Can technological innovations reverse the trend toward premature deindustrialization? Fresh evidence from middle-income countries

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Abstract

The increased worry over the decline of industrial growth, technological innovation and the rise of globalization has brought the concept of premature deindustrialization to the scientific, economic and political forefront in recent years. Premature deindustrialization is a phenomenon in which before being fully industrialized and reaching high levels of income and development, some countries see their manufacturing sectors (employment and output) decline. In recent years, technological innovations have played a significant role in shaping economic development, and one area where its impact is increasingly apparent is in industrialization as they may lead to productivity increases with a reduction in the need for human labor and ultimately the displacement of workers as a result of automation and adoption of advanced technologies in manufacturing processes. This paper aims to scrutinize the effect of technological innovation (TI) measured by total patent applications (Patents) on Premature deindustrialization (PDI) on a panel of 89 middle-income countries over the period 1980-2022. We construct a composite indicator of PDI taking into account income levels and manufacturing sector contributions (value-added share and employment share). The empirical analyses based on the Ordinary Least Squares (OLS) and the Instrumental Variable Generalized Method of Moment (IV-GMM) provide strong evidence that TI has a propitious effect in decreasing likelihood of premature deindustrialization in our sample countries. These results are sturdy to different robustness checks.

Keywords: Premature deindustrialization; Technological innovations; Structural transformation, Middle-income Countries; IV-GMM.

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1. Introduction

Technological innovation has been a driving force in shaping the modern world, transforming industries, economies, and societies (Almeida and Fernandes, 2008; Coccia, 2021; Kaplinsky and Kraemer-Mbula, 2022; Cruz, 2015). One of the unintended consequences of technological innovations is deindustrialization, which is a normal phenomenon in high-income countries (Ravindran and Babu, 2023; Destek et al., 2024; Momeni et al., 2020; Coccia, 2021). However, when this phenomenon arises at lower income levels it is coined premature deindustrialization with numerous implications (Rodrick, 2016; Ravindran and Babu, 2023; Rekha, 2022). This paper investigates the impact of technological innovation on premature deindustrialization in middle-income countries.

Characterized by the brace decrease of both manufacturing output (as a percentage of GDP) and employment (in total employment), "deindustrialization" is considered a normal experience in development models, especially for developed countries (Hamid and Khan, 2015; Cruz, 2015). According to Herrendorf et al. (2014) and McMillan et al. (2014), the reallocation of labor and other resources across the broad economic sectors from a low-productive to a high-productive sector; agriculture, manufacturing[2] and services stimulating economic growth and development is the normal path of structural transformation. Consequently, any early deindustrialization trend in developing economies at far earlier levels of income than those historically observed in advanced countries; coined 'premature deindustrialization' raises the concern of blocking the main avenue channels of economic growth as well as the catch-up with more advanced economies (Rekha, 2022; Hamid, and Khan, 2015; Cruz, 2015).

Existing literature documents that the incidence of this stagnation in growth is more flagrant in middle-income countries than in other income groups, prolonging growth slowdowns in these economies, a phenomenon known as the "middle-income trap" (Gill and Kharas, 2007), where most developing economies are unable to progress towards the high-income category[3] (Rekha, 2022). This phenomenon affecting[4] mostly Latin America, Africa, the Middle East, and Asia, is accentuated by several factors, with consequences in both the short and long term. This further cripples the economic growth of middle-income countries, threatening their competitiveness and economic growth and preventing them from penetrating the high-income group (Rekha 2022; Cruz, 2015; Greenstein and Anderson, 2017; Ravindran and Babu 2023; Andriyani and Irawan, 2018). There are several possible explanations for this

[2] Identified as a key player in growth acceleration due to its ability to absorb labor, higher productivity, higher externalities, and tradability amongst others making it a critical component for developing economies (Rekha, 2022; Muluh et al, 2022; Nassif and Morceiro, 2021).
[2] Only 13 out of 101 middle-income countries in the 1960s were able to attain the status of a high-income country by 2008.
[4] Countries irrespective of their state of development (Yazgan et al., 2022).

set of circumstances in the literature, seeking at all times a balance between the general and the particular[5] (e.g. see Coccia, 2021; Rekha 2022; Cruz, 2015; Ravindran and Babu 2023; Andreoni and Tregenna, 2021). The one retained in this study is the technology innovations, which yield more labor-saving production processes, increase productivity and replace workers with automatic functioning machines accentuating the "middle-income technology trap[6]". 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. (Itaman and Awopegba, 2021; Nassif and Morceiro, 2021; Andreoni and Tregenna, 2021).

