UDC 332.144
doi: 10.18323/3034-2074-2025-3-62-3

Technological innovations and premature deindustrialization: evidence from middle-income countries

Dieubenit Tsafack Miafo*[1,3], doctoral student, Dschang School of Economics and Management
Armand Gilbert Noula[1], Associate Professor, Dschang School of Economics and Management
Yokono Dieudonné Bondoma[2], Associate Professor, Faculty of Economics and Management
Deffo Salomon Leroy Ghamsi[1,4], PhD, Dschang School of Economics and Management
[1]*University of Dschang, Dschang (Cameroon)*
[2]*University of Yaounde II, Yaounde (Cameroon)*

***E-mail:** Dieubenit.tsafack@univ-dschang.org

[3]ORCID: https://orcid.org/0009-0007-2665-7616
[4]ORCID: https://orcid.org/0000-0002-2854-4371

Received 27.08.2025 *Revised 08.09.2025* *Accepted 22.09.2025*

Abstract: Premature deindustrialization (PDI) has emerged as a critical challenge for middle-income countries amidst rapid technological innovations and globalization. This study explores how technological innovations (TI), measured by patent applications, influence PDI across 89 middle-income countries from 1980–2022. A novel composite index, integrating income levels and manufacturing sector contributions (value-added and employment shares), is developed to quantify PDI. Employing robust econometric techniques, including Ordinary Least Squares (OLS) with Oster's stability test and Instrumental Variable Generalized Method of Moments (IV-GMM), we find that TI significantly reduces PDI's likelihood. These results, consistent across subsamples and multiple robustness checks, underscore the pivotal role of innovation in fostering sustainable industrial growth. This research offers critical insights for policymakers aiming to balance technological advancement with industrial development in middle-income economies.

Keywords: premature deindustrialization; technological innovations; structural transformation; middle-income countries; IV-GMM.

For citation: Tsafack Miafo D., Noula A.G., Bondoma Yo.D., Ghamsi D.S.L. Technological innovations and premature deindustrialization: evidence from middle-income countries. *Digital Economy & Innovations*, 2025, no. 3, pp. 31–50. DOI: 10. 10.18323/3034-2074-2025-3-62-3.

1. INTRODUCTION

Technological innovation has served as a driving force in shaping the modern world, transforming industries, economies, and societies [1–5]. One unintended consequence of technological innovations is deindustrialization, a widespread phenomenon in high-income countries [2; 6–8]. However, when this phenomenon occurs at lower income levels, it is referred to as premature deindustrialization, which has numerous implications [6; 9; 10]. This paper examines the effect of technological innovation on premature deindustrialization in middle-income countries.

Characterized by a significant decline in both manufacturing output (as a percentage of GDP) and employment (in total employment), "deindustrialization" is viewed as a typical phase in development models, especially for developed countries [4; 11]. According to Herrendorf et al. [12], the reallocation of labor and other resources across various economic sectors from low-productive to high-productive sectors such as agriculture; manufacturing, key player in growth acceleration especially for developing economies due to its ability to absorb labor, higher productivity, higher externalities, and tradability amongst others [10; 13; 14]; and services stimulates economic growth and development, representing the standard path of structural transformation. Consequently, any early trend of deindustrialization in developing economies at much earlier income levels than those historically observed in advanced countries; termed "premature deindustrialization" raises concerns about obstructing the primary channels of economic growth and the ability to catch-up with more advanced economies [4; 10; 11].

Existing literature indicates that the incidence of stagnation in growth is more pronounced in middle-income countries compared to other income groups, prolonging growth slowdowns in these economies, a phenomenon known as the "middle-income trap" [10; 15], with most developing economies struggling to advance towards the high-income category, with only 13 out of 101 middle-income countries in the 1960s were able to attain the status of a high-income country by 2008 [10]. This phenomenon affecting Countries irrespective of their state of development, mainly impacts Latin America, Africa, the Middle East, and Asia, and is exacerbated by several factors, resulting in short and long-term consequences [16]. This situation further undermines the economic growth of middle-income countries, threatening their competitiveness and hindering their ability to enter high-income group [4; 6; 10; 17; 18]. The literature provides several possible explanations for these circumstances, attempting to balance general and specific insights (e.g., see [2; 4; 6; 10; 19]). The recent literature does review theoretical structures with sweeping relevance and applicability considering a broader set of transformations [5]. One aspect that has been overlooked in existing literature, which has captured our attention for this study, is technological innovations that lead to more labor-saving production processes, enhance productivity, and replace workers with automated machines, further highlighting the "middle-income technology trap". The dearth of vital industrial and technological breakthroughs would open up new development avenues while causing dire repercussions for both economic growth and industrial development [19]. The "middle-income technology trap", which is closely linked to the concept of premature deindustrialization, comes with the possibility of a vicious cycle of lack of structural transformation, poor economic growth, weak technological and broader industrial upgrading, and deindustrialization [14; 19; 20].

From the radical technological revolutions in the Industrial Revolution era to the so-called Industry 4.0 revolution and forthcoming industrial revolutions, the global economy has always been, is, and will be, driven by technological innovations with learning by doing and labor specialization, important to mention as underlying sources of increasing returns, productivity, and skill acquisitions [4; 14]. The development and upgrade of new technology are hence crucial to be able to produce complex goods with domestic technology and prepare the labor force through education, amongst other means. As a matter of fact, the expansion of productive capacity is hence more relevant for developing economies, as it is arguably the main constraint on green economic growth and because the manufacturing sector still acts as an engine of growth [4; 14]. The literature has developed abundantly on the possible effects and consequences of technological innovation on the industrial sector and structural change (e.g. [1–4; 7; 14]).

With the chaining effect and high productivity, the industrial sector, compared to the other sectors of the economy, is considered a dominant sector with its high technological spillover effect [20; 21]. Considered putative in developed countries, developing countries are experiencing an early diminishing interest in manufacturing share while services share of gross domestic product and employment are increasing at the top of the Global Value Chain in recent decades. According to Itaman and Awopegba [20] and Nassif and Morceiro [14], this can be prominently explained by ever-increasing technological upgrading, worsened by the effect of globalization, un-sustained rapid liberalizing ("shock therapy") economic reforms, technological transfer and economic diversification a situation described as the "middle-income technology trap" [19]. Though the role of tradable services in both the productive structure and global trade has increased, while the share of manufacturing has dropped (deindustrialization), as a result of these technologies, the manufacturing sector remains in the technology game as the primary source of generation and diffusion of technological advancements [13; 14]. It is hence misleading to expect that the world will mutate into an only services economy [14].

Hence, technological innovation and premature deindustrialization are intricately linked, the latter often driven by the former. Hence, while technological innovation has the potential to revolutionize industries and economies, it can also contribute to the decline of manufacturing sectors in many countries [2; 8; 14]. Understanding the causes and consequences of premature deindustrialization is crucial for policymakers, economists, and business leaders to develop strategies to mitigate its effects and foster sustainable economic development. Ultimately, addressing the challenges of premature deindustrialization requires a multi-faceted approach that combines technological innovation with appropriate policy interventions to ensure balanced and inclusive economic growth.

Given this background, premature deindustrialization (PDI) distinguished from general cases of deindustrialization is a main concern [9; 10]. It may lead to a lack of diversification in the economies, hinder a country's ability to move up the value chain and compete in higher value-added industries, limit long-term economic growth and innovation potential, as well as exacerbate income inequality within the country, decrease skilled employment opportunities (as many traditional industrial jobs are lost), leaving it vulnerable to external shocks and fluctuations in global markets. The present study analyzes the bond between technological innovation and premature deindustrialization in middle-income economies, revealing sector-specific vulnerabilities to premature deindustrialization. By pursuing this objective, we make two main contributions to the existing literature. First, only a few studies in the literature (for instance, [10]) have examined the link between premature deindustrialization and the middle-income trap. Of these studies, few have focused on the determinants of PDI, and none, to the best of our knowledge, has focused on technological innovation as the main variable. This work aims to attempt to bridge this gap by providing empirical evidence on the determinants of premature deindustrialization in middle-income economies, focusing primarily on the possible effect of technological innovation. By conducting a longitudinal case study of selected countries over the 1980–2022 period, this study illustrates the nuanced effects of technological innovations on premature industrial decline, providing qualitative insights alongside quantitative data. Second, we use a very large sample of 89 countries from 1980–2022 and employ a set of three conditions (specified by Rodrik [9]) that trace the phases of premature deindustrialization in an economy and apply robust estimation techniques. This permits us to create a novel composite index for measuring not only deindustrialization but also its premature aspect, premature deindustrialization, and develop a policy framework aimed at mitigating the adverse effects of technological advancement on employment in manufacturing, emphasizing retraining programs and innovation incentives tailored for vulnerable sectors. In sum, our findings indicate that the incidence of technological innovation degrades the likelihood of the occurrence of premature deindustrialization in these countries.

The rest of the paper consists of the following sections: The selected relevant literature is discussed in Section 2. Section 3 is devoted to data and estimation strategy description. Section 4 presents and discusses the empirical findings, while Section 5 concludes, gives some policy recommendations, and presents the limitations of the study.

