Premature deindustrialization: an empirical analysis in latecomer developing countries

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Abstract

This study examines whether latecomer developing countries worldwide have experienced premature deindustrialization. The main findings of this study are as follows. First, the fixed effect model based on panel data, as a baseline analysis for examining the manufacturing-income nexus using the latecomer index, identified the existence of premature deindustrialization in latecomer developing economies under globalization in the post-1990 period. Second, from a geographical perspective, the acceleration of premature deindustrialization was confirmed in Latin America and some areas of Africa. Third, the quantile regression, which served for checking the robustness of the fixed effect model estimation results, also supported the existence of premature deindustrialization in latecomer developing economies. Finally, alternative estimations demonstrated that partaking in global value chains (GVC) facilitated industrialization, whereas natural resource abundance prevented it. Regarding policy implications, GVC participation can be a viable policy for mitigating premature deindustrialization in latecomer developing economies; for resource-rich economies to prevent the Dutch disease effect from accelerating premature deindustrialization, their resource revenues could be mobilized to productive uses, like infrastructure development.

Keyword: Premature deindustrialization, latecomer developing countries, fixed effect model, globalization, global value chains

JEL Classification Codes: O14, F10

1. Introduction

In the literature, premature deindustrialization is defined as an economic phenomenon wherein latecomer economies transition into service economies without having undergone a full-fledged industrialization process (Dasgupta and Singh, 2007; Rodrik, 2016). While Dasgupta and Singh (2007) were the first to use the term “premature deindustrialization”, they focused only on employment and not on output, as well as argued that the decline in manufacturing is not necessarily a pathological phenomenon; specifically, while such deindustrialization has been pathological in Latin American and African countries under the context of import substitution strategies, it has been accompanied by information technology and knowledge-based innovation, as a new engine of growth, in India and East Asian countries.

Then, Rodrik (2016) refined the arguments about premature deindustrialization, positing that it refers to the early shrinking of manufacturing regarding employment and output in developing countries. This author constructed a simple two-sector theoretical model with manufacturing and non-manufacturing sectors to demonstrate that developing countries that liberalize trade tend to be price-takers in the global markets for manufacturing, and that those who lack a strong comparative advantage in manufacturing must become net importers of manufactured products because of the decline in the relative price of manufacturing and the rise of China, thereby leading to deindustrialization in manufacturing employment and output.

Rodrik (2016) provided the following empirical evidence for these affirmations: late industrializers attain peak levels of industrialization lower than those experienced by early industrializers at lower income levels (post-1990 peak incomes are approximately 40% of pre-1990 peak incomes). From a geographical perspective, countries in Latin America and sub-Saharan Africa have been hit hard by premature deindustrialization, whereas Asian countries, as a group with comparative advantages in manufacturing, have managed to avoid this trend.

Since the seminal work of Rodrik (2016), numerous empirical studies have been conducted to identify the existence of premature deindustrialization in multiple and specific countries, including the following: Sato and Kuwamori (2019) in non-OECD countries, Nayyar et al. (2021) in lower-income developing countries, Daymard (2020) in Latin American and African countries, Caldentey and Vernengo (2021) in Latin American countries, Ssozi and Howard (2018) in Sub-Saharan African countries, Taguchi and Tsukada (2022) in Asian latecomer economies, Lee (2020) in Malaysia, and Hamid and Khan (2015) in Pakistan.

Most of these previous empirical studies have concentrated on the comparison of industrialization peaks between forerunner and latecomer economies, reporting that lower peaks with lower incomes in latecomers indicate premature deindustrialization. However, while latecomers face a high probability of falling into premature deindustrialization, not all latecomers necessarily reach their industrialization peaks. In this context, Taguchi and Tsukada (2022) focused on Asian latecomer developing economies and adopted the “latecomer index” for examining the positions of the manufacturing–income nexus. The latecomer index facilitates the identification of downward shifts in latecomers' manufacturing–income nexus, regardless of the existence of an industrialization peak. Even for a latecomer that has not reached its peak, its downward shift suggests an upcoming peak-out at a lower manufacturing share in a lower income stage, implying a symptom of premature deindustrialization.