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[7] (Nassif and Morceiro, 2021). 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 (Cruz, 2015; Nassif and Morceiro, 2021). The literature has developed abundantly on the possible effects and consequences of technological innovation on structural change (e.g., Cruz, 2015; Nassif and Morceiro, 2021; Almeida and Fernandes, 2008; Coccia, 2021; Kaplinsky and Kraemer-Mbula, 2022; Destek al., 2024).

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 (de Oliveira and da Fonseca Nicolay, 2022; Itaman and Awopegba, 2021). 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, (2021) and Nassif and Morceiro (2021), this can be prominently explained by ever-increasing technological upgrading, worsened by the effect of globalization,

[5] The recent literature does review theoretical structures with sweeping relevance and applicability considering a broader set of transformations (Gollin and Kaboski, 2023).

[6] The dearth of vital industrial and technological breakthroughs that would open up new development avenues while causing dire repercussions for both economic growth and industrial development (Andreoni and Tregenna, 2021).

[7] Learning by doing and labor specialization are important to mention as underlying sources of increasing returns, productivity, and skill acquisitions (Cruz, 2015).

unsustained rapid liberalizing ("shock therapy") economic reforms, technological transfer and economic diversification a situation described as the “middle-income technology trap” (Andreoni and Tregenna, 2021). 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 (Nassif and Morceiro, 2021; Muluh et al., 2022). It is hence misleading to expect that the world will mutate into a service economy (Nassif and Morceiro, 2021).

Hence, technological innovation and premature deindustrialization are intricately linked, with the latter often driven by the former. While technological innovation has the potential to revolutionize industries and economies, it can also contribute to the decline of manufacturing sectors in many countries (Nassif and Morceiro, 2021; Momeni et al., 2020; Coccia, 2021). 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) is a main concern as 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 in skilled employment opportunities (as many traditional industrial jobs are lost), leaving it vulnerable to external shocks and fluctuations in global markets. The present study analyses the bond between technological innovation and premature deindustrialization in middle-income economies, r4evealing 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, Rekha 2022) 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 period 1980-2022 period,

this study illustrate the nuanced effects of technological innovations on industrial decline, providing qualitative insights alongside quantitative data. Our findings indicate that the incidence of technological innovation degrades the likelihood of the occurrence of premature deindustrialization in these countries. Second, we use a very large sample of 89 countries from 1980-2022 and employ a set of three conditions (specified by Rodrick (2016)) 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 premature deindustrialization and develop a policy framework aimed at mitigating the adverse effects of technological advancement on employment in manufacturing, emphasizing retraining program and innovation incentives tailored for vulnerable sectors.

The rest of the paper consists of the following sections: The relevant literature is discussed in Section 2. Section 3 is devoted to data and empirical strategy. 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[8]" and "premature deindustrialization" have signposted the past couple of decades. First coined by Dasgupta and Singh (2007) 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 (Tekay, 2018; Cruz, 2015; Tsukada, 2023). This is due to the early transformation of these countries into service-based countries without an established and comprehensive industrialization experience or process (Rodrik, 2015). 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 Andriyani and Irawan, 2018).

