645	46,065.14	39.87	30,756.33	30,796.199	−1609.934	67,798.652	66,188.717
Slope at max.	4006.131**	36,651.89	40,658.022	1746.54	29,549.292	31,295.832	−1130.185	46,881.346	45,751.161
L-M *P*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Country-clustered standard errors are in parentheses. Year dummies are included with 2000–2005 as the reference period. Observations refer to country-industry-year cells in the panel. Panel units represent unique country-industry pairs. ***$P < 0.01$. **$P < 0.05$. *$P < 0.1$.

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Table 5. Fixed effects panel regression results: Manufacturing productivity growth and GDP per capita with country-clustered standard errors for HIC

	High-tech sectors			Medium-tech sectors			Low-tech sectors		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
$ln\,(gdppc_{ct})$	3.964	10.95	12.99	4.846	10.95	−7.271	0.703	−0.601	−0.341
	(4.576)	(11.62)	(14.38)	(6.794)	(11.62)	(10.23)	(1.409)	(6.050)	(6.090)
$[ln\,(gdppc_{ct})]^2$	−0.0977	−0.0954	−0.155	−0.207	−0.0954	0.402	0.0229	0.109	0.143
	(0.171)	(0.365)	(0.482)	(0.299)	(0.365)	(0.342)	(0.0572)	(0.183)	(0.188)
$ln\,(pop_{ct})$	3.066	1.022	2.483	1.506	1.022	2.377	0.995	−0.445	0.349
	(2.101)	(6.990)	(8.032)	(1.912)	(6.990)	(5.739)	(0.856)	(4.311)	(4.182)
$[ln\,(pop_{ct})]^2$	−0.0622	0.213	0.186	−0.0771	0.213	−0.0654	−0.0152	0.0529	0.0401
	(0.0722)	(0.220)	(0.268)	(0.0745)	(0.220)	(0.196)	(0.0258)	(0.131)	(0.121)
$ln\,(gdppc_{ct}) \times ln\,(pop_{ct})$	−0.145	−0.596*	−0.670*	0.0375	−0.596*	−0.0729	−0.0586	−0.0804	−0.126
	(0.110)	(0.326)	(0.379)	(0.0775)	(0.326)	(0.246)	(0.0377)	(0.177)	(0.173)
Year									
2005–2010	0.663***	0.0404	0.682*	−0.291***	0.0404	−0.519*	−0.0696*	−0.151	−0.227
	(0.150)	(0.274)	(0.344)	(0.0954)	(0.274)	(0.275)	(0.0349)	(0.154)	(0.152)
2010–2015	0.256	0.0565	0.283	−0.467***	0.0565	−0.308	−0.0252	−0.146	−0.193
	(0.185)	(0.415)	(0.546)	(0.162)	(0.415)	(0.321)	(0.0375)	(0.207)	(0.203)
2015–2019	0.273	0.557	0.784	−0.579**	0.557	−0.169	−0.0318	−0.171	−0.214
	(0.266)	(0.557)	(0.729)	(0.245)	(0.557)	(0.442)	(0.0649)	(0.276)	(0.273)
Constant	−38.96	−77.43	−95.70	−37.54	−77.43	23.97	−11.97	0.938	−7.298
	(29.81)	(89.16)	(102.7)	(37.21)	(89.16)	(73.24)	(9.564)	(50.81)	(51.56)
Observations	424	424	424	354	424	354	612	612	612
R^2	0.046	0.032	0.026	0.093	0.032	0.113	0.018	0.016	0.031
Number of panel units	109	109	109	91	109	91	157	157	157
Slope at min.	2.126	9.159	10.064	0.941	9.159	0.302	1.134*	1.450	2.358
Slope at max.	1.723	8.765*	9.422*	0.085	8.765*	1.963	0.229**	1.899	2.951
L-M *P*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Country-clustered standard errors are in parentheses. Year dummies are included with 2000–2005 as the reference period. Observations refer to country-industry-year cells in the panel. Panel units represent unique country-industry pairs. ***$P < 0.01$. **$P < 0.05$. *$P < 0.1$.

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Table 6. Fixed effects panel regression results: Manufacturing wage growth and GDP per capita with country-clustered standard errors for HIC

	High-tech sectors			Medium-tech sectors			Low-tech sectors		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$ln\,(gdppc_{ct})$	3.708	−41.47	−37.76	−1.830	−33.53**	−35.36*	−2.129	−7.306	−9.435
	(7.509)	(24.99)	(26.32)	(9.691)	(14.93)	(17.37)	(4.810)	(12.03)	(10.43)
$[ln\,(gdppc_{ct})]^2$	−0.195	1.818*	1.623	0.169	1.328**	1.497**	0.138	0.286	0.424
	(0.308)	(0.882)	(0.997)	(0.433)	(0.517)	(0.629)	(0.202)	(0.404)	(0.329)
$ln\,(pop_{ct})$	7.811	21.07*	28.88*	−2.650	13.90***	11.25*	−1.504	3.907	2.402
	(6.597)	(10.80)	(13.94)	(5.637)	(4.854)	(5.930)	(1.679)	(6.873)	(6.271)
$[ln\,(pop_{ct})]^2$	−0.288	−0.992	−1.280*	0.117	−0.740**	−0.624*	0.0685	−0.209	−0.141
	(0.268)	(0.578)	(0.669)	(0.216)	(0.282)	(0.311)	(0.0560)	(0.299)	(0.271)
$ln\,(gdppc_{ct}) \times ln\,(pop_{ct})$	−0.0712	0.304	0.232	−0.0189	0.398	0.379	−0.0168	0.117	0.0998
	(0.131)	(0.475)	(0.441)	(0.151)	(0.295)	(0.323)	(0.0895)	(0.266)	(0.244)
Year									
2005–2010	1.136***	−0.321	0.815**	−0.580**	−0.232	−0.811***	−0.339***	−0.0914	−0.430*
	(0.211)	(0.291)	(0.327)	(0.206)	(0.196)	(0.257)	(0.0916)	(0.245)	(0.248)
2010–2015	0.647**	0.0372	0.685	−0.734**	0.0327	−0.701	−0.120	−0.0565	−0.176
	(0.299)	(0.805)	(0.703)	(0.302)	(0.434)	(0.623)	(0.105)	(0.517)	(0.475)
2015–2019	0.836	−0.300	0.536	−0.958*	−0.188	−1.146*	−0.151	−0.179	−0.330
	(0.520)	(0.736)	(0.711)	(0.491)	(0.373)	(0.607)	(0.176)	(0.494)	(0.492)
Constant	−53.68	112.0	58.29	15.36	114.2	129.6	15.66	19.26	34.92
	(39.77)	(109.9)	(112.0)	(52.77)	(71.33)	(89.62)	(27.89)	(70.00)	(62.50)
Observations	428	428	428	354	354	354	618	618	618
R^2	0.037	0.053	0.024	0.041	0.086	0.122	0.054	0.007	0.043
Number of panel units	111	111	111	91	91	91	159	159	159
Slope at min.	2.126	9.159	10.064	0.941	9.159	0.302	1.134*	1.450	2.358
Slope at max.	1.723	8.765*	9.422*	0.085	8.765	1.963	1.229	1.899	2.951
L-M *P*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Country-clustered standard errors are in parentheses. Year dummies are included with 2000–2005 as the reference period. Observations refer to country-industry-year cells in the panel. Panel units represent unique country–industry pairs. ***$P < 0.01$. **$P < 0.05$. *$P < 0.1$.