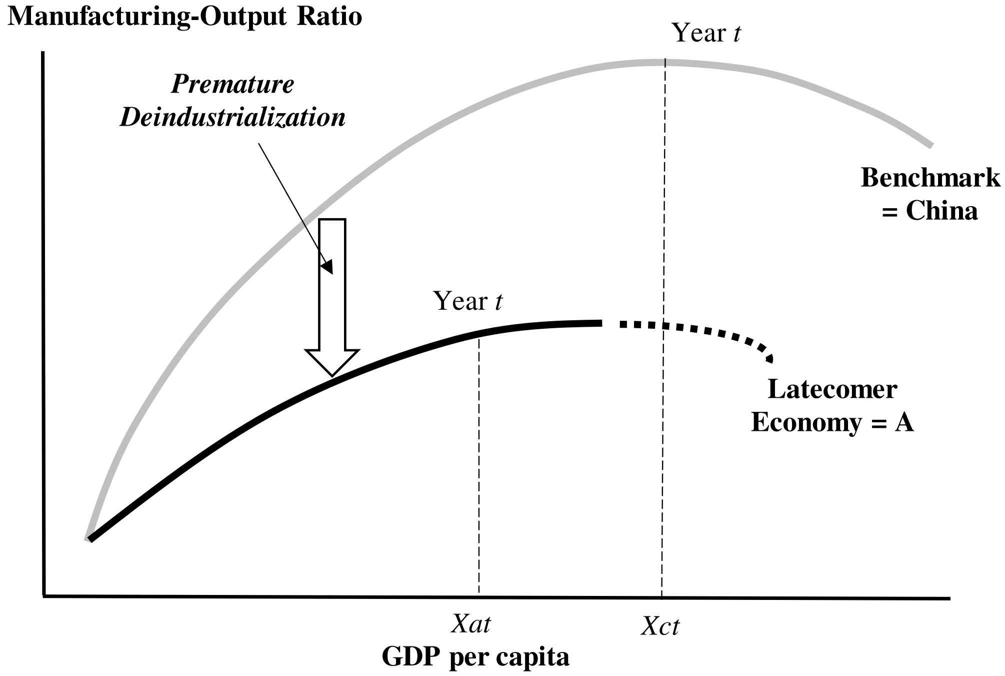
This study aims to identify the existence of premature deindustrialization in all developing countries (110 countries) worldwide from 1980 to 2020 by applying the latecomer index, namely, the extension proposed by Taguchi and Tsukada (2022). The study is structured as follows. First, we estimate a fixed effect model in the panel setting as a baseline analysis to examine the manufacturing–income nexus with the latecomer index. Second, we examine the regional heterogeneity of premature deindustrialization by incorporating the cross-terms of the latecomer index and regional dummies in the fixed effect model. Third, we check the robustness of the fixed effect model estimation results using quantile regression, which is as an alternative approach for allowing the complete conditional distribution of dependent variables over different years and countries. Fourth, to propose policy directions for mitigating and avoiding premature deindustrialization, we conduct alternative estimations considering country participation in global value chains (GVCs) and natural resource abundance. Finally, we summarize the study and conclude the paper.

2. Baseline Estimation

This section presents a baseline estimation using the fixed effect model in the panel setting. Regarding the specification, we apply the equation with the inverted U-shaped manufacturing–income nexus proposed by Rodrik (2016), which controls for the effect of demographic and income trends with their quadratic terms. However, this study modifies the Rodrik specification by adopting the latecomer index (Taguchi and Tsukada, 2022), which in turn serves to demonstrate the shifts in the manufacturing–income nexus of a latecomer economy and verify the existence of premature deindustrialization.