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 (Greenstein and Anderson, 2017). These economies are hence experiencing early tertiarization or accelerated "servitization" of their economies (Fujimoto and Whittaker, 2021). Cruz (2015) 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

[8] A significant decrease in the relative share of manufacturing both in GDP and employment (Cruz, 2015; Tsukada, 2023).

and develop. Hence, the premature deindustrialization trend hit long-term growth reason 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 (Muluh and al., 2022). Rekha (2022) highlights that globalization, automation and labor-saving technological advances may be the main drivers of the premature deindustrialization trend along with a shift towards services. This might restrict the ability of the manufacturing sector to furnish jobs for unskilled workers and low-skilled, which thereby hunk the channels of economic growth (Rekha, 2022). 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 (Rekha, 2022).

Araujo et al. (2021) 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 (2015), suggests that premature deindustrialization is explained by income evolution, capital accumulation, manufacturing labor productivity, trade openness and exchange rate. According to Andriyani and Irawan, (2018) however, its speed may vary between indicators and between contexts. Using the bootstrap-corrected dynamic fixed-effects and panel fixed-effects models, Ravindran and Babu (2023) 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, (2018) in their study 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. They 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 (2023) 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. (2020) 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 (2017) 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, stemming 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 (2022) 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 out 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. (2023) 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 (2017) 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 (2021) 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, and gas and oil also indicates a notable negative impact on the country's manufacturing sector. Conversely, financial institution's 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 Methodology

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[9] (see Table A1 in the appendix). The sample

[9] Europe and Asia (Europe, East Europe, and Central Asia.), America and the Caribean (Latin America, North America, and Caribean.), the Middle East and North Africa, Sub-Saharan Africa, Asia and Pacific, and Oceanic countries.

for the study has been rigidly disciplined in terms of data availability[10], especially those used in the construction of the technological innovation index.

3.1.1. Dependent variable

The dependent variable of the study is premature deindustrialization (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 (Rekha, 2022; Felipe et al., 2019; Rodrik, 2016; Ravindran and Babu, 2023). 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 and build a composite indicator that takes into account three criteria for a country to be considered as experiencing premature deindustrialization, as summarized below.

$$Y_t \leq \$11{,}750 \quad (1)$$

$$MAN_VA_t \leq 18\% \quad (2)$$

$$MAN_Emp_t \leq 18\% \quad (3)$$

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 constrain 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 (Felipe, 2017). Hence, deindustrialization is considered "premature" if it takes place below this income level, signaling the element in the shrinking manufacturing share (Rekha 2022; Cruz, 2015). The second and third constrain specify that a nation in the year "t" should not have manufacturing employment and value-added shares of manufacturing surpassing 18%. Felipe et al. (2019) highlight that the chances of graduating into a rich country status surge if the economy has above 18% of manufacturing shares (employment

[10] This study uses data from two sources: The World Intellectual Property Organization Database (WIPO) and World Bank Development indicators (WDI).

and output). This condition implies that the manufacturing sector is not the foremost sector in the economy (Ravindran and Babu, 2023). Hence, the premature deindustrialization variable is given by the expression below

$$PDI_t = \begin{cases} 1 \; if \;\; Y_t \leq \$11{,}750 \, , and \; MAN_Emp_t \leq 18\%, and \; MAN_VA_t \leq 18\% \} \\ 0 \qquad elsewise \end{cases} \tag{4}$$

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 (Araujo et al., 2021; Ullah et al., 2021; Muluh et al., 2022; Wang et al., 2021; Qayyum et al., 2021; de Oliveira and da Fonseca Nicolay, 2022). Patent application employed in this study is a composite indicator (summing) of the residence and the non-residence patent applications[11]. 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 (de Oliveira and da Fonseca Nicolay, 2022) 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. Rekha, 2022; Romer, 1986; Ahmad and Khan, 2019) 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 (Rekha, 2022). 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 (2022), putting in place opening-up strategies encourages technological

[11] 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; non-residence and with national patent offices; Resident) for (World Bank glossary, 2022).

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. (Rekha, 2022; Cruz, 2015). Next, we control for human capital as it is relevant to influences production as it obstructs returns to the capital from falling and enhances capabilities for innovation (Romer, 1986). 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 (Ahmad and Khan, 2019; Rekha, 2022). Urbanization (% of total population) is increasingly considered as 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 (Destek et al., 2022). 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 (Rodrick, 2016).