2. LITERATURE REVIEW

"Deindustrialization", a significant decrease in the relative share of manufacturing both in GDP and employment before high-income levels [4; 22] and "premature deindustrialization" have been signposted in the past couple of decades [9; 23]. Unlike growth slowdown, which involves a deceleration in economic expansion often linked to reduced productivity or structural inefficiencies, and the absence of industrialization, where industrial development fails to take root due to technological gaps or poor infrastructure, premature deindustrialization involves a premature shift away from manufacturing at an early stage [9; 10; 21]. It is the latter that retains our attention in this study. First coined by [21] and considered to occur mostly in developing countries, premature deindustrialization is described as a depletion of real manufacturing sector contribution (employment and value-added shares) at income levels far below those experienced by developed countries in the past [4; 22; 24]. This is due to the early transformation of these countries into service-based countries without an established and comprehensive industrialization experience or process [9]. Research on premature deindustrialization in both developing and developed countries has caught the attention of many researchers, largely focused on the effects of premature deindustrialization from different perspectives (e.g., see [18])

The available literature highlights the fact that earlier industrializers are following a pattern of sectoral change and employment different from that previously followed by later industrializers have not been to [17]. These economies are hence experiencing early tertiarization or accelerated servitization of their economies [25]. Cruz [4], argues that industrialization and economic growth are integrated parts of each other, becoming a source of improvement and a crucial factor for nations to grow and develop. Hence, the premature deindustrialization trend hit long-term growth which is why this concept has called the attention of many scholars providing empirical and theoretical contributions in the literature, though few works have been done concerning the factors affecting premature deindustrialization.

Generally, the manufacturing industries are highlighted to display hefty unconditional convergence in labor productivity and generally act as the requisite condition for catching up to the developed economies, inducing economic growth and a positive spillover effect on employment generation [13]. Rekha [10] highlights that globalization, automation, and labor-saving technological advances may be the main drivers of the premature deindustrialization trend, along with a shift toward services. This might restrict the ability of the manufacturing sector to furnish jobs for unskilled and low-skilled workers, which thereby hunk the channels of economic growth [10]. This may be explicated by the fact that globalization has conceited technological advancement and opportunities to raise an innovative manufacturing sector in developing countries. Consequently, the extent to which premature deindustrialization influences countries is conditioned by the ability of the alternative sector to become the potential driver(s) of economic growth [10].

Araujo et al. [26] empirically and theoretically investigate premature deindustrialization from 1970 to 2017 in a group of selected countries, utilizing the generalized method of moments (GMM). Their results revealed that, in less developed economies, exchange rate depreciation is positively correlated with premature deindustrialization, as is trade openness yet negatively. In advanced nations, conversely, the degree of financialization and the relocation of physical production are spotlighted as factors that negatively affect premature deindustrialization, while trade openness is positive. Parallelly, after confirming the hypothesis of premature deindustrialization, Cruz [4], suggests that premature deindustrialization is explained by income evolution, capital accumulation, manufacturing labor productivity, trade openness, and exchange rate. According to Andriyani and Irawan [18], however, its speed may vary between indicators and contexts. Using the bootstrap-corrected dynamic fixed-effects and panel fixed-effects models, Ravindran and Babu [6] empirically confirmed the bond between income inequality and premature deindustrialization. Their finding revealed that income inequity rises with premature deindustrialization, provided that the displaced workers are absorbed into market services. Also, if the non-market services or business services are the governing employment providers, it will help to lessen income inequities even in the presence of premature deindustrialization.

Van der Heijden [27] revisits the discussions on the propinquity between globalization and industrialization and scrutinizes if it differs between economies using a panel of 40 countries (developing and developed) covering the period from 1960 to 2010. This work found a positive connection for both developed and developing economies. There equally revealed a regional difference amid developing regions regarding the evolution of the manufacturing sector with Latin America and Sub-Saharan Africa prematurely deindustrializing and gaining the least from globalization, which can hurt their economic growth path. In another study, Taguchi [28] used the fixed effect model and quantile regression on panel data to examine if latecomer developing nations worldwide have experienced premature deindustrialization. This study had two main conclusions. Firstly, in latecomer developing economies, the existence of premature deindustrialization was confirmed under globalization in the post-1990 period, with its acceleration verified in Latin America and some areas of Africa. Finally, participating in global value chains (GVC) eased industrialization, whilst natural resource abundance accelerated premature deindustrialization through the Dutch disease effect if resource returns were mobilized to productive uses, like infrastructure expansion.

Oreiro et al. [29] analyze the determinants of premature deindustrialization in Brazil for the period between 1998 and 2017 using the ordinary least squares (OLS), affixed with a manifold of other estimation techniques. This study revealed that real exchange rate overvaluation was the main cause of premature deindustrialization. This was because the high-interest rate differential and commodity prices boom increased the value of Brazilian exports and, hence, increased trade account surpluses. Conversely, Grabowski [30] investigates why premature deindustrialization mostly occurs in many developing countries. Their results indicated that rising inequality among several developing countries has reduced the home market for labor-intensive manufactured goods, thus causing manufacturing stagnation. Also, the rising inequality in developed economies has reduced international demand for labor-intensive manufacturing. Thus, according to these authors, developing countries have fewer opportunities to export labor-intensive manufacturing.

Taguchi and Elbek [31], on the other hand, examined deindustrialization in the post-Soviet nations from the perspective of the premature deindustrialization hypothesis and scrutinized the factors that caused the deindustrialization on a panel data sample ranging from 2001 to 2020. Using the fixed-effect model and factor analyses, their results first confirmed the prevalence of premature deindustrialization in two-thirds of the total 15 retained post-Soviet middle-income nations.

They also unearth that deindustrialization in these 10 countries was fully explained by their comparative disadvantages in manufacturing as the gross contributor, and further by the sub-factors: human capital deficiency, the Dutch Disease effect and immature institutions.

Considering a sample of 36 countries (developed and developing) from 1980 to 2017, emphasizing on emerging and developing (EDE) economies in a context of increasing financial integration, Botta et al. [32] used an OLS panel corrected standard error to inquire into the role of net capital inflows as a prospect source of premature deindustrialization. Their results revealed that abundant capital inflow periods may have caused the significant reduction of manufacturing share to employment and GDP, as well as the contraction of the economic complexity index. They also show that phenomena of "perverse" structural change are significantly more relevant in EDE nations than advanced ones.

Hoyos López [33] equally scrutinizes the phenomenon of premature deindustrialization in eight Latin American nations using the Koyck transformation model, OLS, and panel data fixed effects model from 1970 to 2014. Their work revealed that the fall in the average effective tariff was the prime economic explanation behind the premature depletion in the manufacturing share in the region. They also provide evidence that relates the depleting performance of manufacturing to the Dutch disease and foreign investment flows. Using the Autoregressive Distributed lag estimation for the period 1981–2018, Itaman and Awopegba [20] examine the involvement of finance as a potential causal component for Nigeria's premature deindustrialization. Their finding revealed a noteworthy negative impact of banks' domestic credit on premature deindustrialization. Additionally, the unequal flow of bank domestic credit to the services sectors, gas, and oil also indicates a notable negative impact on the country's manufacturing sector. Conversely, financial institutions' net domestic credit, including financial flows by home development banks, had a significant positive effect on manufacturing.

Given these empirical conclusions, a more censorious analysis of the determinants and costs of premature deindustrialization is observed important, especially in developing and middle-income countries.

3. DATA AND ESTIMATION STRATEGY DESCRIPTION

3.1. Data description

For a period ranging from 1980 to 2022, this study used non-cylindrical panel data on 89 middle-income countries from different regions including Europe and Asia (Europe, East Europe, and Central Asia), America and the Caribbean (Latin America, North America, and Caribbean), the Middle East and North Africa, Sub-Saharan Africa, Asia and Pacific, and Oceanic countries (see Table in the appendix). The sample for the study has been rigidly disciplined in terms of data availability issued from the World Intellectual Property Organization Database (WIPO) and World Bank Development indicators (WDI), especially those used in the construction of the technological innovation index. All calculations and visualizations were performed using STATA 18.

3.1.1. Dependent variable

The dependent variable of the study is PDI. PDI is a multidimensional and relatively new concept. Therefore, there exists no consensus in the literature regarding which variable or method is a better guess for capturing the deindustrialization trend. Similarly, there is ambiguity in defining a deindustrialization phase as premature or not. According to the literature, however, the declaration of deindustrialization as premature implies that the economy is not at high-income levels (<$ 11,750) and is still to maneuver the possibilities of manufacturing-driven economic growth [6; 9; 10; 34]. Consequently, to identify the 'premature' element in economies, the income and manufacturing share (in employment and value-added) threshold levels are to be considered. In this study, we draw inspiration from these recent works [9; 10] and build a composite indicator that takes into account three criteria for a country to be considered as experiencing premature deindustrialization, distinguishing general cases of deindustrialization from 'premature' cases, as summarized below:

$$Y_t \leq \$11{,}750\ ; \tag{1}$$

$$MAN\_VA_t \leq 18\%\ ; \tag{2}$$

$$MAN\_Emp_t \leq 18\%\ , \tag{3}$$

where time t=1, 2, …T, where T is the most current period of data availableness;
Y_t, MAN_Emp_t and MAN_VA_t are GDP per capita, employment share (in total employment) and manufacturing value-added share (in total output) in year "t" respectively.