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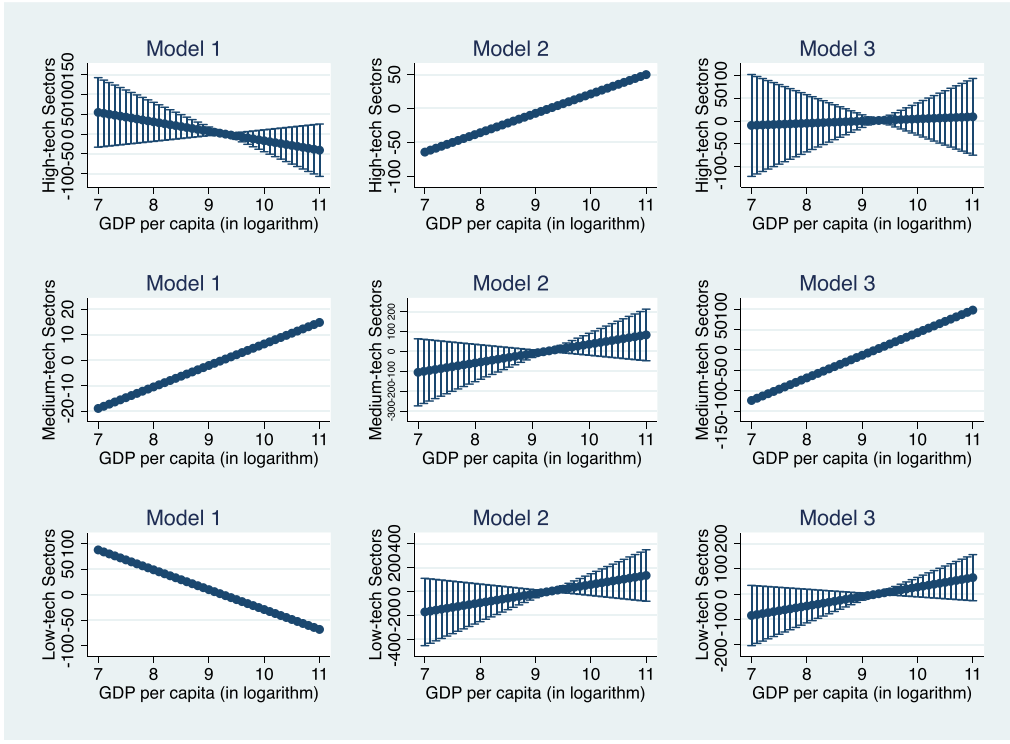

Figure 1. The relationship between manufacturing productivity growth and GDP per capita by technology intensity levels: Fixed effects panel regression results for the MIC. *Source*: Authors' calculations using Stata 15 based on fixed effects panel regression with country-clustered standard errors. *Note:* Manufacturing productivity growth is measured using shift-share structural decomposition (sum of static, dynamic, and intrasectoral components). Ln(pop) is held constant at the mean value across all observations when generating predicted values.

manufacturing expansion are strong, but as income rises and economies approach the upper-middle-income threshold, the returns to further expansion in manufacturing—especially in high-tech sectors—diminish. This pattern is consistent with the "middle-income trap" hypothesis: economies may struggle to sustain growth if they cannot upgrade their industrial structure beyond medium-tech manufacturing, or if service sector-led growth is not strong enough to offset the plateau in manufacturing gains.

For HIC, the nonlinear pattern is less pronounced but still present in some sectors. The results suggest that the gains from manufacturing productivity and wage growth become more muted or even negative as countries reach very high-income levels. This may reflect a shift toward services, innovation, and knowledge-intensive activities, where the traditional link between manufacturing expansion and growth weakens.

Notably, medium-tech manufacturing often exhibits the strongest nonlinear relationship and the highest significance. This underscores the pivotal role of medium-tech industries as the "engine room" of structural transformation. For both MIC and HIC, these sectors offer the largest window of opportunity for boosting productivity and wages through industrial upgrading, but also face the greatest risk of stagnation once the inverted-U turning point is reached.

Figures 1–4 display predictive margins (with 95% confidence intervals) for the relationship between GDP per capita and manufacturing productivity and wage growth, disaggregated by technology intensity and model specification. Within each figure, the three rows correspond to Models 1–3 (decomposition components), and the three columns represent high-, medium-, and low-tech sectors.

Contrary to the classic Rodrik hypothesis, the figures do not uniformly exhibit an inverted-U-shaped relationship between manufacturing's contribution to development and GDP per capita

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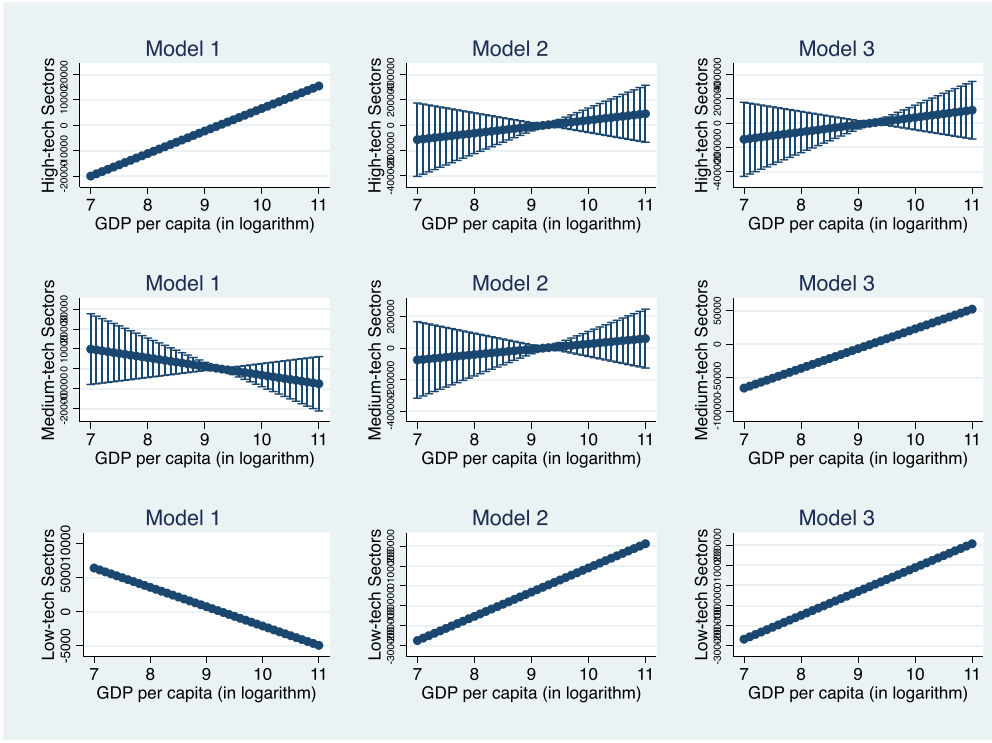