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.

Table 1: Descriptive statistics and correlations matrix.

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

3.2. Estimation Strategy

This study evaluates the effect of technological innovation on premature deindustrialization in middle-income economies. Given this and following 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:

$$lnPDi_{it} = \alpha_0 + \beta_1 LnTI_{it} + \beta_2 Z_{it} + \mu_i + \varepsilon_{it} \tag{6}$$

Where: i:1-89; t:1980–2022; lnPDI: natural logarithm of premature deindustrialization; LnTI 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); β: constant parameter to be estimated; α_0 constant parameter to be estimated; μ incorporates the specific fixed effects not observed for each country; Ɛ 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 downwards-biased (Acheampong et al., 2022). As a result of some flaws presented by this technique[12] (Avom et al., 2022; Fang et al., 2023; Acheampong et al., 2023) although simple to implement especially when a couple of conditions are fulfilled[13] (Fang et al., 2023), we equally estimate equation (6) using the Baum et al. (2003) instrumental variable generalized method of moment (IV-GMM) technique. This technique is the best convenient for this study as it can address endogeneity sources (Acheampong et al., 2022).

In supplement to handling the endogeneity issue, the IV-GMM computation allows consistent estimations in the presence of AR (1) heteroscedasticity and autocorrelation within

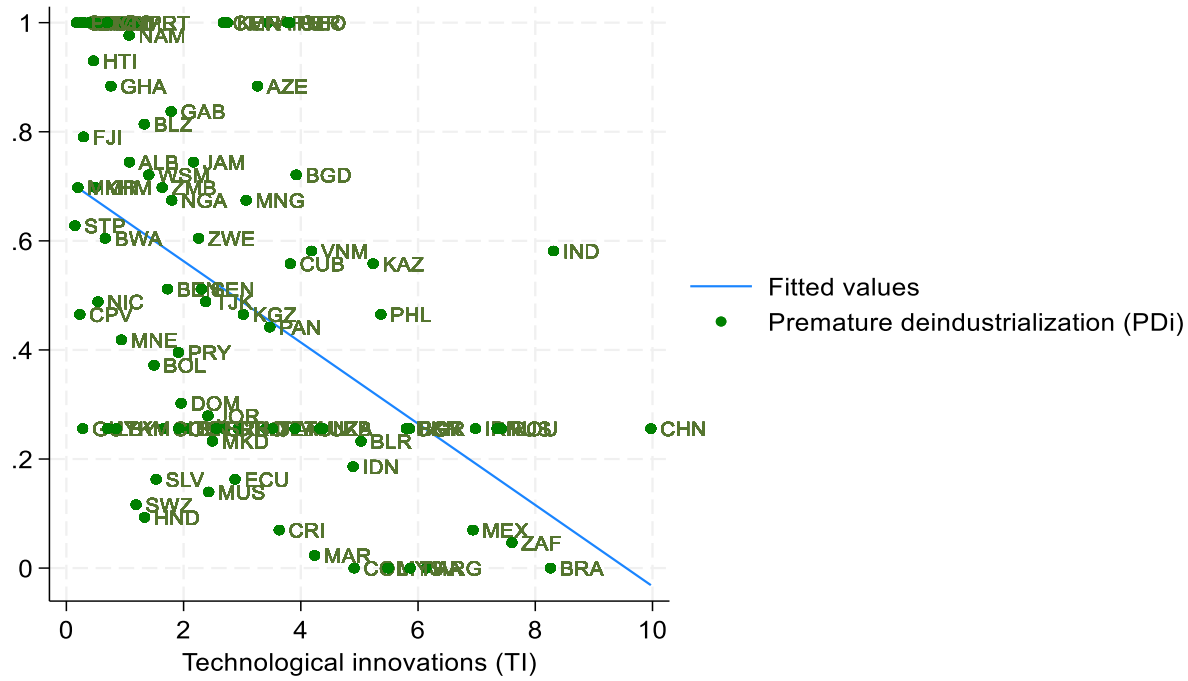
[12] Among other things, none consider the unobserved differences or the endogeneity of some right-hand side variables, which can falsely affect the estimation of parameters.