The first constraint stipulates that Y_t (GDP per capita in 2015 constant US $) should be inferior to $ 11,750, the superior threshold level to justify an economy as a middle-income economy. An income level surpassing this threshold signifies that the economy has already reached the high-income category [35]. Hence, deindustrialization is considered "premature" if it takes place below this income level, signaling the element in the shrinking manufacturing share [4; 10]. The second and third constraints specify that a nation in the year "t" should not have manufacturing employment and value-added shares of manufacturing surpassing 18 %. Felipe et al. [34] highlight that the chances of graduating into a rich country status surge if the economy has above 18 % of manufacturing shares (employment and output). This condition implies that the manufacturing sector is not the foremost sector in the economy [6]. Hence, the premature deindustrialization variable is given by the expression in equation:

$$DPI_t = \begin{cases} 1 \text{ if } Y_t \leq \$11{,}750, \text{ and} \\ MAN\_Emp_t \leq 18\%, \text{ and} \\ MAN\_VA_t \leq 18\%; \\ 0 \text{ elsewise} \end{cases} . \tag{4}$$

Wherever all three conditions are satiated, we consider an economy to be witnessing "premature deindustrialization".

3.1.2. Independent variable of interest

The independent variable of interest is technological innovations (TI). Increasingly used in the literature, technological innovation is proxied in this study by the total number of patent applications [13; 21; 26; 36–38]. Patent application employed in this study is a composite indicator (summing) of the residence and the non-residence patent applications (worldwide patent applications for exclusive rights for an invention, a product or process that provides a new way of doing something or offers a new technical solution to a problem filed through the Patent Cooperation Treaty procedure (via foreign patent cooperation offices and with national patent offices (World Bank glossary, 2022). The data on technological innovations is obtained from the WIPO (2024) Database. We equally use the number of scientific and technical journal articles published from the WDI (2024) database [21] as an alternative measure to TI for robustness analyses.

3.1.3. Control variables

The selection of control variables added to our econometric model was guided by at least two factors: firstly, the still very nascent state of the literature on the determinants of PDI. Secondly, a large sample size was used for our study. To curb the bias that may arise from omitted variables, we draw on the few existing empirical studies on the determinants of PDI (e.g. [10; 39; 40] and use five control variables: (i) gross fixed capital formation (GFCF), (ii) Trade openness (Trade), (iii) labor force participation rate (LABFPR), (iv) urban population (Urbpop), and (v) Mineral resources rent (MineralR).

Gross fixed capital formation (% of GDP) is a relevant factor influencing premature deindustrialization since countries with higher levels of Gross fixed capital formation are likely to experience higher economic growth [10]. It is, hence, expected to have a negative coefficient. Another crucial effect on PDI is derived from trade openness (Trade % of GDP). According to Rekha [10], putting in place opening-up strategies encourages technological diffusion and is conducive to increasing productivity. For this reason, a higher degree of trade openness toward international markets is generally assumed to harm premature deindustrialization, as it means raising access to external markets for manufacturing exports [4; 10]. Next, we control human capital as it is relevant to influence production as it obstructs returns to the capital from falling and enhances capabilities for innovation [39]. In this study, we consider it as a control variable captured by the total labor force participation rate (% of total population, ages 15–64). In line with the literature, this variable is expected to have a negative coefficient [10; 40]. Urbanization (% of total population) is increasingly considered an important factor affecting premature deindustrialization, as high levels of urbanization are generally associated with high levels of industrialization and increased demand for goods and services [7]. Similarly, the level of mineral resources rent (% of GDP) is significant as higher levels of mineral rent income from natural resource exploitation are generally attached to high levels of premature deindustrialization [9].

In addition to our key control variables, we look upon other determinants of premature deindustrialization as additional control variables for robustness analyses, viz: carbon emission (metric tons per capita), foreign direct investment (net inflows, % of GDP), control of corruption (estimate) and General government final consumption expenditure (% of GDP). Table 1 presents our study baseline summary of descriptive statistics and pairwise correlation matrix.

3.2. Estimation Strategy

This study evaluates the effect of technological innovation on premature deindustrialization in middle-income economies. Given this and per empirical studies, we state that premature deindustrialization (PDI) depends on technological innovation (TI) and other control covariates (Z) given below:

$$PDI = f(TI, Z). \tag{5}$$

Redesigning equation (5) into its semi-log-linear form provides an empirical equation for estimating the effect of technological innovation on premature deindustrialization outcomes. The semi-log-linear empirical model for PDI is stated below:

$$\ln PDI_{\mathrm{it}} = \alpha_0 + \beta_1 \ln TI_{\mathrm{it}} + \beta_2 Z_{\mathrm{it}} + \mu_{\mathrm{i}} + \varepsilon_{\mathrm{it}}, \tag{6}$$

where i is 1–89;
T is 1980–2022;
ln*PDI* is natural logarithm of premature deindustrialization;
ln*TI* is natural logarithm of technological innovations captured by the total number of patents application;
Z represents our chosen control variables coefficients to be estimated (GFCF, Trade, LABFPR, Urbpop, and Gini);
B is constant parameter to be estimated;
α_0 is constant parameter to be estimated;
μ incorporates the specific fixed effects not observed for each country;
Ɛ is error term.

We execute diverse estimation techniques to investigate the bond outlined in Equation (6). We spring this exercise by implementing the OLS estimation technique, controlling for a number of its potential determinants. It is considered that using a conventional estimator such as the ordinary least square (OLS) to estimate an empirical model with endogeneity issues can create attenuation bias, whereby OLS estimates are downward-biased [41]. As a result of some flaws presented by this technique (among other things, none consider the unobserved differences or the endogeneity of some right-hand side variables, which can falsely affect the estimation of parameters) [42–44] although simple to implement especially when a couple of conditions are fulfilled (error term normality, absence of autocorrelation, and heteroscedasticity) [43], we equally estimate equation (6) using the instrumental variable generalized method of moment (IV-GMM) technique [45]. This technique is the most convenient for this study as it can address endogeneity sources [44]. In supplement to handling the endogeneity issue, the IV-GMM computation allows consistent estimations in the presence of AR (1) heteroscedasticity and autocorrelation within panels [45]. Contractive to the dynamic system-GMM estimator, which computes short-run coefficients, the IV-GMM static estimator provides long-run coefficients. Additionally, the IV-GMM estimator is compatible when the time dimension becomes relatively considerable [45]. In computing

Table 1. *Descriptive statistics and correlations matrix*
Таблица 1. *Описательная статистика и матрица корреляции*

Variables	(1) PDI	(2) Ln TI	(3) GFCFP	(4) Trade	(5) LABFPR	(6) Urbpop	(7) MineralR
Obs	3827	3827	3071	3244	2751	3827	3496
Mean	0.496	2.901	23.08	75.394	62.975	49.514	1.056
Std. Dev.	0.5	2.873	8.598	35.329	9.788	18.876	2.803
Min	0	0	0	0.021	38.058	6.091	0
Max	1	14.277	93.547	274.973	83.889	92.347	39.668
(1)	1.000						
(2)	-0.336	1.000					
(3)	0.031	0.062	1.000				
(4)	-0.026	-0.226	0.220	1.000			
(5)	0.169	0.145	0.011	0.064	1.000		
(6)	-0.327	0.282	-0.104	-0.090	-0.050	1.000	
(7)	0.125	-0.049	0.130	0.148	0.011	-0.042	1.000

Note. PDI is premature deindustrialization; TI is technological innovations; GFCF is gross fixed capital formation; Trade is trade openness; LABFPR is labor force participation rate; Urbpop is urban population; MineralR is mineral resources rent.

Примечание. PDI – преждевременная деиндустриализация; TI – технологические инновации; GFCF – валовый прирост основного капитала; Trade – открытость торговли; LABFPR – доля экономически активного населения; Urbpop – городское население; MineralR – рента от добычи полезных ископаемых.

equation (6) using the IV-GMM, we applied the robust command to control for heteroskedasticity. We equally used the Hansen J-statistics, the Kleibergen–Paap rk LM statistic, and the Chi-sq(1) P-value test for instrument validity. The Hansen J-statistics tests for instrument over-Identification, while the Kleibergen–Paap rk LM statistic and Chi-sq(1) P-value test for weak instrument identification. This technique is used for the sake of verification and in agreement with the existing literature [41].

4. EMPIRICAL RESULTS

4.1. Baseline OLS results

The results of the baseline analysis are reported in Table 2. Part A displays the estimated OLS results of the effect of technological innovations on premature deindustrialization, while Part B presents the results of the Oster [46] stability test. First, we will discuss part A (Table 2). In line with Fig. 1, column (1) presents the results of a bivariate regression. We unearth that the coefficient associated with TI is negative and statistically significant at the 1 % level for our panel sample. The weight of this coefficient suggests that *all else equal*, a unit increase in the number of patent applications is associated on average with a 0.0726-unit abatement in the magnitude of PDI. This suggests that the more and more a country innovates technologically, the more it reduces the pace of PDI. This outcome may be legitimated by the effects of technological innovation on industrial productivity equity through technology diffusion, adoption, and knowledge spillover. This may be accompanied by the development of new technologies, new products, or new business models which may promote total factor productivity growth, especially in the manufacturing sector [9; 13; 26; 43; 47] This result exhibits the salutary effects of technological innovations in controlling PDI and overcoming its challenges, helping countries to navigate the structural transformation transition and build a more inclusive and sustainable economy.