Figure 2. The relationship between manufacturing wage growth and GDP per capita by technology intensity levels: Fixed effects panel regression results for the MIC. *Source*: Authors' calculations using Stata 15 based on fixed effects panel regression with country-clustered standard errors. *Note:* Manufacturing productivity growth is measured using shift-share structural decomposition (sum of static, dynamic, and intrasectoral components). Ln(pop) is held constant at the mean value across all observations when generating predicted values.

across all sectors and models. Figure 1 visualizes the predictive margins for manufacturing productivity growth by technology intensity and model specification for MIC. In high-tech sectors, the predicted relationship with GDP per capita varies by model, showing both flat and nonmonotonic (inverted-U) trends, with large confidence intervals at the tails. Medium-tech sectors display a generally upward-sloping pattern, suggesting that productivity growth improves with development, although the effect is not always robust. In low-tech sectors, productivity growth shows a clear declining trend as GDP per capita rises—again, consistent with premature deindustrialization and supporting Rodrik's inverted-U hypothesis. The wide confidence intervals highlight substantial cross-country heterogeneity. Figure 2 plots predicted margins for manufacturing wage growth for MIC. The trends are generally flat or weakly monotonic, with large and overlapping confidence intervals across the full range of GDP per capita. This visual evidence is consistent with regression results, further reinforcing the view that manufacturing wage dynamics in MIC are largely unrelated to development level once fixed effects are accounted for. Figure 3 illustrates the predicted relationship between productivity growth and GDP per capita in HIC. For high- and medium-tech sectors, predicted productivity growth is generally flat or increases slightly with GDP per capita, but for low-tech sectors, the relationship is downward-sloping, similar to the pattern in MIC, reflecting advanced deindustrialization at high-income levels. The overall message is that productivity growth potential in low-tech manufacturing continues to diminish as countries get richer, while high-tech sectors are less sensitive to development stages. Figure 4 shows predicted margins for wage growth in HIC. Across all sectors and models, the margins are largely flat, with no clear pattern or significant nonlinear trend across GDP per capita levels. This echoes the regression findings and suggests that wage growth in manufacturing is not strongly

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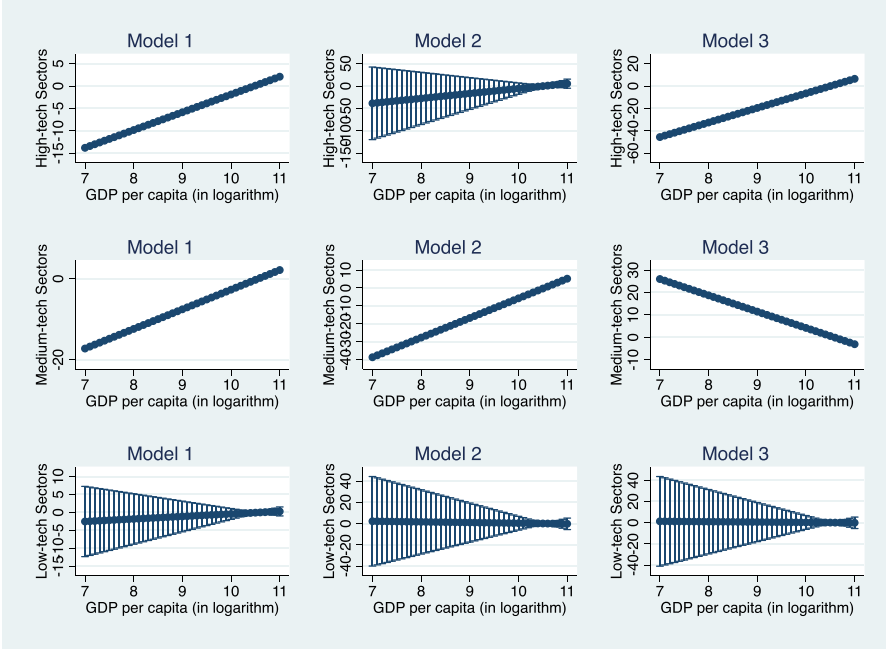

Figure 3. The relationship between manufacturing productivity growth and GDP per capita by technology intensity levels: Fixed effects panel regression results for the HIC. *Source*: Authors' calculations using Stata 15 based on fixed effects panel regression with country-clustered standard errors. *Note:* Manufacturing productivity growth is measured using shift-share structural decomposition (sum of static, dynamic, and intrasectoral components). Ln(pop) is held constant at the mean value across all observations when generating predicted values.

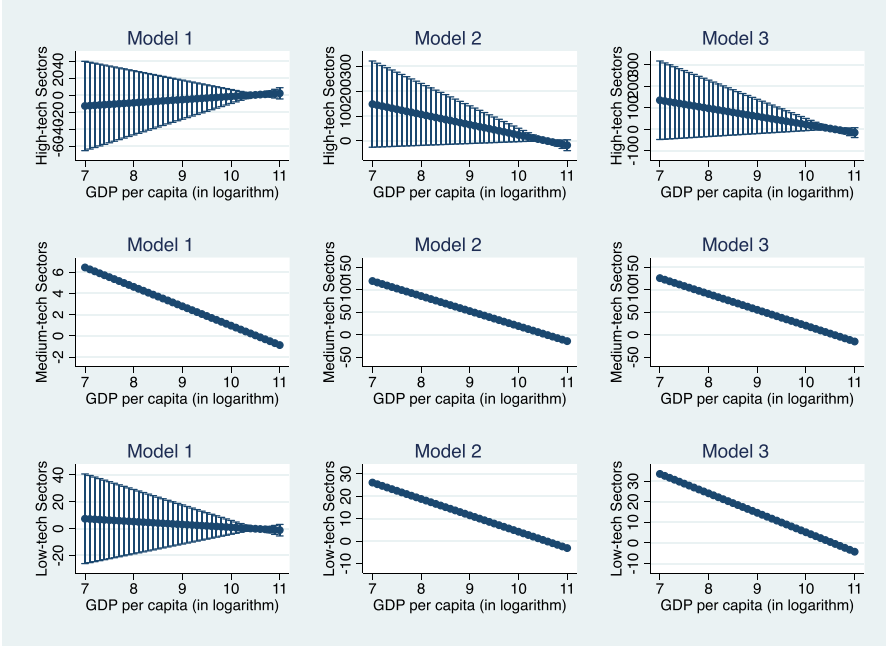

Figure 4. The relationship between manufacturing wage growth and GDP per capita by technology intensity levels: Fixed effects panel regression results for the HIC. *Source*: Authors' calculations using Stata 15 based on fixed effects panel regression with country-clustered standard errors. *Note:* Manufacturing productivity growth is measured using shift-share structural decomposition (sum of static, dynamic, and intrasectoral components). Ln(pop) is held constant at the mean value across all observations when generating predicted values.