[13] Error term normality, absence of autocorrelation, and heteroscedasticity (homogeneity of variance).

panels (Baum et al., 2003). 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 (Baum et al., 2003).

In computing 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 Chi-sq(1) P-value test for instruments validity. The Hansen J-statistics tests for instrument over-identification, while the Kleibergen-Paap rk LM statistic and Chi-sq(1) P-val test for weak instrument identification. This technique is used for the sake of verification and in agreement with the existing literature (Acheampong et al., 2022).

Figure 1: Relationship between technological innovation and Premature deindustrialization



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 (2019) stability test. In line with Figure 1, column 1 (part A) presents the results of a bivariate regression. We unearth that the coefficient associated with

technological innovations (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 premature deindustrialization. This suggests that the more and more a country innovates technologically, the more it reduces the pace of premature deindustrialization. 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 (Araujo et al., 2021; Fan et al., 2023; Matos et al., 2022; Rodrik, 2016; Muluh et al., 2022). This result exhibits the salutary effects of technological innovations in controlling premature deindustrialization 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 (part A), 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 (Rekha, 2022). Our results are however inconsistent with those of Weiss and Clara (2016) and Beg et al. (2017) for whom low investment in GFCF will curb aggregate demand, restrict productive capacities, and restrain industrialization.

In column 3, trade is revealed to harm premature deindustrialization, outlying that an increase in trade levels will lead to a reduction in the levels of premature deindustrialization. According to Weiss and Clara (2016), 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 (Almeida and Fernandes, 2008; Rekha, 2022; Kali et al., 2007; Beg et al., 2017). These results however contradict those of Hoyos López (2017) and Araujo et al. (2021) who found a negative relation existing between trade openness (liberalization/lower tariff) and PDI.

Column 4 shows a positive (0.0111) and statistically significant association between 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 (Taguchi and Elbek, 2022).

Contrarily,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 (Ahmad and Khan, 2019; Rekha, 2022). This result can be explained by the fact that urbanization has an inimical effect on PDI and boosts economic growth and development (Ahmad and Khan, 2019; Rekha, 2022; Destek et al., 2024; Sikder et al., 2022). 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 to serious deindustrialization especially in state-led import substitution countries (Rekha, 2022; Palma, 2014). This result is in line with previous studies that display the perversive effect of unproperly managed natural resource rent/revenue on PDI (Taguchi, 2023; Taguchi and Elbek, 2022; Hoyos López, 2017).

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. (2021) who argue that trade openness leads to new technology development and diffusion, competitiveness; new products; or new business models, promoting total factor productivity growth (Fan et al., 2023; Matos et al., 2022; Rodrik, 2016; Muluh et al., 2022). 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 premature deindustrialization.

Inspired by the existing literature (Tadadjeu et al., 2023; Fang et al., 2023), we stage the results of the coefficient stability test in Part B of 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 (2019) coefficient stability test (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 (2019), 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.

Table 2: Baseline ordinary least squares (OLS) results

	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; denotes significance at 1%, 5%, and 10%, respectively. Robust standard errors are reported in parentheses. 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.

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 premature deindustrialization, the fact remains that premature deindustrialization can, in turn, affect TI, thus creating a bias

resulting from reverse causality. To limit this bias, we use the Baum et al. (2003) 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 (Acheampong et al., 2022). The basic *criterion* is that the number of sample countries should be greater than the number of instruments (Roodman, 2009). Results are exhibited in Table 3.

Table 3. Baseline IV-GMM results

	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

Notes: *** 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-val for weak instrument identification.

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 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.

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 (Masi et al., 2024). Moreover, we may note that our interest variable (technological innovation) 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 (Masi et al., 2024). All of this may stack the odds against our findings.