From column (2) to column (6), we display the estimation outcomes, infusing gross fixed capital formation, trade, labor force participation rate, urbanization, and mineral resources rent as control variables. We spot that the coefficient associated with technological innovations remains negative and statistically significant. Regarding the control variables, we find that they show the anticipated signs. Anent column (2), we note that the coefficient ancillary to gross fixed capital formation (GFCF) is positive and statistically significant, documenting a positive association between GFCF and PDI. This can be explained by the fact that countries experiencing low economic growth are likely to have lower levels of GFCF [10]. Our results are, however, inconsistent with those of [48; 49], for whom low investment in GFCF will curb aggregate demand, restrict productive capacities, and restrain industrialization.

In column (3), trade is revealed to harm PDI, outlying that an increase in trade levels will lead to a reduction in the levels of PDI. According to Weiss and Clara [48], this can be justified by the fact that trade positively affects domestic investment, both through exports and imports. Although trade is considered an important channel for the transfer of technology, the outlined results will, however, depend on the goods compositions, specialization areas, and domestic environment foreign technologies adaption ease [1; 10; 49; 50]. These results, however, contradict those of [26; 33], who found a negative relationship between trade openness (liberalization / lower tariff) and PDI. Column (4) shows a positive (0.0111) and statistically

Table 2. *Baseline ordinary least squares (OLS) results*
Таблица 2. *Основные результаты по методу наименьших квадратов (МНК)*

	Dependent Variable: Premature Deindustrialization (PDI)					
Part A. OLS estimates						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
LnTI	-0.0726***	-0.0684***	-0.0738***	-0.0678***	-0.0563***	-0.0564***
	(0.00256)	(0.00286)	(0.00291)	(0.00321)	(0.00327)	(0.00329)
GFCF		0.00362***	0.00586***	0.00491***	0.00324***	0.00268**
		(0.000954)	(0.000980)	(0.00108)	(0.00106)	(0.00107)
Trade			-0.00205***	-0.00205***	-0.00200***	-0.00222***
			(0.000240)	(0.000264)	(0.000256)	(0.000260)
LABFPR				0.0111***	0.0102***	0.0102***
				(0.000886)	(0.000865)	(0.000870)
Urbpop					-0.00576***	-0.00581***
					(0.000484)	(0.000486)
MineralR						0.0224***
						(0.00355)
Constant	0.706***	0.581***	0.702***	-0.0572	0.297***	0.309***
	(0.0104)	(0.0251)	(0.0293)	(0.0617)	(0.0670)	(0.0674)
Part B. Oster (2019) stability test						
Oster bounds ($\hat{\beta}$, β* (Rmax = 0.88939, δ=1))						[-0.05604, -0.05636]
Delta (δ) statistic for β = 0						7.98737 > 1
Observations	3,827	3,071	3,055	2,423	2,423	2,352
R-squared	0.174	0.159	0.178	0.182	0.227	0.244

*Note. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported in parentheses.*
TI is technological innovations; GFCF is gross fixed capital formation;
Trade is trade openness; LABFPR is labor force participation rate; Urbpop is urban population; MineralR is mineral resources rent.
Column (6) reports the results of the coefficient stability test of Oster (2019).
The δ statistic represents the degree of selection on unobserved variables connexe to that on observed variables.
β is the bias-adjusted coefficient assuming δ = 1.*
Part A displays the estimated OLS results of the effect of technological innovations on premature deindustrialization, while Part B presents the results of the Oster (2019) stability test.
Column (1) presents the results of a bivariate regression, in the next columns we progressively include control variables and in the last column (column (6)), we present the complete model with all control variables.
*Примечание. *** p<0,01; ** p<0,05; * p<0,1. В скобках указаны робастные стандартные ошибки.*
TI – технологические инновации; GFCF – валовый прирост основного капитала; Trade – открытость торговли; LABFPR – доля экономически активного населения; Urbpop – городское население; MineralR – рента от добычи полезных ископаемых.
В столбце (6) представлены результаты теста на устойчивость коэффициентов Остер (2019).
Статистика δ представляет собой степень отбора ненаблюдаемых переменных по сравнению со степенью отбора наблюдаемых переменных.
β – коэффициент с поправкой на смещение, предполагающий, что δ=1.*
В части A представлена оценка результатов МНК для определения влияния технологических инноваций на преждевременную деиндустриализацию, в части B представлены результаты теста на устойчивость Остер (2019).
В столбце (1) представлены результаты двумерной регрессии, в последующих столбцах постепенно добавляются контрольные переменные, в столбце (6) представлена полная модель со всеми контрольными переменными.

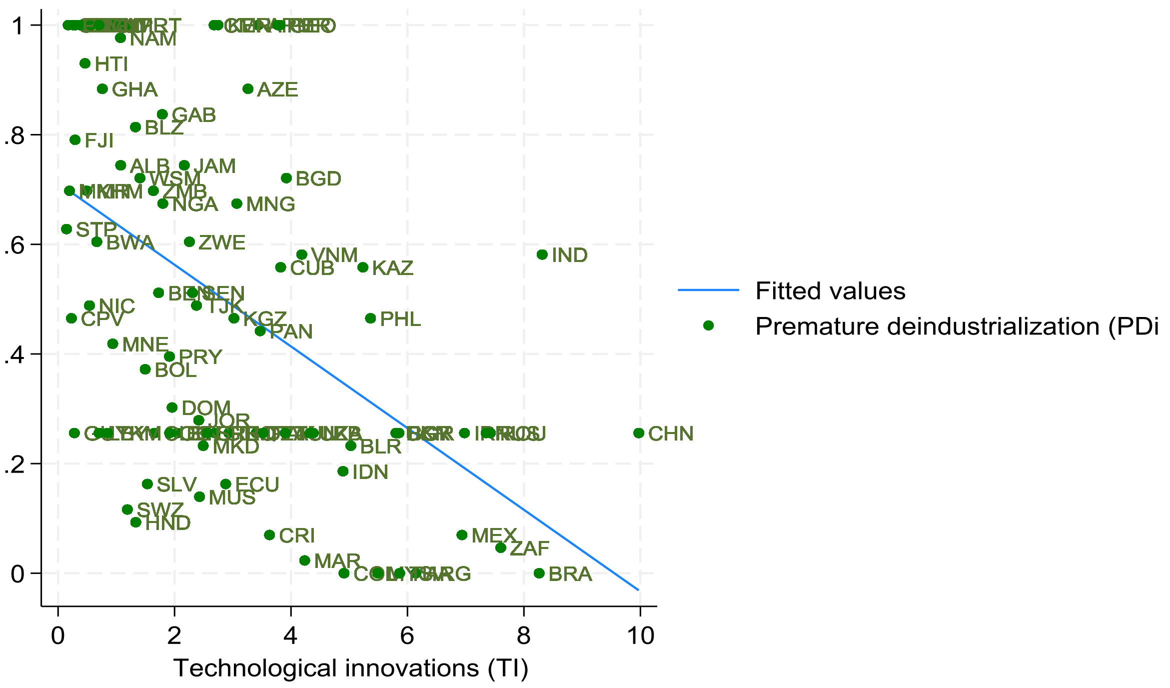

Fig. 1. Relationship between technological innovation (TI) and premature deindustrialization (PDI).
Each dote represent the mean value per country avec the studied period
Рис. 1. Взаимосвязь между технологическими инновациями (TI) и преждевременной деиндустриализацией (PDI).
Каждая точка представляет среднее значение по стране за исследуемый период

significant association between the labor force participation rate and premature deindustrialization. This result shows that an increase in labor force participation is associated with an increase in PDI, as this may result from the lack of human capital [28].

Contrary to trade, urbanization is revealed to display a negative and significant effect on PDI in our sample countries (column (5)). This can be explained by the advantageous contribution of an economically active population and labor force participation, crucial country-specific determinants that influence production and pave the way for economic growth [10; 40]. This result can be explained by the fact that urbanization has an inimical effect on PDI and boosts economic growth and development [7; 10; 40; 51]. Column (6) summarizes the results of our benchmark model, encompassing all our control variables, including the mineral resource rent, which outlay a positive and strongly significant effect on PDI. This result may be explained by the contraction of non-mineral sectors and the Dutch Disease resulting in serious deindustrialization, especially in state-led import substitution countries [10; 52]. This result is in line with previous studies that display the perverse effect of improperly managed natural resource rent/revenue on PDI [28; 31; 33].

In tune with the results in the antecedent columns, the coefficient accessory to technological innovations is negative and statistically significant. This result is harmonious with that of Liu et al. [53] who argue that trade openness leads to new technology development and diffusion, competitiveness; new products; or new business models, promoting total factor productivity growth [9; 13; 43; 47]. Notably, our primary variable of interest, PDI, remains significant despite the addition of these control variables. This advocates that, on average, technologically advanced countries are more credible in developing technologies that will lead to a curb in PDI.