The latecomer index indicates the degree of development lateness computed as the ratio of the gross domestic product (GDP) per capita of a latecomer economy in a particular year relative to that of a benchmark economy in that year. China is chosen as the benchmark economy because it has become a global manufacturing center, as described in a prior research (Sung, 2007), and a top runner in manufacturing–output ratios among developing economies. In Figure 1, the latecomer index in year t is shown by the GDP per capita of economy A (Xat) divided by that of China (Xct). If the index (Xat / Xct) is linked to a lower manufacturing–output ratio, economy A's manufacturing–output curve is positioned downward from the China's curve, as shown in Figure 1.

Figure 1. Analytical Framework of Premature Deindustrialization



Source: Author's description

This implies the existence of premature deindustrialization in the latecomer economy because the downward position of the manufacturing-income curve (vs. China's curve) suggests a peak-out or an upcoming peak-out at a lower manufacturing–output ratio in a lower income stage. The equation for the baseline estimation is as follows:

$$mar_{it} = \gamma_0 + \gamma_1 \ln pop_{it-1} + \gamma_2 (\ln pop_{it-1})^2 + \gamma_3 \ln ypc_{it-1} + \gamma_4 (\ln ypc_{it-1})^2 + \varphi_1 lac_{it-1} + \varphi_2 lac_{it-1} d90 + f_i + \varepsilon_{it} \quad (1)$$

where the subscripts *i* and *t* denote countries (110 developing economies) and years (1980–2020), respectively; *mar* represents a country's manufacturing–output ratio in a real term; *pop* and *ypc* refer to a country's population size and real GDP per capita, respectively; *lac* denotes the latecomer index; *d*90 represents the time dummy for 1990–2020; f_i is a time-invariant, country-specific fixed effect; ε denotes a residual error term; $\gamma_{0...4}$ and $\varphi_{0...2}$ are the estimated coefficients; and ln represents a logarithm form. The explanatory variables in Equation (1) are lagged by one year in order to help avoid reverse causality owing to the endogenous interactions between the dependent and independent variables in the model specifications. The logarithm forms of *pop* and *ypc* are set to avoid scaling issues regarding population size and real GDP per capita, respectively. The data sources of these variables are the UNCTAD Stat (Section 4 adds variables with data that stem from the UNCTAD-Eora Global Value Chain

Database and World Bank Open Data). The list and descriptive statistics for the variables, including those for the estimation in Section 4, are displayed in Tables 1 and 2, respectively. This study constructs a set of panel data for 110 sample countries for the period 1980–2020.

Table 1. List of Variables, Definitions, and Sources

Var.	Description	Sources
Dependent Variable		
mar	*Manufacturing in US dollars at constant prices (2015), percentage of Gross Domestic Product (GDP)*	UNCTAD Stat
Explanatory Variables		
pop	*Populaiton in thousands, log term, one-year lagged*	UNCTAD Stat
ypc	*GDP in US dollars at constant prices (2015) per capita, log term, one-year lagged*	
lac	*Latecomer index, a ratio of GDP per capita of an economy to that of benchmark country (China) in a certain year, one-year lagged*	
gvc	*Global value chains (GVC) indicator, GVC values devided by gross export values, one-year lagged*	UNCTAD-Eora
nrr	*Total natural resources rents, percantage of GDP, one-year lagged*	World Bank

Notes: UNCTAD Stat: https://unctadstat.unctad.org/EN/
UNCTAD-Eora: UNCTAD-Eora Global Value Chain Database (https://worldmrio.com/unctadgvc/)
World Bank: World Bank Open Data (https://data.worldbank.org/)
Source: Author's description

Table 2. Descriptive Statistics

Variables	Obs.	Median	Std. Dev.	Min.	Max
Dependent Variable					
mar	4,510	12.590	7.227	0.010	70.790
Explanatory Variables					
pop	4,510	9.014	2.165	2.079	14.170
ypc	4,510	7.546	1.068	4.564	10.035
lac	4,510	0.850	3.166	0.010	52.980
gvc	2,581	0.434	0.109	0.180	0.942
nrr	3,248	4.071	10.696	0.000	67.890