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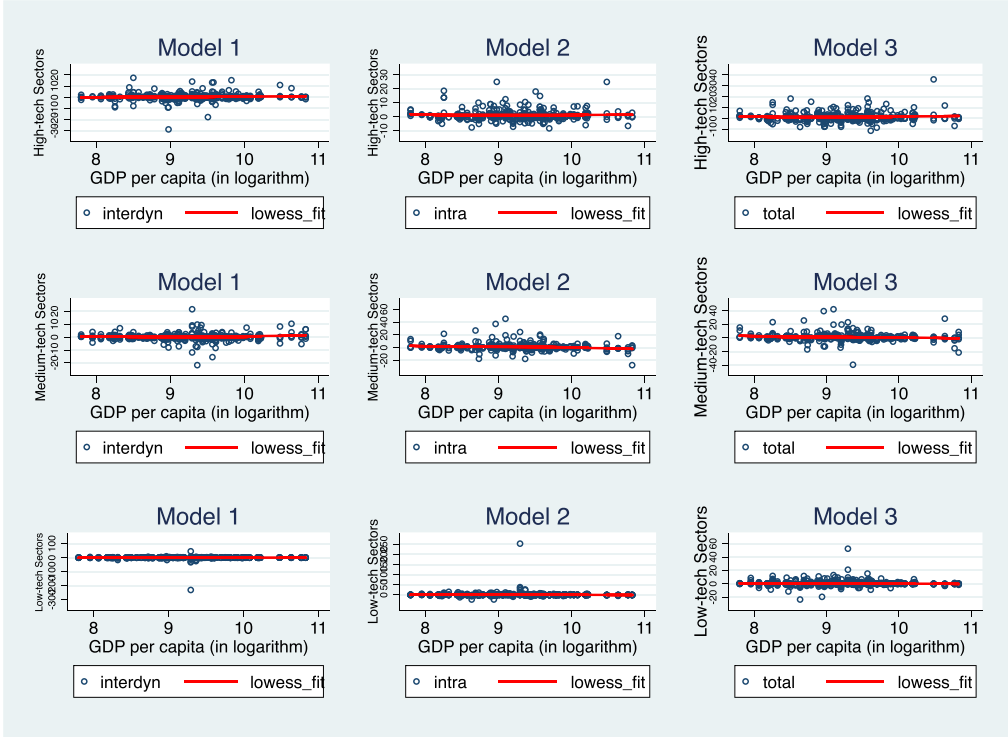

Figure 5. LOWESS fitted curves for manufacturing productivity growth and GDP per capita by technology intensity and structural decomposition models for MIC. *Source*: Authors' visualizations using Stata 15 based on LOWESS regression. *Note:* The rows represent different technology intensity sectors (high-tech, medium-tech, low-tech), and the columns represent the structural decomposition models (Model 1: intersectoral, Model 2: intrasectoral, Model 3: total).

associated with development level in high-income contexts, especially after controlling for fixed effects.

5. Robustness check: Nonparametric (locally weighted scatterplot smoothing) Locally Weighted Scatterplot Smoothing analysis

To complement the parametric regression analysis and visually explore the nonlinear relationships between GDP per capita and manufacturing productivity/wage growth, we conducted a Locally Weighted Scatterplot Smoothing (LOWESS) analysis. This nonparametric technique allows for a flexible estimation of the conditional mean of the dependent variable across the range of the independent variable, without imposing a pre-defined functional form. The results of this LOWESS analysis are presented in Figures 5 to 8, which illustrates the fitted curves for different technology intensity sectors (high-tech, medium-tech, low-tech) and across various structural decomposition models (Model 1: intersectoral, Model 2: intrasectoral, Model 3: total).

Upon examining Figures 5–8, several key patterns emerge from the nonparametric LOWESS analysis, offering a visual complement to the parametric regression findings. Generally, the LOWESS fitted lines across most technology sectors and models appear relatively flat, suggesting that the relationship between GDP per capita and manufacturing productivity/wage growth, when viewed nonparametrically, tends to be more stable or weakly monotonic within the observed range of GDP per capita. This visual flatness, despite the statistically significant nonmonotonic relationships identified by the Lind-Mehlum *U*-test in the parametric models, might indicate that while turning points exist, the overall magnitude of the nonlinearity is not always pronounced enough to be visually striking across all data points. This could be particularly true if the turning

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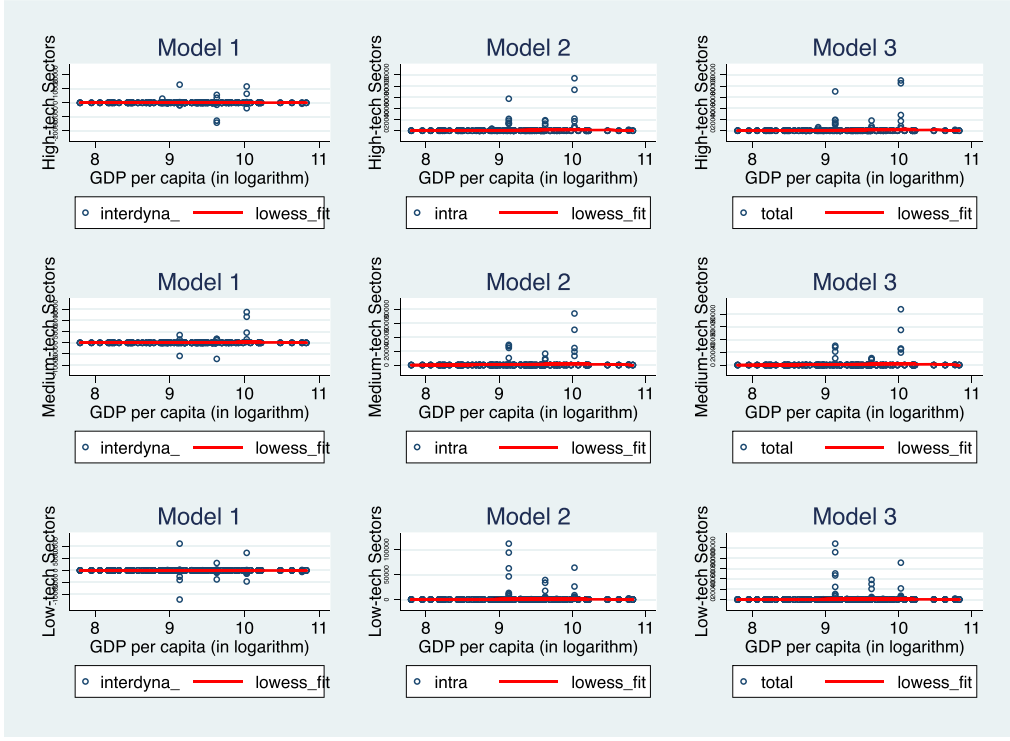