Inspired by the existing literature [54], we stage the results of the coefficient stability test in Part B (Table 2). Though the result of the OLS analysis confirms our main hypothesis that TI deceases PDI, our results may be subject to variable omission bias. As shown by the Oster coefficient stability test [46] (Part B, Table 2) in column (6), the proportionality coefficient indicates that the potential selection bias of the unobserved confounders must be at least seven times as essential as the amount of selection on observed variables to reduce the estimated coefficients of technological innovations to zero (δ=7.98737). As suggested by Oster stability test [46], baseline results are robust to potential omitted variable bias when the δ statistic is greater than unity (δ>1). It is also important to note that the set bounded by the baseline coefficient and β^* safely keeps out the value zero. This outcome excludes the possibility that the main results are accredited to the selection of possible unobserved confounders.

4.2. Endogeneity issue: GMM results

Table 2 confirms, on the one hand, our main hypothesis that TI lessens PDI and, on the other hand, that these results are not the result of the omission bias of the variable. Although the objective of this article is to analyze the effect of TI on PDI, the fact remains that PDI can, in turn, affect TI, thus creating a bias resulting from reverse causality. To limit this bias, we use the Baum et al. [45] instrumental variable generalized method of moment (IV-GMM) estimation technique. This technique is used for the sake of verification and in agreement with the existing literature [44]. The basic *criterion* is that the number of sample countries should be greater than the number of instruments [9]. The results are exhibited in Table 3. The diagnostic tests conducted on the dynamic IV-GMM estimator present the following findings. The Hansen J-statistics tests for instrument over-identification suggest that instruments are exactly identified in the models; this is because a sole instrument was used to avert instrument over-identification. The Kleibergen–Paap rk LM statistic and the Chi-sq(1) P-value test for weak instrument identification also suggest that the instruments are strong. Also, the maximum number of generated instruments (7) is lower than the number of countries (89). Overall, the diagnostic tests of our model lead us to conclude that the estimated model has a suitable specification. Considering our results, they reassuringly correlate with our earlier findings showing that, at the widely recognized threshold of significance, technological innovations diminish PDI. In sum, our results consistently remain valid to endogeneity control.

Table 3. *Baseline Instrumental variable generalized method of moment (IV-GMM) results*
Таблица 3. *Основные результаты оценки с использованием обобщенного метода моментов с инструментальными переменными (IV-GMM)*

	Dependent Variable: Premature Deindustrialization (PDI)					
	(1)	(2)	(3)	(4)	(5)	(6)
LnTI	-0.0765***	-0.0732***	-0.0794***	-0.0733***	-0.0614***	-0.0616***
	(0.00244)	(0.00271)	(0.00267)	(0.00302)	(0.00327)	(0.00331)
GFCF		0.00363***	0.00596***	0.00513***	0.00348***	0.00295***
		(0.000913)	(0.000939)	(0.00108)	(0.00104)	(0.00104)
Trade			-0.00214***	-0.00216***	-0.00210***	-0.00232***
			(0.000230)	(0.000251)	(0.000246)	(0.000258)
LABFPR				0.0114***	0.0105***	0.0105***
				(0.000850)	(0.000831)	(0.000823)
Urbpop					-0.00553***	-0.00558***
					(0.000485)	(0.000490)
MineralR						0.0223***
						(0.00400)
Constant	0.711***	0.593***	0.723***	-0.0485	0.291***	0.302***
	(0.0109)	(0.0253)	(0.0286)	(0.0569)	(0.0647)	(0.0648)
Observations	3,738	3,02	3,004	2,423	2,423	2,352
R-squared	0.169	0.156	0.174	0.181	0.226	0.243
Hansen-J	0.000	0.000	0.000	0.000	0.000	0.000
Number of instruments	2	3	4	5	6	7
Kleibergen-Paap rk LM statistic	1163.389	996.018	1035.873	894.668	861.855	837.883
Kleibergen-Paap rk Chi-sq(1) P-val	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*Note. *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity-robust standard errors are reported in parentheses.*
Kleibergen-Paap rk LM statistic / Chi-sq(1) P-val for weak instrument identification.
TI is technological innovations; GFCF is gross fixed capital formation; Trade is trade openness;
LABFPR is labor force participation rate; Urbpop is urban population; MineralR is mineral resources rent.
The column (1) exposes a bivariate regression specification in which technological innovation is used as the sole determinant of PDI, while columns (2) to (6) represent the robustness of the baseline model in which a subset of the contemporaneous controls that were found to be non-negligible for PDI were included.
*Примечание. *** p<0,01; ** p<0,05; * p<0,1. В скобках указаны стандартные ошибки гетероскедастичности.*
Kleibergen–Paap rk LM statistic / P-val для теста на слабые инструменты, Chi-sq(1).
TI – технологические инновации; GFCF – валовое накопление основного капитала; Trade – открытость торговли;
LABFPR – доля экономически активного населения; Urbpop – городское население;
MineralR – рента от добычи полезных ископаемых.
В столбце (1) представлена спецификация двумерной регрессии, в которой технологические инновации используются в качестве единственного фактора, определяющего преждевременную деиндустриализацию.
Столбцы со (2) по (6) отражают устойчивость базовой модели, в которую было включено подмножество текущих контрольных факторов, которые оказались значительными для преждевременной деиндустриализации.

The first column in Table 3 exposes a bivariate regression specification in which technological innovation is used as the sole determinant of PDI, while columns (2) to (6) represent the robustness of the baseline model in which a subset of the contemporaneous controls that were found to be non-negligible for PDI were included. Consistent with the OLS estimate results presented above, Table 3 shows the diminishing effect of technological innovation on PDI, as the coefficients associated with technological innovations remain negative and statistically significant (columns (1) to (6)). Regarding the control variables, they are quite satisfactory and statistically significant per our baseline OLS results. We can, therefore, conclude that our findings are valid using a dynamic estimating method.

4.3. Robustness check

The panel regression results are already robust in controlling for all time-invariant variables, the time effect, and the number of time-varying variables included in the regression [55]. Moreover, we may note that our interest variable (TI) may suffer from measurement errors arising from the disparity between the reported value and the actual observed value. Additionally, our model may suffer from variable omissions. These errors may either inflate the standard error of the estimations or be a source of attenuation bias [55]. All of this may stack the odds against our findings.

To confirm our results and in addition to the stability test [46] and endogeneity control, we implemented a chain of robustness checks. Firstly, we implement additional controls; secondly, we verify the validity of the results using two alternative estimation techniques. Thirdly, we use alternative variables to measure TI (three) and PDI (two). Finally, we test for alternative subsample results. The outcomes from all five robustness checks are strictly homogenous and largely confirm our findings on the beneficial effects of technological innovations in checking premature deindustrialization.

4.3.1. Additional covariates

Firstly, we tested the robustness of our results by bringing in some supplementary control variables, viz, carbon emission (COemis), foreign direct investment (FDI), control of corruption (CtrCorrup), and general government final consumption expenditure (GGFCE). Our results are presented in Fig. 2. Often much relevant, easier to read and remember, space-conserving, and providing more pictorial presentation than tables, the graphical display of regression results is increasingly popular in the scientific literature. For this reason, we apply the "coefplot" command for graphical coefficients plotting introduced by Jann [56]. The estimation outcomes are summarized in Fig. 2. It is noteworthy that the coefficient associated with technological innovations (abbreviated as "LnPatents") is still negative and statistically significant as we successively introduce each additional control variable. This authenticates the negative and significant effect of technological innovation