Source: Author's estimation

To ensure a more thorough description of Equation (1), the following notes on its specifications are required. The latecomer index (*lac*) is the most critical variable for identifying premature deindustrialization. A significant positive value of φ, which refers to the linkage between a country's delayed development and its lower manufacturing–output ratio and represents the downward shift of the country's manufacturing–income curve, can substantiate the occurrence of premature deindustrialization. Premature deindustrialization is explicitly triggered by the globalization trends in manufacturing markets, as Rodrik (2016) argued (see the Introduction). This cited author regarded the post-1990 period as the period in which globalization gained momentum. Thus, the equation contains the cross-term of *lac* and the time dummy for 1990–2020 (*d*90).

Regarding the control variables for the trends in population size (*pop*) and real GDP per capita (*ypc*), the inverted U-shaped nexuses between the manufacturing–output ratio (*mar*) and these control variables are confirmed if γ_1, $\gamma_3 > 0$ and γ_2, $\gamma_4 < 0$ are significant. The time-invariant country-specific fixed effect (f_i) also has to be controlled for in the panel estimation because this study considers the existence of exogenous country-specific factors (e.g., geography, endowments, and history) that differ among sample countries and correlate with *mar*. Thus, adopting the fixed effect model contributes to alleviating the endogeneity problem by absorbing unobserved heterogeneity among countries.

For the subsequent estimation, we investigate the stationary property of the constructed panel data by employing panel unit root tests, as follows: the Levin, Lin, and Chu test (Levin et al., 2002) as a common unit root test, and the Fisher–ADF and Fisher–PP tests (Choi, 2001; Maddala and Wu, 1999) and the Im, Pesaran, and Shin test (Im et al., 2003) as individual unit root tests. The common unit root test assumes the existence of a common unit root process across cross sections, whereas the individual unit root test assumes individual unit root processes that differ across cross sections. These tests are conducted based on the null hypothesis that a series of panel data in levels have a unit root by incorporating the "individual intercept" and "individual intercept and trend" into the test equations. Table 3 shows that the results of the Levin, Lin, and Chu test reject the null hypothesis of a unit root at the conventional significance level for all variables in both test equations. The individual unit root tests do not necessarily reject the null hypothesis in all cases; however, the Fisher–PP test, with the individual intercept and trend, rejects the null hypothesis at the conventional level for all variables. Therefore, we assume that there is no serious problem with the existence of unit roots in the panel data, allowing us to use the panel data in levels for subsequent estimations.

Table 3. Panel Unit Root Tests Results

tests	*mar*	*pop*	*ypc*	*lac*	*gvc*	*nrr*
			individual intercept			
Levin, Lin & Chu	-2.867 ***	-7.684 ***	1.411	-43.088 ***	-11.020 ***	-14.223 ***
Fisher ADF	289.2 ***	426.7 ***	192.3	1,676.9 ***	195.4	499.9 ***
Fisher PP	274.9 ***	1,394.4 ***	159.4	2,523.4 ***	328.4 ***	509.3 ***
Im, Pesaran & Shin	-0.387	-1.641 *	6.101	-35.982 ***	-1.922 **	-12.464 ***
			individual intercept and trend			
Levin, Lin & Chu	-4.584 ***	-6.183 ***	-5.285 ***	-26.609 ***	-11.281 ***	-12.727 ***
Fisher ADF	306.6 ***	394.9 ***	279.9 ***	840.5 ***	153.3	635.3 ***
Fisher PP	282.2 ***	312.7 ***	248.8 *	1,732.4 ***	224.5 **	698.6 ***
Im, Pesaran & Shin	-1.773 **	-0.606	-0.124	-14.841 ***	3.863	-8.244 ***

Notes: *, **, and *** denote the rejection of the null hypothesis at the 90%, 95%, and 99% levels of significance, respectively.
Source: Author’s estimation.