Figure 6. LOWESS fitted curves for manufacturing wage growth and GDP per capita by technology intensity and structural decomposition models for MIC. *Source*: Authors' visualizations using Stata 15 based on LOWESS regression. *Note:* The rows represent different technology intensity sectors (high-tech, medium-tech, low-tech), and the columns represent the structural decomposition models (Model 1: intersectoral, Model 2: intrasectoral, Model 3: total).

points occur at the extremes of the GDP per capita range, or if the confidence intervals around the nonparametric fit are wide.

More specifically, for MIC, in the high-tech and low-tech sectors, the LOWESS curves are largely flat, indicating that productivity growth in these sectors does not show a strong, consistent nonlinear pattern with GDP per capita. However, in the medium-tech sector, there appears to be a slight upward trend, suggesting that as GDP per capita increases, the productivity growth in medium-tech manufacturing might experience a modest positive association. This hints at the ongoing potential for productivity gains in medium-tech industries as MIC develops. Also, across all technology sectors (high-tech, medium-tech, low-tech) and all models, the LOWESS fitted lines for wage growth are notably flat. This suggests that for MIC, manufacturing wage growth generally does not exhibit a clear U-shaped, inverted-U-shaped, or even a strong monotonic relationship with GDP per capita. This could imply that other factors, such as labor market regulations, supply–demand dynamics, or global wage trends, might exert a more dominant influence on wage growth in MIC than the direct level of GDP per capita.

For HIC, similar to MIC, the LOWESS curves for high-tech and low-tech sectors in HIC are predominantly flat, indicating limited nonlinear or strong monotonic relationships between GDP per capita and productivity growth. However, the medium-tech sector again shows a subtle upward trend, particularly in Model 1 (intersectoral effects), suggesting that even in HIC, medium-tech manufacturing continues to offer some potential for productivity growth as economies mature. This might be linked to ongoing innovation and upgrading within these established sectors. Consistent with the patterns observed in MIC, the LOWESS curves for manufacturing wage growth in HIC across all technology sectors and models are largely flat. This reinforces

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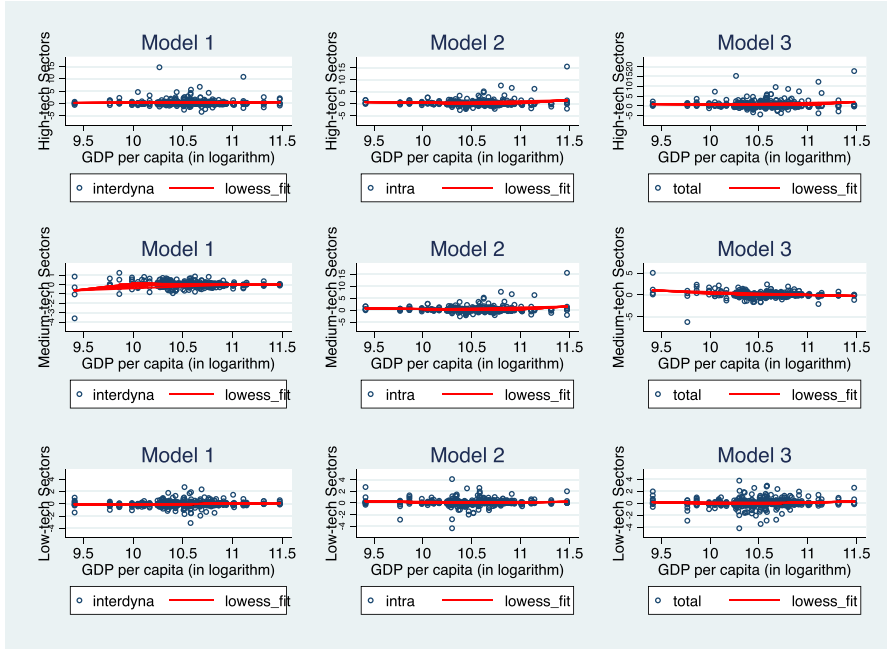

Figure 7. LOWESS fitted curves for manufacturing productivity growth and GDP per capita by technology intensity and structural decomposition models for HIC. *Source*: Authors' visualizations using Stata 15 based on LOWESS regression. *Note:* The rows represent different technology intensity sectors (high-tech, medium-tech, low-tech), and the columns represent the structural decomposition models (Model 1: intersectoral, Model 2: intrasectoral, Model 3: total).

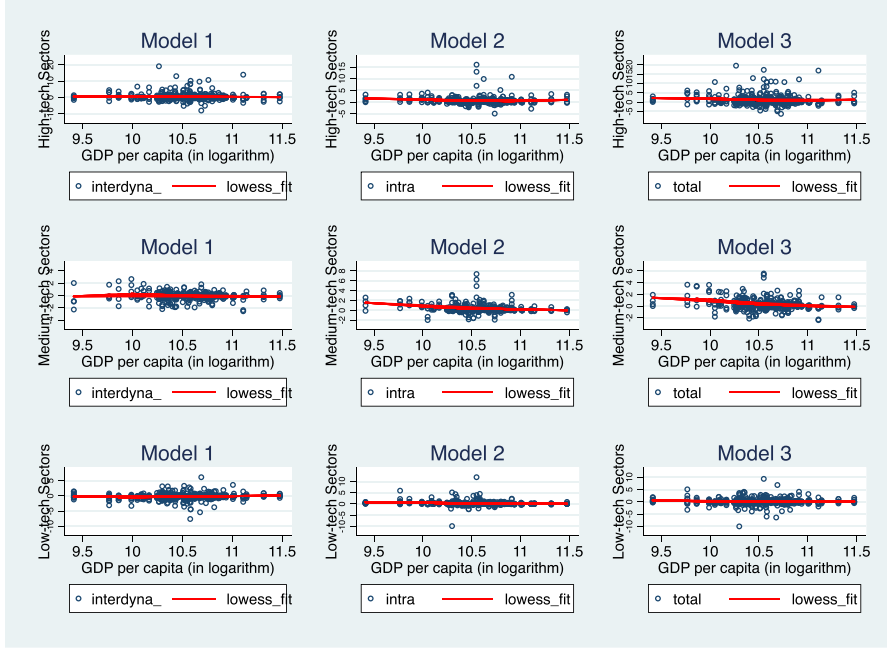

Figure 8. LOWESS fitted curves for manufacturing productivity growth and GDP per capita by technology intensity and structural decomposition models for HIC. *Source*: Authors' visualizations using Stata 15 based on LOWESS regression. *Note:* The rows represent different technology intensity sectors (high-tech, medium-tech, low-tech), and the columns represent the structural decomposition models (Model 1: intersectoral, Model 2: intrasectoral, Model 3: total).