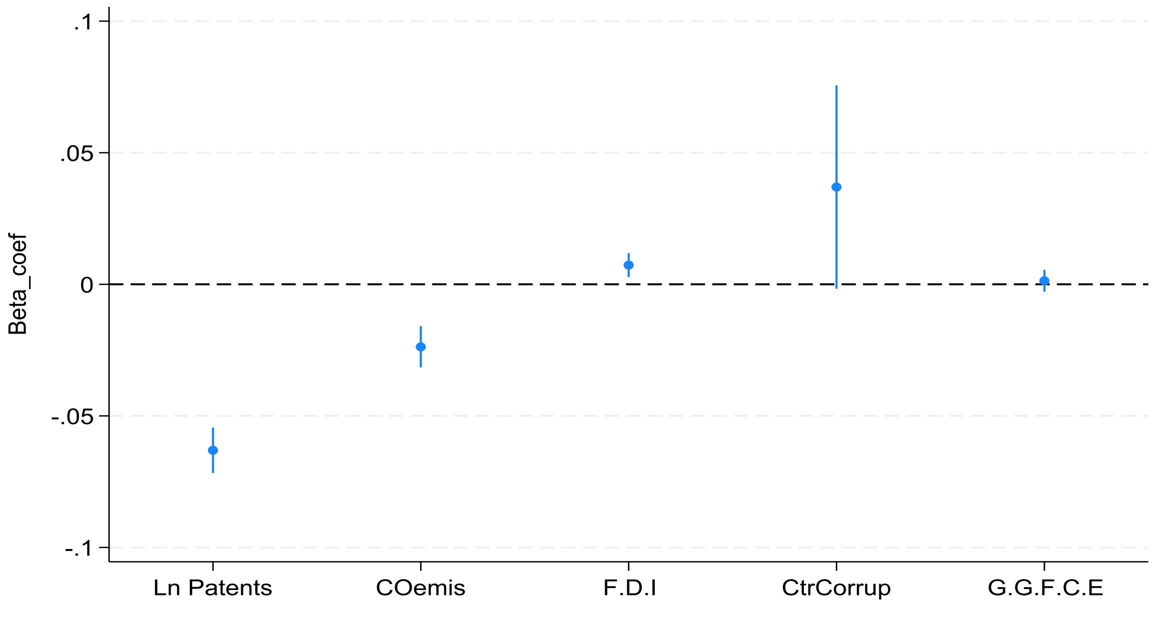

Fig. 2. *Robustness to additional controls regression coefficients using the instrumental variable generalized method of moment (IV-GMM) (dependent variable: premature deindustrialization)*
Beta_coef is the estimated coefficient.
Ln Patent is technological innovations, COemis is carbon dioxide emission; F.D.I is foreign direct investment; CtrCorrup is control of corruption; G.G.F.C.E is gross government final consumption expenditures
Рис. 2. *Устойчивость к коэффициентам регрессии дополнительных элементов управления, рассчитанная с использованием обобщенного метода моментов с инструментальными переменными (IV-GMM) (зависимая переменная: преждевременная деиндустриализация).*
Beta_coef – расчетный коэффициент.
Ln Patent – технологические инновации, COemis – выбросы углекислого газа, F.D.I – прямые иностранные инвестиции, CtrCorrup – борьба с коррупцией, G.G.F.C.E – валовые государственные расходы на конечное потребление

on premature deindustrialization. The claim that highly technologically innovative countries are associated with low levels of premature deindustrialization is thus robust to the incorporation of supplementary control variables.

4.3.2. Robustness to alternative estimation strategies

The methods used so far have allowed us to assess the average effect of IT on PDI. However, given the heterogeneity of the level of technological development in our sample countries, it seems important to analyze the existence of a potential asymmetric relationship. To do this, we utilized the Machado and Silva [57] moment quantiles method (MMQR). The MMQR tech nique permits a more punctilious investigation of the empirical connection by analyzing the various effects of the exogenous variables over various quantiles of the conditional distribution [58] of PDI. Hence, the MMQR technique provides us with a more exhaustive picture of the repercussions of TI on PDI. The results of this exercise are displayed in part 1 (Table 4). Globally, the results display that TI has a negative and statistically significant effect on PDI. We also observe that TI discourages PDI in all quantiles at an increasing rate as the magnitude of the influence becomes greater as we approach the top quantiles. These results further confirm the lessening effect of TI on PDI.

Table 4. *Robustness to method of moment quantile and Lewbel (2012) results*
Таблица 4. *Устойчивость к результатам метода квантиля момента и метода Льюбеля (2012)*

	Dependent variable: Premature Deindustrialization (PDI)									
	Part (1)									Part (2)
	Moment Quantile									Lewbel (2012)
	Lower quantile			Middle quantile			Upper quantile			
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90	Lewbel
LnTI	-0.0277***	-0.0310***	-0.0352***	-0.0402***	-0.0471***	-0.0567***	-0.0723***	-0.0824***	-0.0999***	-0.0669***
	(0.00222)	(0.00224)	(0.00233)	(0.00253)	(0.00288)	(0.00363)	(0.00456)	(0.00521)	(0.00671)	(0.00883)
GFCF	0.00284***	0.00282***	0.00280***	0.00277***	0.00273***	0.00268**	0.00260*	0.00254	0.00245	0.00321***
	(0.000806)	(0.000805)	(0.000823)	(0.000870)	(0.000974)	(0.00117)	(0.00156)	(0.00183)	(0.00234)	(0.00106)
Trade	-0.00189***	-0.00193***	-0.00198***	-0.00203***	-0.00211***	-0.00222***	-0.00240***	-0.00252***	-0.00272***	-0.00243***
	(0.000180)	(0.000180)	(0.000185)	(0.000195)	(0.000219)	(0.000262)	(0.000349)	(0.000411)	(0.000524)	(0.000292)
LABFPR	0.00657***	0.00700***	0.00753***	0.00816***	0.00905***	0.0103***	0.0122***	0.0135***	0.0157***	0.0107***
	(0.000612)	(0.000613)	(0.000629)	(0.000669)	(0.000752)	(0.000914)	(0.00120)	(0.00140)	(0.00179)	(0.000917)
Urbpop	-0.00354***	-0.00381***	-0.00414***	-0.00453***	-0.00508***	-0.00583***	-0.00707***	-0.00786***	-0.00924***	-0.00535***
	(0.000344)	(0.000345)	(0.000354)	(0.000377)	(0.000424)	(0.000517)	(0.000677)	(0.000790)	(0.00101)	(0.000609)
MineralR	0.0175***	0.0181***	0.0188***	0.0197***	0.0208***	0.0225***	0.0251***	0.0268***	0.0298***	0.0221***
	(0.00298)	(0.00298)	(0.00305)	(0.00322)	(0.00361)	(0.00433)	(0.00576)	(0.00678)	(0.00864)	(0.00394)
Constant	-0.129***	-0.0777*	-0.0134	0.0619	0.168***	0.314***	0.552***	0.706***	0.972***	0.296***
	(0.0468)	(0.0469)	(0.0482)	(0.0513)	(0.0578)	(0.0709)	(0.0922)	(0.107)	(0.137)	(0.0653)
Observations	2,352	2,352	2,352	2,352	2,352	2,352	2,352	2,352	2,352	2,352
R-squared										0.241
Hansen-J										0.0000
Kleibergen-Paap rk LM statistic										18.779
Kleibergen-Paap rk Chi-sq(1) P-val										0.0021

*Note. *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity robust standard errors are reported in parentheses. Kleibergen-Paap rk LM statistic / Chi-sq(1) P-val for weak instrument identification.*

Part 1 present the method of moment quantile regressions (MMQR) technique results of the repercussions of TI on PDI.

Part 2 presents the results obtained from Lewbel's (2012) estimation technique

*Примечание. *** p<0,01; ** p<0,05; * p<0,1. В скобках указаны стандартные ошибки гетероскедастичности. Kleibergen–Paap rk LM statistic / P-val для теста на слабые инструменты, Chi-sq(1).*

В части 1 представлены результаты, полученные с помощью метода квантильной регрессии момента (МКРМ) для оценки влияния технологических инноваций на преждевременную деиндустриализацию.

В части 2 представлены результаты, полученные с помощью метода оценки Льюбеля (2012).

Additionally, the Lewbel approach is used [59]. This technique is vital for determining structural parameters in regression models without conventional identification information that has endogenous or poorly quantified regressors. By developing an internal instrumental variable based on the heteroscedasticity of the random error term, this approach allows us to scrutinize the causal liaison between TI and PDI. These endogenous instruments are produced by a mean-entered multiplication of the auxiliary equation’s residuals by each external variable [60]. In addition to the fact that Lewbel [59]. 2SLS strategy avoids the typical exclusion limitations, as estimates without external instruments are quite similar to those obtained with external instruments. This technique is used due to its ability to operate independently of standard exclusion restrictions [43]. Part 2 (Table 4) presents the results obtained from Lewbel’s (2012) estimation technique. In terms of instruments’ suitability, the Kleibergen–Paap rk LM statistic and Chi-sq(1) P-value are employed to evaluate the instruments’ shortcomings [61]. Also, the Hansen J-statistics values do not reject the null hypothesis that the instruments do not correlate with the error term and outlays that our model is exactly-identified, which suggests that our model is well specified, and there is no evidence to refute the exogenous instrument hypothesis. Considering our results, the coefficient associated with TI is negative and statistically significant, corroborating previous results that TI reduces PDI.

4.3.3. Robustness to alternative technological innovation variable

We test the robustness of our results by using alternative measures of technological innovation, namely abroad patents application (LnAbroadP) and resident patents application (LnResidentP) obtained from the disaggregation of total patent applications and the number of scientific and technical journal articles published (LnScientific). We apply the same methodology as in Table 3, and the reported results are in Fig. 3. Overall, results support our baseline estimation, as the mitigating effect of technological innovation on PDI remains negative and statistically significant in all regressions.