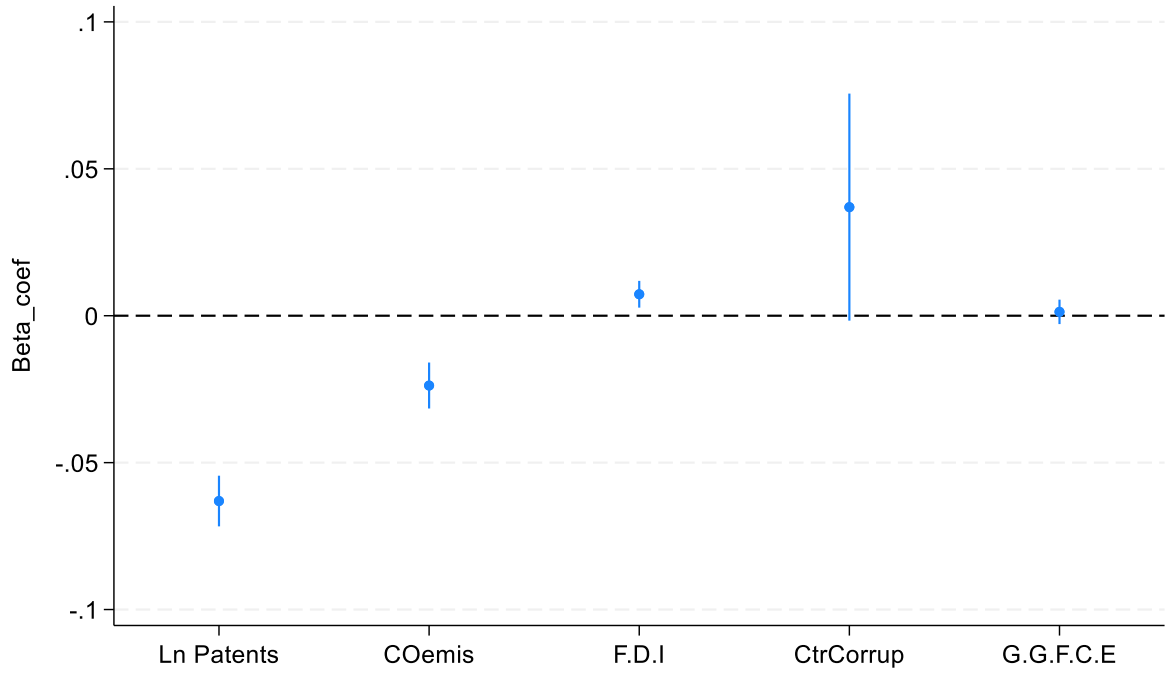
To confirm our results and in addition to the Oster (2019) stability test and endogeneity control, we implemented a chain of robustness checks. Firstly, we implement additional controls; secondly, we verify the validity of the results using two alternative estimation techniques. Thirdly, we use alternative variables to measure technological innovation (three) and premature deindustrialization (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 (F.D.I), control of

corruption (CtrCorrup) and general government final consumption expenditure (G.G.F.C.E). Our results are presented in Figure 2 below[14]. 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 (2014). The estimation outcomes are summarized in Figure 2. It is noteworthy that the coefficient associated with technological innovations (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 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.

Figure 2: Robustness to Additional Controls regression coefficients (Dependent variable: Premature Deindustrialization)



4.3.2. Robustness to alternative estimation strategies

The methods used so far allowed us to assess the average effect of technological innovations (IT) on premature deindustrialization (PDI). However, given the heterogeneity of

[14] In this study, we presented the coefficients for some results using graphs The extensive tables containing the estimates for technological innovations and its control variables on premature deindustralization across our sample countries would be made available upon request.

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 (2019) moment quantiles method (MMQR). The MMQR technique 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 (Adebayo et al. 2022a) 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 technological innovation on premature deindustrialization.