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the notion that in advanced economies, the direct relationship between GDP per capita and manufacturing wage growth is not strongly nonlinear or consistently monotonic. This could reflect the convergence of wages, the dominance of service sectors, or the influence of global value chains on manufacturing wages in high-income contexts.

6. Discussion and conclusions: New challenges and the changes in the nature of industrial policy

This paper analyzes manufacturing's contribution to development high-income and middle-income countries. While the analysis offers novel insights, it adopts an intra-manufacturing perspective, focusing on dynamics within manufacturing rather than its aggregate role in the economy. This scope allows for a detailed understanding of sectoral heterogeneity, even with the results should not be interpreted as a direct measure of manufacturing's economy-wide contribution to development.

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 generalized decline in the contribution of manufacturing to development among MIC and HIC as they attain higher levels of per capita income. These results align with Dosi *et al.*'s (2021) findings on the varieties of deindustrialization, which show that technologically intensive industries ("microchips") follow trajectories distinct from those of low-tech industries ("potato chips").
ii. In MICs, the empirical evidence reveals a broadly consistent pattern whereby rising per capita income is associated with an increasing contribution of manufacturing to development, whether measured in terms of productivity growth or wage growth. The most notable exception to this pattern emerges when examining the structural change effect (Model 1) within low-technology sectors. In these sectors, as expected in a virtuous process of structural transformation, rising per capita income leads to a negative reallocation effect of workers into such activities, thereby reducing their contribution to overall development.
iii. For 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. Regarding the wage variable, there is an almost generalized tendency for its contribution to development to decline as per capita income rises, except—within the structural change component (Model 1)—for high-technology sectors. This indicates that higher income levels are associated with a rising relative share of employment in these sectors and with a continued expansion of wages. It is important

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to emphasize, however, that this phenomenon is confined to only 1 of the 9 model specifications.

In other words, between 2000 and 2019, there has been an almost widespread tendency among HIC for the growth rate of industrial wages to diminish as they reach higher levels of per capita income. Although seemingly counterintuitive, such a pattern may reflect the intensification of international competition—mainly through global value chains—exerting downward pressure on the cost structure of manufactured goods in high-income economies.

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.

As the shift toward a techno-productive paradigm, driven by digital and green transitions, has redefined the structure of manufacturing activities and their innovation dynamics, new technologies such as artificial intelligence, robotics, and additive manufacturing have reshaped production and services. Our study 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; Ciarli *et al*., 2021; Cefis *et al*., 2023; Diegues *et al*., 2023). 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 (Rodrik, 2018; Gereffi, 2019).

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 combine 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, manufacturing is still playing an essential role to promote inclusive and sustainable economic growth, but which manufacturing matters depends on technological intensity and the country's stage of development. Recognizing this heterogeneity is crucial for designing industrial

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policies that not only adapt to global technological shifts but actively shape them to foster inclusive and sustainable growth.

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Data availability

The data that support the findings of this study are available in UNIDO—Indstat 22,022—at https://stat.unido.org/database/INDSTAT.

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Appendix

Figure A1. Sectors Removed from the Productivity U-Curve Estimation due to Insufficient Disaggregated Data.

Country	Disconsidered sectors from the productivity analysis (ISIC Rev. 3)
Australia	16, 18, 19, 30, 31, 32, 33, 35, 37
Austria	16, 23, 32, 33, 37
Belgium	16, 19, 23, 32, 33, 35, 37
Brazil	32, 33, 37
Canada	30, 32, 33, 37
China	19, 30, 32, 33, 35, 37
China, Taiwan Province	16, 19, 23, 30, 32, 33, 37
Colombia	16, 32, 33, 37
Czechia	16, 30, 32, 33, 37
Denmark	16, 23, 32, 33, 37
Egypt	16, 18, 19, 23, 24, 32, 33, 37
France	32, 33, 37
Germany	16, 23, 32, 33, 37
India	32, 33, 37
Indonesia	32, 33, 37
Iran (Islamic Republic of)	28, 32, 33, 37
Italy	32, 33, 37
Japan	16, 32, 33, 37
Malaysia	16, 18, 31, 32, 33, 35, 37
Mexico	32, 33, 37
Morocco	32, 33, 37
Netherlands	16, 32, 33, 37
Oman	32, 33, 37
Pakistan	16, 30, 32, 33, 35, 37
Peru	15, 19, 22, 29, 30, 31, 32, 33, 34, 35, 36, 37
Philippines	16, 32, 33, 37
Poland	32, 33, 37
Republic of Korea	24, 28, 32, 33, 37
Romania	32, 33, 37
Russian Federation	23, 32, 33, 37
Singapore	32, 33, 37
South Africa	16, 32, 33, 37
Spain	16, 37
Sweden	16, 23, 32, 33, 37
Switzerland	16, 18, 19, 23, 24, 32, 33, 37
Thailand	15, 32, 33, 37
Türkiye	32, 33, 37
United Kingdom	16, 32, 33, 37
United States of America	32, 33, 37
Viet Nam	32, 33, 37

Source: Own elaboration based on data from UNIDO

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Sectors Figure A2. Removed from the Mean Wages U-Curve Estimation due to Insufficient Disaggregated Data