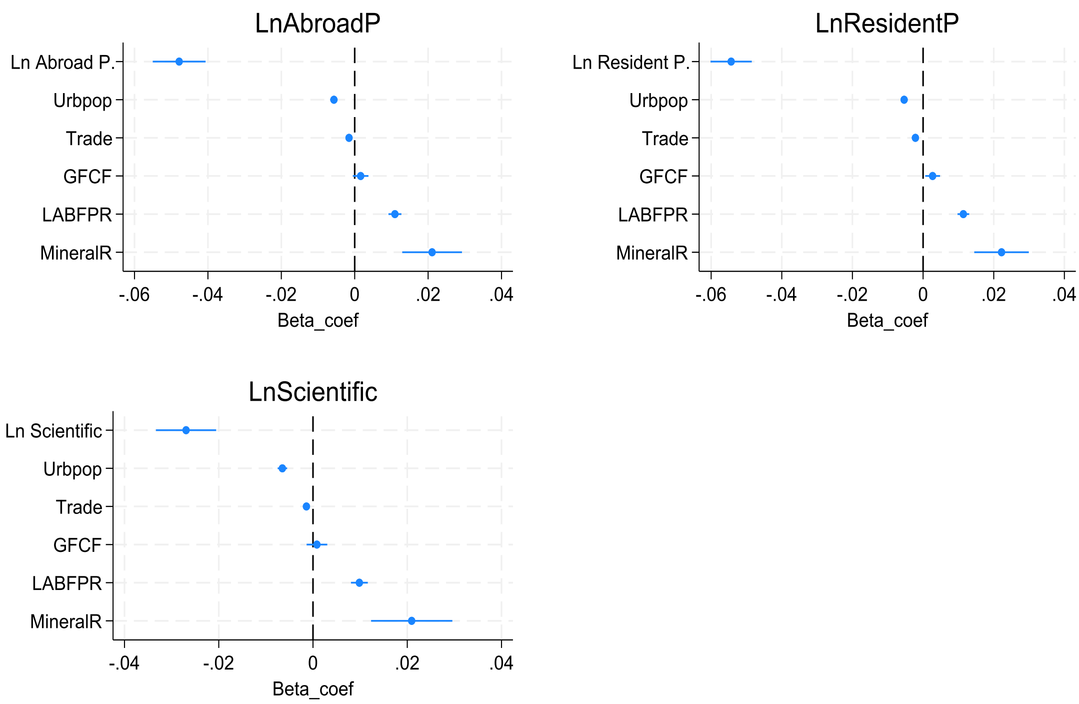

Fig. 3. *Robustness to alternative measures of technological innovations regression coefficients using the Instrumental variable generalized method of moment (IV-GMM) (Dependent variable: Premature Deindustrialization). All regression models include baseline control variables.*
LnAbroadP is abroad patents application and LnResidentP is resident patents application obtained from the disaggregation of total patent applications and LnScientific is the number of scientific and technical journal articles published. Beta_coef is the estimated coefficient. TI is technological innovations; GFCF is gross fixed capital formation; Trade is trade openness; LABFPR is labor force participation rate; Urbpop is urban population; MineralR is mineral resources rent
Рис. 3. *Устойчивость к альтернативным показателям коэффициентов регрессии технологических инноваций с использованием обобщенного метода моментов с инструментальными переменными (IV-GMM) (зависимая переменная: преждевременная деиндустриализация). Все регрессионные модели включают базовые контрольные переменные.*
LnAbroadP – количество зарубежных патентных заявок; LnResidentP – количество патентных заявок резидентов, полученное путем дезагрегирования общего количества патентных заявок; LnScientific – количество опубликованных статей в научных и технических журналах. Beta_coef – расчетный коэффициент. TI – технологические инновации; GFCF – валовый прирост основного капитала; Trade – открытость торговли; LABFPR – доля экономически активного населения; Urbpop – городское население; MineralR – рента от добычи полезных ископаемых

4.3.4. Robustness to alternative dependent variable

As an additional check, we develop two alternative measures of premature deindustrialization and conduct additional analysis to ensure the validity of our findings. At each moment, we only evaluate two of the three criteria for a country to be classified as experiencing premature deindustrialization proposed by Rodrik [9]. While only revenue and manufacturing employment share (Rev&Em) are taken into account in the second alternative definition for identifying premature deindustrialization phases, the first alternative only takes into consideration the trend in revenue and sectoral value-added share (Rev&VA) [6; 10]. Fig. 4 shows the findings with these substitute dependent variables using the same methods as the baseline regression.

These results overall confirm our baseline estimation, highlighting the auspicious role of technological innovation in reducing PDI. This supports our previous claim that technologically innovating countries will be more accurate in cubing PDI than countries that do not technologically innovate. The constancy of these results shows that our findings are reliable for informing the design and implementation of technological innovations and reindustrialization policies in middle-income countries.

4.3.5. Robustness to alternative subsample

Though our prior findings support our theoretical intuition on the negative effect of technological innovation on premature deindustrialization, it can be assumed thatthe baseline estimates are driven by including groups of countries with wildly disparate macroeconomic profiles [54]. Hence, we re-estimated the baseline model using six different subsamples, precluding, in turn, Europe and Asia (E&A), America and Caribean (A&C), Middle East and North Africa (MENA), Sub-Saharan Africa (Sub-SA), Asia and Pacific (A&P), and Oceanic (OCN) countries. As illustrated in Table 5, the coefficient attached to our variable of interest (TI) remains negative and statistically significant in each specification. We can, therefore, conclude that no specific region of our sample does not drives our baseline result. These results report the healthful effect of TI in downsizing PDI.

5. CONCLUSION, POLICY IMPLICATION, AND LIMITS OF THE STUDY

Premature deindustrialization has been a main concern in recent decades, with industries faced with significant challenges in adapting to the rapid pace of technological

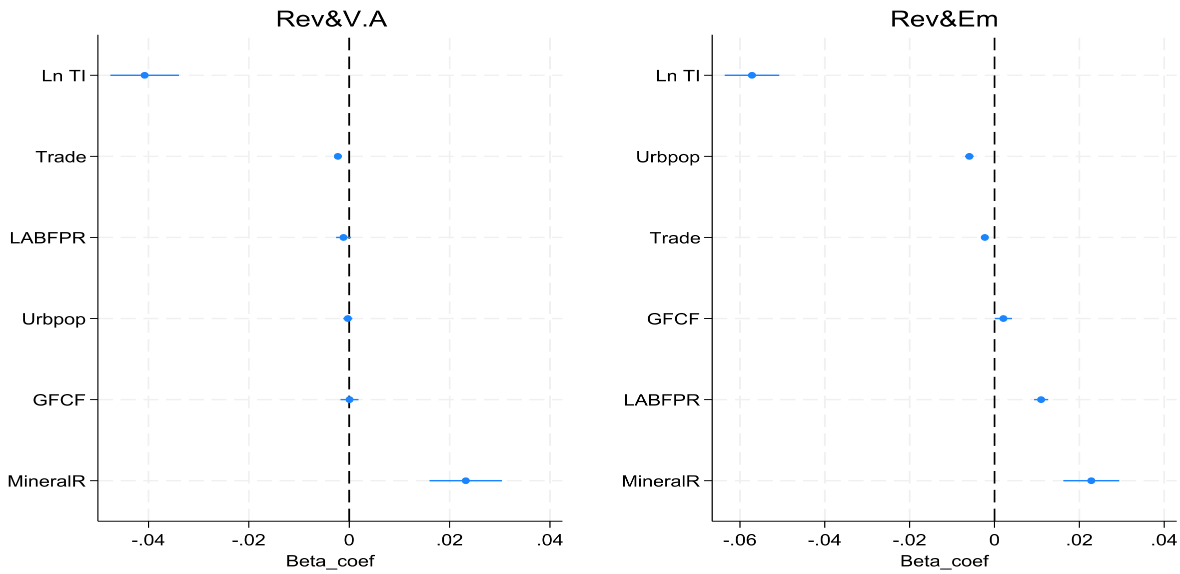

Fig. 4. *Robustness to alternative measures of Dependent variable: Premature Deindustrialization (PDI) regression coefficients using the Instrumental variable generalized method of moment (IV-GMM). All regression models include baseline control variables. Rev&Em is Revenue and manufacturing employment share; Rev&V.A is revenue and sectoral value-added share. Beta_coef is the estimated coefficient. TI is technological innovations; GFCF is gross fixed capital formation; Trade is trade openness; LABFPR is labor force participation rate; Urbpop is urban population; MineralR is mineral resources rent*

Рис. 4*. Устойчивость к альтернативным показателям зависимой переменной: коэффициенты регрессии преждевременной деиндустриализации (PDI) с использованием обобщенного метода моментов с инструментальными переменными (IV-GMM). Все регрессионные модели включают базовые контрольные переменные. Rev&Em – валовый доход и доля занятости в обрабатывающей промышленности; Rev&V.A – доля выручки и отраслевой добавленной стоимости. Beta_coef – расчетный коэффициент. TI – технологические инновации; GFCF – валовый прирост основного капитала; Trade – открытость торговли; LABFPR – доля экономически активного населения; Urbpop – городское население; MineralR – рента от добычи полезных ископаемых*

Table 5. *Robustness to alternative subsample using the Instrumental variable generalized method of moment (IV-GMM)*
Таблица 5. *Устойчивость к альтернативной подвыборке с использованием обобщенного метода моментов с инструментальными переменными (IV-GMM)*