Table 4 reports the results of the baseline estimation. Across all estimation results from columns (a) to (c) (including those in Tables 5, 6, and 7 in columns d–m), γ_1, $\gamma_3 > 0$ and γ_2, $\gamma_4 < 0$ hold significantly, demonstrating an inverted U-shaped relationship between a country’s manufacturing–output ratio and its control variables (population size and real GDP per capita). The turning points, computed using $-\gamma_3/2\gamma_4$ in Equation (1), fell within the reasonable ranges of real GDP per capita, namely between 3,682 and 3,885 USD. The main research focus in this study was, however, the position of a country’s manufacturing–income curve, not its shape.

Table 4. Baseline Estimation Results

Estimation	a	b	c
ln *pop*	4.598 ***	4.092 ***	3.996 ***
	(30.682)	(27.740)	(25.791)
ln $(pop)^2$	-0.349 ***	-0.323 ***	-0.318 ***
	(-29.876)	(-28.646)	(-28.189)
ln *ypc*	18.948 ***	18.428 ***	18.218 ***
	(34.269)	(33.574)	(33.791)
ln $(ypc)^2$	-1.154 ***	-1.117 ***	-1.102 ***
	(-32.431)	(-31.184)	(-31.607)
lac		-0.012 **	-0.003
		(-2.039)	(-0.492)
lac * *d*09			0.071 ***
			(4.416)
Turning point of *ypc* (USD)	3,682	3,819	3,885
Country fixed effect	Yes	Yes	Yes
No. of Countries	110	110	110
No. of Observations	4,510	4,510	4,510

Note: ** and *** denote the rejection of the null hypothesis at the 95% and 99% levels of significance, respectively. T-statistics are shown in parentheses.
Sources: Author's estimation

Estimation results in column (b) show that *lac* had a negative coefficient, and those in column (c) show an insignificant *lac* coefficient and a significantly positive coefficient of the cross-term, *lac***d*90. This positive coefficient represents the downward position of the latecomer's manufacturing–income curve during the post-1990 period, suggesting that globalization in manufacturing markets has caused the premature deindustrialization of latecomers. This result is consistent with those of the study by Rodrik (2016).

3. Regional Estimation

We also examine the regional heterogeneity of premature deindustrialization by incorporating the cross-terms of the latecomer index and regional dummies into the fixed effect model. The model is specified as follows.

$$mar_{it} = \gamma_0 + \gamma_1 \ln pop_{it-1} + \gamma_2 (\ln pop_{it-1})^2 + \gamma_3 \ln ypc_{it-1} + \gamma_4 (\ln ypc_{it-1})^2 + \varphi_1\, lac_{it-1} + \varphi_2\, lac_{it-1} * d90 + \varphi_3\, darea\; lac_{it-1} * d90 + f_i + \varepsilon_{it} \quad (2)$$

Equation (2) adds an additional cross-term that includes the regional dummy, *darea*, to Equation (1). A significant positive value of φ_3 represents the additional region-specific effect of premature deindustrialization under globalization in that region. The regional dummy comprises four types, as described herein: dummies for African countries (*dafri*), East African countries (*dafri_e*), Asian countries (*dasia*), and Latin American countries (*dlame*). Country classification is shown in the Appendix.[1]

Table 5 presents the results of the regional estimations. Focusing on the cross-terms with regional dummies, the coefficient of the African dummy in column (d) is significantly negative, offsetting the positive worldwide effect of premature deindustrialization. However, the coefficient of the East African dummy, in column (e), is significantly positive, accelerating the worldwide effect of premature deindustrialization. The coefficient of the Asian dummy, in column (f), is positive and weakly significant, and that of the Latin American dummy, in column (g), is positive and highly significant. The findings on the acceleration of premature deindustrialization in Latin America and some areas of Africa are in line with those of the studies by Dasgupta and Singh (2007), Rodrik (2016), Daymard (2020), Caldentey and Vernengo (2021), and Ssozi and Howard (2018). Meanwhile, the weak acceleration of premature deindustrialization in Asia seems to reflect the heterogeneity of the countries in the region, with Taguchi and Tsukada (2022) having previously argued that the risk of premature deindustrialization is larger for South Asian than for Southeast Asian countries.