Country	Disconsidered sectors from the mean wages analysis (ISIC Rev. 3)
Australia	16, 18, 19, 30, 31, 32, 33, 35, 37
Austria	16, 23, 32, 33, 37
Belgium	16, 19, 23, 32, 33, 35, 37
Brazil	31, 32, 33, 37
Canada	30, 32, 33, 37
China	19, 30, 32, 33, 35, 37
China, Taiwan Province	16, 32, 33, 37
Colombia	16, 30, 32, 33, 37
Czechia	16, 23, 32, 33, 37
Denmark	16, 18, 19, 23, 24, 32, 33, 37
Egypt	32, 33, 37
France	16, 23, 32, 33, 37
Germany	32, 33, 37
India	32, 33, 37
Indonesia	32, 33, 37
Iran (Islamic Republic of)	32, 33, 37
Italy	16, 32, 33, 37
Japan	16, 18, 31, 32, 33, 35, 37
Malaysia	32, 33, 37
Mexico	32, 33, 37
Netherlands	32, 33, 37
Oman	16, 30, 32, 33, 35, 37
Pakistan	19, 30, 32, 33, 35, 37
Peru	16, 20, 30, 32, 33, 35, 37
Philippines	32, 33, 37
Poland	24, 28, 32, 33, 37
Republic of Korea	32, 33, 37
Romania	23, 31, 32, 33, 35, 37
Russian Federation	32, 33, 37
Singapore	16, 32, 33, 37
South Africa	16
Spain	23, 32, 33, 37
Sweden	16, 18, 19, 23, 24, 32, 33, 37
Switzerland	16, 19, 23, 30, 32, 33, 37
Thailand	15, 32, 33, 37
Türkiye	32, 33, 37
United Kingdom	16
United States of America	32, 33, 37
Viet Nam	32, 33, 37

Source: Own elaboration based on data from UNIDO

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Table A.1. Descriptive statistics for variables in empirical analysis for MIC

	Mean	Max	Min	SE
ln(*gdppc*)	9.265	10.827	7.800	0.658
ln(*pop*)	18.243	21.056	14.674	1.325
Tech intensity of productivity				
Intrasectral component	0.945	252.653	−27.461	7.650
Dynamic component	−0.357	16.490	−228.674	6.182
Intersectoral component	0.171	36.486	−38.231	2.605
Tech intensity of wage				
Intrasectral component	486.150	112,000.772	−55.187	4951.463
Dynamic component	8.488	13,737.060	−14,246.164	773.447
Intersectoral component	0.098	39.562	−23.188	2.052

Table A.2. Descriptive statistics for variables in empirical analysis for HIC

	Mean	Max	Min	SE
ln(*gdppc*)	16.986	19.599	7.607	1.529
ln(*pop*)	10.556	11.476	9.412	0.328
Tech intensity of productivity				
Intrasectral component	0.143	15.587	−6.239	0.846
Dynamic component	0.011	7.357	−3.457	0.278
Intersectoral component	0.057	8.804	−3.134	0.663
Tech intensity of wage				
Intrasectral component	454.505	112,000.772	−55.187	4788.952
Dynamic component	7.935	13,737.060	−14,246.164	747.831
Intersectoral component	0.095	39.562	−23.188	2.015

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Table A.3. Robustness checks for fixed effects panel regression results: An example of manufacturing productivity growth and GDP per capita (MIC, country-clustered standard errors)

	High-tech sectors			Medium-tech sectors			Low-tech sectors		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$Y_{cst} = \beta_1 ln\left(gdppc_{ct}\right) + \beta_2\left[ln\left(gdppc_{ct}\right)\right]^2 + \beta_3 ln\left(pop_{ct}\right) + \beta_4\left[ln\left(pop_{ct}\right)\right]^2 + \beta_5 ln\left(gdppc_{ct}\right) \times ln\left(pop_{ct}\right) + \alpha_c + \gamma_s + \lambda_t + \varepsilon_{cst}$									
$ln\left(gdppc_{ct}\right)$	−23.80	28.51*	4.717	8.443	47.02	55.46	−39.01	76.55	37.55
	(19.58)	(16.09)	(24.89)	(13.75)	(38.10)	(44.54)	(39.88)	(63.61)	(26.91)
$\left[ln\left(gdppc_{ct}\right)\right]^2$	0.0851	−0.281	−0.196	0.0935	−1.931	−1.837	1.242	−1.998	−0.755
	(0.788)	(0.841)	(1.199)	(0.678)	(1.837)	(2.153)	(1.422)	(2.290)	(1.002)
$ln\left(pop_{ct}\right)$	28.13	33.75**	61.88***	−7.437	17.69	10.25	−34.02	73.88	39.86
	(18.89)	(14.83)	(20.09)	(14.84)	(33.92)	(42.45)	(38.87)	(61.58)	(27.38)
$\left[ln\left(pop_{ct}\right)\right]^2$	−1.387**	−0.436	−1.823**	0.327	−0.730	−0.403	0.895	−1.744	−0.849
	(0.604)	(0.556)	(0.736)	(0.546)	(1.267)	(1.602)	(1.169)	(1.828)	(0.862)
$ln\left(gdppc_{ct}\right) \times ln\left(pop_{ct}\right)$	1.308***	−1.403***	−0.0953	−0.542**	−0.922	−1.464	0.819	−2.038*	−1.219**
	(0.390)	(0.374)	(0.535)	(0.247)	(0.737)	(0.861)	(0.755)	(1.177)	(0.521)
Year									
2005–2010	0.721	−0.00827	0.713	0.366	0.480	0.846	0.0335	−0.462	−0.429
	(0.647)	(1.133)	(1.405)	(0.738)	(2.045)	(2.269)	(0.735)	(1.474)	(0.995)
2010 − 2015	0.825	0.0725	0.897	0.350	3.059	3.409	−1.728	2.104	0.376
	(1.111)	(1.747)	(2.317)	(1.323)	(3.724)	(4.352)	(2.475)	(4.039)	(2.017)
2015–2019	0.0101	1.149	1.159	−0.216	4.985	4.769	−0.477	0.249	−0.229
	(1.737)	(2.383)	(3.137)	(1.655)	(4.869)	(5.565)	(1.807)	(3.371)	(2.251)
Constant	−57.29	−472.6**	−529.9**	31.18	−193.1	−161.9	437.2	−957.3	−520.0
	(208.2)	(167.4)	(246.6)	(150.2)	(336.9)	(408.6)	(456.1)	(725.1)	(303.2)
Observations	452	452	452	396	396	396	692	692	692
R^2	0.085	0.093	0.025	0.028	0.055	0.054	0.010	0.024	0.041
Number of panel units	113	113	113	99	99	99	173	173	173
$Y_{cst} = \beta_1 \ln\left(gdppc_{ct}\right) + \beta_2\left[\ln\left(gdppc_{ct}\right)\right]^2 + \beta_3 \ln\left(pop_{ct}\right) + \beta_4 \ln\left(gdppc_{ct}\right) \times \ln\left(pop_{ct}\right) \alpha_c + \gamma_s + \lambda_t + \varepsilon_{cst}$									
$ln\left(gdppc_{ct}\right)$	−32.31*	25.84*	−6.467	11.45	40.32	51.76	−31.33	61.60	30.27
	(17.25)	(14.62)	(23.08)	(10.81)	(35.51)	(39.88)	(31.76)	(51.15)	(23.90)
$\left[ln\left(gdppc_{ct}\right)\right]^2$	0.626	−0.111	0.515	−0.0624	−1.583	−1.645	0.825	−1.185	−0.360
	(0.582)	(0.677)	(0.899)	(0.511)	(1.599)	(1.793)	(0.946)	(1.551)	(0.798)