	Dependent Variable: Premature Deindustrialization (PDI)					
	Without E&A	Without MENA	Without Sub-SA	Without A&C	Without A&P	Without OCN
	(1)	(2)	(3)	(4)	(5)	(6)
LnTI	-0.0757***	-0.0651***	-0.0487***	-0.0736***	-0.0451***	-0.0621***
	(0.00358)	(0.00368)	(0.00347)	(0.00370)	(0.00428)	(0.00331)
GFCF	0.00505***	0.00299***	0.00160	0.00302***	0.00307**	0.00255**
	(0.00103)	(0.00115)	(0.00120)	(0.00106)	(0.00142)	(0.00105)
Trade	-0.00336***	-0.00251***	-0.00150***	-0.00243***	-0.00207***	-0.00231***
	(0.000279)	(0.000276)	(0.000270)	(0.000314)	(0.000332)	(0.000258)
LABFPR	0.00860***	0.00831***	0.0102***	0.0118***	0.0127***	0.0107***
	(0.000828)	(0.00120)	(0.000904)	(0.000930)	(0.000917)	(0.000826)
Urbpop	-0.00566***	-0.00501***	-0.00661***	-0.00451***	-0.00600***	-0.00530***
	(0.000497)	(0.000576)	(0.000513)	(0.000617)	(0.000652)	(0.000493)
MineralR	0.0263***	0.0207***	0.0166***	0.0229***	0.0211***	0.0229***
	(0.00491)	(0.00404)	(0.00482)	(0.00435)	(0.00457)	(0.00401)
Constant	0.483***	0.455***	0.270***	0.253***	0.108	0.281***
	(0.0658)	(0.0819)	(0.0721)	(0.0705)	(0.0790)	(0.0652)
Observations	1,8	2,079	1,886	1,779	1,876	2,34
R-squared	0.304	0.207	0.235	0.300	0.198	0.242
Hansen-J	0.000	0.000	0.000	0.000	0.000	0.000
Number of instruments	7	7	7	7	7	7
Kleibergen-Paap rk LM statistic	544.030	724.511	697.014	642.658	746.934	834.273
Kleibergen-Paap rk Chi-sq(1) P-val	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note. *** *p<0.01;* ** *p<0.05;* * *p<0.1 denotes significance at 1, 5, and 10 %, respectively.*
Heteroscedasticity robust standard errors are reported in parentheses.
Kleibergen–Paap rk LM statistic / Chi-sq(1) P-value for weak instrument identification.
TI is technological innovations; GFCF is gross fixed capital formation; Trade is trade openness;
LABFPR is labor force participation rate; Urbpop is urban population; MineralR is mineral resources rent.
E&A is Europe and Asia; A&C is America and Caribbean; MENA is Middle East and North Africa;
Sub-SA is Sub-Saharan Africa; A&P is Asia and Pacific; OCN is Oceanic countries.
Примечание. *** *p<0,01;* ** *p<0,05;* * *p<0,1 обозначает значимость на уровне 1, 5 и 10 % соответственно.*
В скобках указаны стандартные ошибки гетероскедастичности.
Kleibergen–Paap rk LM statistic / P-val для теста на слабые инструменты, Chi-sq(1).
TI – технологические инновации; GFCF – валовый прирост основного капитала; Trade – открытость торговли;
LABFPR – доля экономически активного населения; Urbpop – городское население; MineralR – рента от добычи полезных ископаемых. E&A – Европа и Азия; A&C – Америка и Карибские острова; MENA – Средний Восток и Северная Африка;
Sub-SA – страны черной (субсахарской) Африки; A&P – Азия и страны Тихоокеанского региона; OCN – страны Океании.

change. This phenomenon has far-reaching implications for economies, particularly regarding job displacement, economic growth, and development. While some individuals and businesses may thrive in a more automated and digitized economy, many workers in traditionally industrial sectors may find themselves facing unemployment or underemployment. This can be explained by the fact that rapid automation and the adoption of advanced technologies in manufacturing processes may lead to a reduced need for human labor and ultimately result in the displacement of workers. This can exacerbate existing inequalities and create significant social and political tensions. Hence, reversing and breaking down the trend of premature deindustrialization with associated adverse effects is primordial in middle-income economies.

This study aimed to examine the effect of technological innovation on premature deindustrialization (PDI) in a panel of 89 middle-income countries (MICs). To do this, we create a composite measure of PDI respecting the three main conditions of premature deindustrialization proposed by Rodrik [9]. Based on the Ordinary Least Squares and the Instrumental Variable GMM (IV-GMM), our empirical analyses show evidence that TI leads to a decrease in PDI in MICs. The obtained results were robust to additional control variables, different estimation methods [59], alternative measures to technological innovation and premature deindustrialization, and alternative subsample results. Additionally, in terms of the asymmetry analysis, the results obtained from the quantile regression indicate that the impact of technological innovations on PDI is significant for all quantiles of PDI.

Based on these results, we recommend that public authorities and policymakers must therefore be proactive in addressing these challenges by including policies to support industrial diversification, investing in training and education programs to help workers earn the skills needed to thrive in a rapidly changing job market, as well as macroeconomic policies that promote job creation and support the growth of new industries. Additionally, investment in R&D, trade liberalization to ease technological transfer, as well as providing support for workers who are negatively impacted by technological advancements must be encouraged. Policymakers should equally take effectual measures to improve social and economic freedom and carry out practical and stronger property protection that prompts incentives and spurs inventors to engage in innovation activities. By addressing these issues head-on, in a proactive way managing the impact of technological innovation on industrial sectors, societies can ensure a more equitable and sustainable transition to a technologically-driven economy.

To sum up, our results highlight that technological innovations are detrimental to PDI. Consequently, our empirical results strengthen the significance of the manufacturing sector in enhancing economic growth and development as well as the primal role of TI in curbing PDI in middle-income economies. This research is limited by the fact that both developed and developing economies in diverse contexts with the jeopardy of early deindustrialization are considered in groups in this research. Hence, this study lacks circumstantial research on individual nations. Examining the entanglement of PDI mechanisms and policy performance in specific countries through detailed case studies would enable the development of country-specific and concrete recommendations, helping in the prescription of targeted measures for mitigating and avoiding PDI while promoting TI.

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Appendix

Table. *Countries Included in our Core Estimates*

Albania	Colombia	Indonesia	Namibia	Thailand
Algeria	Congo, Rep.	Iran, Islamic Rep.	Nepal	Tunisia
Angola	Costa Rica	Iraq	Nicaragua	Turkmenistan
Argentina	Cuba	Jamaica	Nigeria	Ukraine
Armenia	Dominica	Jordan	North Macedonia	Uzbekistan
Azerbaijan	Dominican Republic	Kazakhstan	Pakistan	Vanuatu
Bangladesh	Ecuador	Kenya	Panama	Viet Nam
Belarus	Egypt, Arab Rep.	Kyrgyz Republic	Papua New Guinea	Zambia
Belize	El Salvador	Lao PDR	Paraguay	Zimbabwe
Benin	Eswatini	Lebanon	Peru	
Bhutan	Fiji	Libya	Philippines	
Bolivia	Gabon	Malaysia	Romania	
Bosnia and Herzegovina	Georgia	Marshall Islands	Russian Federation	
Botswana	Ghana	Mauritania	Samoa	
Brazil	Grenada	Mauritius	Sao Tome and Principe	
Bulgaria	Guatemala	Mexico	Senegal	
Cabo Verde	Guyana	Mongolia	Serbia	
Cambodia	Haiti	Montenegro	South Africa	
Cameroon	Honduras	Morocco	Sri Lanka	
China	India	Myanmar	Tajikistan	

Технологические инновации и преждевременная деиндустриализация: пример стран со средним уровнем дохода

Цафак Миафо Дойбенит*[1,3], докторант, факультет экономики и менеджмента
Ноула Арманд Гилберт[1], доцент, факультет экономики и менеджмента
Бондома Йоконо Дойдонне[2], доцент, факультет экономики и менеджмента
Гамси Деффо Саломон Лерой[1,4], доктор наук, факультет экономики и менеджмента
[1]*Университет Дшанг, Дшанг (Камерун)*
[2]*Университет Яунде 2, Яунде (Камерун)*

***E-mail:** Dieubenit.tsafack@univ-dschang.org
[3]ORCID: https://orcid.org/0009-0007-2665-7616
[4]ORCID: https://orcid.org/0000-0002-2854-4371

Поступила в редакцию 27.08.2025 *Пересмотрена 08.09.2025* *Принята к публикации 22.09.2025*

Аннотация: Преждевременная деиндустриализация в условиях быстрого развития технологических инноваций и глобализации стала критической проблемой для стран со средним уровнем дохода. В данном исследовании рассматривается влияние технологических инноваций, измеряемых патентными заявками, на преждевременную деиндустриализацию в 89 странах со средним уровнем дохода в период с 1980 по 2022 г. Для количественной оценки преждевременной деиндустриализации разработан принципиально новый составной индекс, объединяющий уровни доходов и вклад обрабатывающей промышленности (добавленную стоимость и долю занятости). Используя надежные эконометрические методы, включая метод наименьших квадратов (МНК) в сочетании с тестом на устойчивость Остера и обобщенный метод моментов с инструментальными переменными (IV-GMM), мы обнаружили, что технологические инновации значительно снижают вероятность преждевременной деиндустриализации. Эти результаты, согласующиеся по всем подвыборкам и многократно проверенные на устойчивость, подчеркивают ключевую роль инноваций в содействии устойчивому промышленному росту. Исследование предлагает ценные идеи для законодателей, стремящихся сбалансировать технологический прогресс и промышленное развитие в странах со средним уровнем дохода.

Ключевые слова: преждевременная деиндустриализация; технологические инновации; структурная трансформация; страны со средним уровнем дохода; IV-GMM.

Для цитирования: Цафак Миафо Д., Ноула А.Г., Бондома Й.Д., Гамси Д.С.Л. Технологические инновации и преждевременная деиндустриализация: пример стран со средним уровнем дохода // Цифровая экономика и инновации. 2025. № 3. С. 31–50. DOI: 10.18323/3034-2074-2025-3-62-3.