[1] The estimation for Oceanian countries is excluded because the samples are quite limited.

Table 5. Estimation Results with Regional Dummies

Estimation	d	e	f	g
ln pop	3.977 ***	4.015 ***	3.928 ***	4.051 ***
	(25.879)	(25.199)	(21.499)	(25.884)
ln (pop) ^{2}	-0.316 ***	-0.318 ***	-0.314 ***	-0.321 ***
	(-28.019)	(-24.233)	(-29.190)	(-29.223)
ln ypc	18.228 ***	18.192 ***	18.339 ***	18.298 ***
	(35.959)	(33.706)	(33.575)	(35.202)
ln (ypc) ^{2}	-1.104 ***	-1.101 ***	-1.112 ***	-1.107 ***
	(-34.225)	(-31.429)	(-31.315)	(-32.992)
lac	-0.002	-0.004	-0.003	-0.007
	(-0.320)	(-0.579)	(-0.484)	(-1.058)
*lac * d09*	0.093 ***	0.059 ***	0.049 ***	0.021
	(5.062)	(3.982)	(3.997)	(0.786)
*dafri * lac * d90*	-0.083 ***			
	(-0.083)			
*dafri_e * lac * d90*		0.804 ***		
		(4.909)		
*dasia * lac * d90*			0.189 *	
			(1.835)	
*dlame * lac * d90*				0.092 ***
				(2.901)
Country fixed effect	Yes	Yes	Yes	Yes
No. of Countries	110	110	110	110
No. of Observations	4,510	4,510	4,510	4,510

Note: *** and * denote rejection of the null hypothesis at the 99% and 90% levels of significance, respectively, in the coefficients. T-statistics are shown in parentheses.
Sources: Author's estimation

4. Quantile Regression

In this section, we report the estimation using quantile regression, which serves to check the robustness of the findings using the fixed effect model. Most regression models are concerned with analyzing the conditional 'mean' of a dependent variable. Meanwhile, the quantile regression, originally proposed by Koenker and Bassett (1978), models the quantile of the dependent variable given a set of conditioning variables by describing how the median (or quantile) of the response variable is affected by regressor variables. This method is robust because its approach is less sensitive to outliers and heteroscedastic residuals, so it does not require a strong distribution assumption (e.g., Buchinsky, 1998; Chang et al., 2018). The quantile regression requires Equation (1) to be respecified as follows:

$$Q_{\zeta} mar_{it} = \gamma_{0\zeta} + \gamma_{1\zeta} \ln pop_{it-1} + \gamma_{2\zeta} (\ln pop_{it-1})^2 + \gamma_{3\zeta} \ln ypc_{it-1} + \gamma_{4\zeta} (\ln ypc_{it-1})^2 + \varphi_{1\zeta}\, lac_{it-1} + \varphi_{2\zeta}\, lac_{it-1}\, d90 + f_i + \varepsilon_{it} \quad (3)$$

The quantiles are set at three levels: $\zeta = 25^{th}$, 50^{th}, and 75^{th}. Table 6 presents the estimation outcomes for each quantile. In the 25^{th} quantile shown in column (h), the coefficients of *lac* and *lac***d*90 are insignificant. Regarding the 50^{th} and 75^{th} quantiles demonstrated in columns in (i) and (j), they are significantly positive, with those of the cross-term accelerating the positiveness. This suggests that, in the countries in our sample, a progressed stage of industrialization allows for premature deindustrialization to be evidently identified, while an earlier stage of industrialization makes deindustrialization less obvious. Thus, the quantile regression model confirms the existence of premature deindustrialization in the sampled economies.