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Table A.3. Continued

	High-tech sectors			Medium-tech sectors			Low-tech sectors		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$ln\,(pop_{ct})$	−13.94***	20.53***	6.585	2.542	−4.565	−2.023	−6.707	20.67*	13.96**
	(4.090)	(6.678)	(8.277)	(5.274)	(13.99)	(16.19)	(7.083)	(10.80)	(6.642)
$ln\,(gdppc_{ct}) \times ln\,(pop_{ct})$	1.227**	−1.428***	−0.201	−0.548**	−0.907	−1.456	0.820	−2.040	−1.220**
	(0.469)	(0.367)	(0.599)	(0.240)	(0.772)	(0.881)	(0.776)	(1.218)	(0.537)
Year									
2005–2010	0.356	−0.123	0.233	0.460	0.269	0.729	0.288	−0.957	−0.670
	(0.584)	(1.056)	(1.231)	(0.663)	(1.820)	(1.956)	(0.620)	(1.167)	(0.852)
2010–2015	0.0276	−0.178	−0.150	0.562	2.587	3.149	−1.165	1.007	−0.157
	(0.894)	(1.553)	(1.870)	(1.076)	(3.193)	(3.594)	(1.754)	(2.878)	(1.618)
2015–2019	−1.182	0.774	−0.408	0.0992	4.281	4.381	0.361	−1.385	−1.024
	(1.349)	(2.078)	(2.394)	(1.352)	(4.121)	(4.551)	(1.070)	(2.237)	(1.839)
Constant	293.1**	−362.5**	−69.37	−54.79	−1.359	−56.15	202.8	−500.5	−297.7
	(110.1)	(129.2)	(191.3)	(92.58)	(287.6)	(323.3)	(206.4)	(324.0)	(174.9)
Observations	452	452	452	396	396	396	692	692	692
R^2	0.073	0.092	0.011	0.027	0.054	0.053	0.009	0.022	0.037
Number of panel units	113	113	113	99	99	99	173	173	173
$Y_{cst} = \beta_1 \ln(gdppc_{ct}) + \beta_2 [\ln(gdppc_{ct})]^2 + \beta_3 \ln(pop_{ct}) + \alpha_c + \gamma_s + \lambda_t + \varepsilon_{cst}$									
$ln\,(gdppc_{ct})$	2.875	−15.12	−12.24	−4.553	13.85	9.297	−7.392	2.039	−5.354
	(9.415)	(15.53)	(15.22)	(9.515)	(26.95)	(31.29)	(10.64)	(18.55)	(11.62)
$[ln\,(gdppc_{ct})]^2$	−0.00296	0.621	0.618	0.224	−1.110	−0.886	0.391	−0.104	0.287
	(0.514)	(0.836)	(0.868)	(0.541)	(1.596)	(1.847)	(0.591)	(1.039)	(0.650)
$ln\,(pop_{ct})$	0.801	3.365	4.165	−4.201	−15.72*	−19.92*	3.315	−4.264	−0.949
	(4.856)	(4.154)	(4.840)	(4.029)	(8.544)	(10.32)	(4.862)	(7.586)	(3.705)
Year									
2005–2010	−0.348	0.696	0.349	0.840	0.898	1.738	−0.248	0.375	0.127
	(0.790)	(1.009)	(1.117)	(0.609)	(1.629)	(1.699)	(0.536)	(1.240)	(0.868)
2010–2015	−1.076	1.107	0.0308	1.167	3.588	4.755	−2.011	3.113	1.102
	(1.354)	(1.547)	(1.720)	(1.094)	(2.890)	(3.325)	(2.384)	(3.827)	(1.717)
2015–2019	−2.518	2.329	−0.189	0.832	5.494	6.326	−0.664	1.165	0.501
	(1.994)	(2.122)	(2.126)	(1.339)	(3.668)	(4.032)	(1.313)	(2.461)	(1.660)

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Table A.3. Continued

	High-tech sectors			Medium-tech sectors			Low-tech sectors		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	−39.80	25.07	−14.73	98.96*	252.9*	351.9**	−25.62	67.76	42.15
	(102.5)	(85.91)	(105.4)	(53.09)	(137.0)	(151.4)	(66.23)	(103.2)	(71.73)
Observations	452	452	452	396	396	396	692	692	692
R^2	0.046	0.062	0.010	0.021	0.050	0.044	0.008	0.015	0.016
Number of panel units	113	113	113	99	99	99	173	173	173
$Y_{cst} = \beta_1 \ln(gdppc_{ct}) + \beta_2 [\ln(gdppc_{ct})]^2 + \beta_3 \ln(pop_{ct}) + \beta_4 [\ln(pop_{ct})]^2 + \beta_5 \ln(gdppc_{ct}) \times \ln(pop_{ct}) + \alpha_c + \varepsilon_{cst}$									
$ln(gdppc_{ct})$	−23.58	20.50	−3.078	16.18	30.80	46.97	−34.17	63.48	29.31
	(16.22)	(13.84)	(22.31)	(9.664)	(34.16)	(38.23)	(33.65)	(55.89)	(26.34)
$[ln(gdppc_{ct})]^2$	0.217	0.135	0.352	−0.212	−0.858	−1.070	0.901	−1.287	−0.386
	(0.491)	(0.623)	(0.824)	(0.398)	(1.380)	(1.510)	(0.990)	(1.653)	(0.854)
$ln(pop_{ct})$	−16.33***	21.89***	5.564	3.311	6.267	9.577	−7.406	19.40	12.00**
	(4.857)	(3.702)	(4.701)	(2.826)	(8.107)	(9.404)	(6.969)	(11.26)	(5.528)
$ln(gdppc_{ct}) \times ln(pop_{ct})$	1.130**	−1.367***	−0.237	−0.641***	−0.940	−1.581*	0.883	−2.057	−1.174*
	(0.471)	(0.317)	(0.556)	(0.223)	(0.722)	(0.828)	(0.826)	(1.337)	(0.584)
Constant	307.1**	−369.3***	−62.23	−83.86	−166.0	−249.9	224.4	−483.4	−259.0
	(117.9)	(84.34)	(139.0)	(60.40)	(221.1)	(249.0)	(213.3)	(353.4)	(171.9)
Observations	452	452	452	396	396	396	692	692	692
R^2	0.036	0.064	0.007	0.016	0.030	0.039	0.003	0.009	0.023
Number of panel units	20	20	20	20	20	20	20	20	20

Robust standard errors in parentheses. *** $P < 0.01$. ** $P < 0.05$. * $P < 0.1$.

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