Table 6. Quantile Regression Results

Estimation	h	i	j
Quantile levels	25th	50th	75th
ln *pop*	1.552 ***	3.492 ***	3.616 ***
	(13.045)	(28.946)	(18.527)
ln $(pop)^2$	-0.015 **	-0.128 ***	-0.125 ***
	(-2.160)	(-16.228)	(-10.521)
ln *ypc*	14.413 ***	17.502 ***	20.490 ***
	(11.789)	(20.757)	(17.269)
ln $(ypc)^2$	-0.906 ***	-1.086 ***	-1.306 ***
	(-11.090)	(-17.341)	(-16.360)
lac	-0.022	0.169 ***	0.155 ***
	(-0.266)	(6.327)	(4.662)
lac * *d*09	0.116	0.253 ***	0.207 ***
	(0.812	(3.999)	(2.805)
No. of Countries	110	110	110
No. of Observations	4,510	4,510	4,510

Note: ** and *** denote the rejection of the null hypothesis at the 95% and 99% levels of significance, respectively. T-statistics are shown in parentheses.
Sources: Author's estimation

5. Alternative Estimations for Proposing Policy Directions

Finally, this section reports the findings of the alternative estimations while considering participation in GVCs and natural resource abundance, which serve for yielding relevant data to propose policy directions to mitigate and avoid premature deindustrialization.

GVCs have dominated global economic activities over the past few decades, and their production networks have typically revolved around manufacturing activities (Kimura, 2006; Kimura et al. 2007). GVCs facilitate specialization in production processes among countries and relieve a single country from performing all processes of production, thereby enhancing efficiency and productivity and promoting the diffusion of technology along the chains (World Bank, 2020). Thus, the absence of GVC participation leads to sluggish manufacturing.

Another dimension of deindustrialization issues is the nexus with Dutch disease in resource-rich economies. The disease was coined by the *Economist* in a November 1977 issue, and was inspired by the deindustrialization process related to natural gas discoveries by the Netherlands in the late 1950s. Corden and Neary (1982) provided the theoretical basis for this phenomenon, and many quantitative studies have verified the existence of Dutch Disease in resource-rich economies (e.g., Sachs and Warner, 2001). The alternative estimation model is as follows.

$$mar_{it} = \gamma_0 + \gamma_1 \ln pop_{it-1} + \gamma_2 (\ln pop_{it-1})^2 + \gamma_3 \ln ypc_{it-1} + \gamma_4 (\ln ypc_{it-1})^2 + \eta_1 \, gvc_{it-1} + \eta_2 \, nrr_{it-1} + f_i + \varepsilon_{it} \qquad (4)$$

Equation (4) replaces the latecomer index (*lac*) in Equation (1) with the GVC indicator (*gvc*) and natural resource rents (*nrr*; the data description, statistics, and properties are shown in Tables 1–3). Columns (k) to (m) in Table 7 show the estimation results, wherein the coefficient of *gvc*, η_1, is significantly positive and that of *nrr*, η_2, is significantly negative. This suggests that GVC participation facilitates industrialization, whereas natural resource abundance prevents it.

Table 7. Estimation Results while Considering GVC Participation and Natural Resource Rent

Estimation	k	l	m
ln *pop*	-0.458	5.355 ***	0.890 *
	(-1.107)	(24.660)	(1.914)
ln $(pop)^2$	-0.128 ***	-0.392 ***	-0.212 ***
	(-5.749)	(-31.206)	(-8.393)
ln *ypc*	20.360 ***	20.854 ***	23.831 ***
	(27.905)	(35.631)	(24.926)
ln $(ypc)^2$	-1.275 ***	-1.266 ***	-1.504 ***
	(-23.635)	(-33.613)	(-21.662)
gvc	1.361 ***		2.765 ***
	(3.330)		(6.789)
dnrr		-0.026 ***	-0.025 ***
		(-5.045)	(-4.038)
Country fixed effect	Yes	Yes	Yes
No. of Countries	89	108	88
No. of Observations	2,581	4,179	2,481

Note: *** denotes rejection of the null hypothesis at the 99% level of significance. T-statistics are shown in parentheses.
Sources: Author's estimation

These outcomes point toward the following policy implications for mitigating and avoiding the premature deindustrialization verified in Sections 2–4. First, GVC participation can be a viable policy for mitigating premature deindustrialization in latecomer developing economies. Numerous reports by international organizations (UNCTAD, 2013; World Bank, 2016, 2020) have recommended countries to develop GVC participation strategies, such as strategies related to infrastructure and human resource development, institutional improvements, and policy frameworks to create industrial clusters and networks. Second, for resource-rich economies, the Dutch disease effect may accelerate premature deindustrialization. To offset the disease effect, resource revenues should be mobilized for productive uses, such as infrastructure development, to activate manufacturing activities (e.g., Sachs, 2007; Coutinho, 2011).

6. Concluding Remarks

This study examined whether latecomer developing countries worldwide have experienced premature deindustrialization. The main findings of this study are as follows. First, the fixed effect model in the panel setting, as a baseline analysis for examining the manufacturing–income nexus using the latecomer index, identified the existence of premature deindustrialization in latecomer developing economies under globalization in the post-1990 period. Second, from a geographical perspective, the acceleration of premature deindustrialization was confirmed in Latin America and some areas of Africa. Third, the quantile regression, used for checking the robustness of the fixed effect model estimation findings, also supported the existence of premature deindustrialization. Finally, alternative estimations showed that GVC participation facilitated industrialization, whereas natural resource abundance prevented it.

The policy implications of this study are that GVC participation can be a viable policy to mitigate premature deindustrialization in latecomer developing economies. Furthermore, resource-rich economies should mobilize their resource revenues for productive uses, such as allocating them to infrastructure development, in order to prevent the Dutch disease effect from accelerating premature deindustrialization.

A limitation of this study is the lack of detailed research on individual countries. Examining the complexity of premature deindustrialization mechanisms and policy performance in specific countries through detailed case studies would enable the development of country-specific and more concrete recommendations and prescriptions for mitigating and avoiding premature deindustrialization.

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Appendix Country Classification (110 countries and 4 areas)

Africa	Latin America	Asia	Oceania
Algeria	Argentina	Afghanistan	Fiji
Angola	Belize	Bangladesh	Nauru
Benin	Bolivia	Bhutan	Papua New Guinea
Botswana	Brazil	Cambodia	Samoa
Burkina Faso	Colombia	China	Solomon Islands
Burundi *	Costa Rica	India	Tonga
Cabo Verde	Cuba	Indonesia	Tuvalu
Cameroon	Dominica	Iran	Vanuatu
Central African	Dominican Republic	Iraq	
Chad	Ecuador	Jordan	
Comoros *	El Salvador	Korea, Dem.	
Congo	Grenada	Lao People's Dem. Rep.	
Congo, Dem. Rep.	Guatemala	Lebanon	
Côte d'Ivoire	Guyana	Malaysia	
Djibouti *	Haiti	Maldives	
Egypt	Honduras	Mongolia	
Equatorial Guinea	Jamaica	Myanmar	
Eswatini	Mexico	Nepal	
Ethiopia *	Nicaragua	Pakistan	
Gabon	Panama	Philippines	
Gambia	Paraguay	Sri Lanka	
Ghana	Peru	State of Palestine	
Guinea	Saint Lucia	Syrian Arab Republic	
Guinea-Bissau	Saint Vincent and the Grena	Thailand	
Kenya *	Suriname	Turkey	
Lesotho	Venezuela	Viet Nam	
Liberia			
Libya			
Madagascar *			
Malawi *			
Mali			
Mauritania			
Mauritius *			
Morocco			
Mozambique *			
Namibia			
Niger			
Nigeria			
Rwanda *			
Sao Tome and Principe			
Senegal			
Sierra Leone			
Somalia *			
South Africa			
Tanzania *			
Togo			
Tunisia			
Uganda *			
Zambia *			
Zimbabwe *			

Notes: * represents East Africa.
Sources: UNCTAD Stat.