Additionally, the Lewbel (2012) approach is used. 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 (Fang et al., 2023). In addition to the fact that the Lewbel's 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 (Fang et al., 2023; Lewbel, 2012). Part 2 (Table 4) presents the results obtained from Lewbel's 2SLS estimation technique. In terms of instruments' suitability, the Kleibergen-Paap rk LM statistic and Chi-sq(1) P-val are employed to evaluate the instruments' shortcomings (Kleibergen and Paap, 2006). Also, the Hansen-J 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.

Table 4: Robustness to Method of Moment Quantile and Lewbel (2012) results.

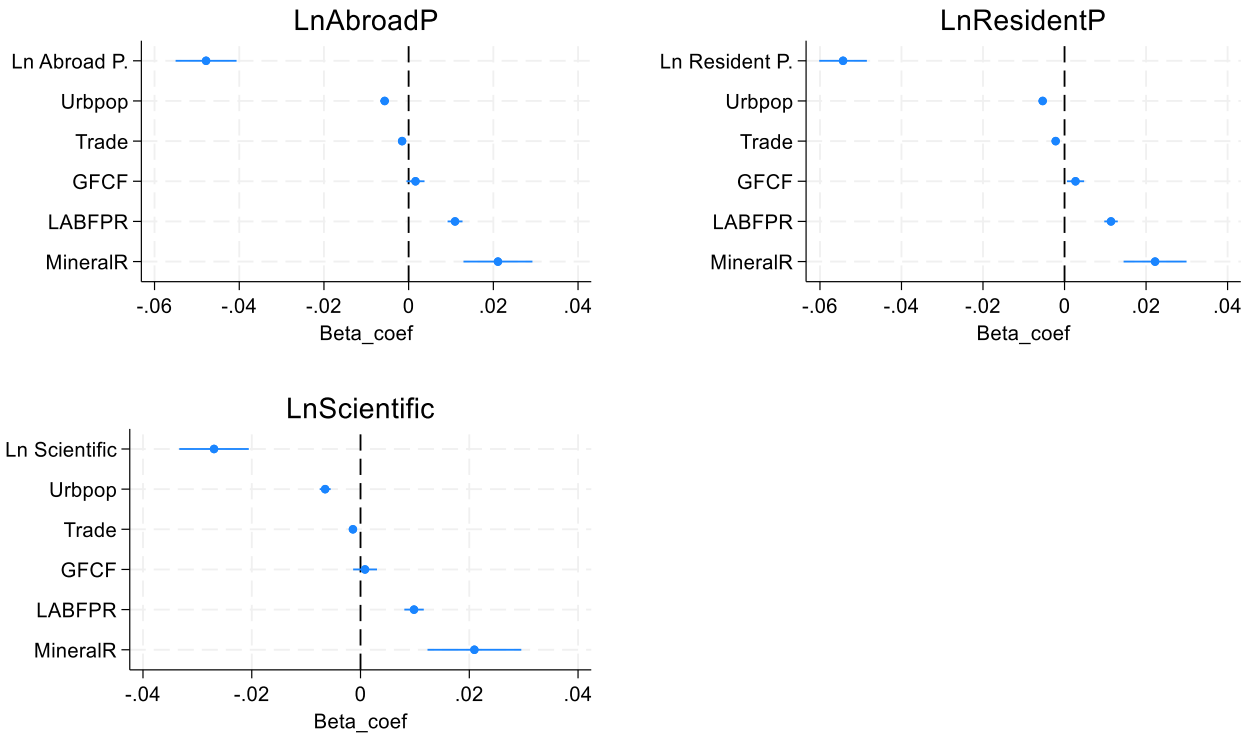
Dependent variable: Premature Deindustrialization												
	Part (1)											**Part (2)**
	Moment Quantile											Lewbel (2012)
			Lower quantile			Middle quantile			Upper quantile			
	Location	Scale	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90	Lewbel
LnTI	-0.0564***	-0.0244***	-0.0277***	-0.0310***	-0.0352***	-0.0402***	-0.0471***	-0.0567***	-0.0723***	-0.0824***	-0.0999***	-0.0669***
	(0.00330)	(0.00216)	(0.00222)	(0.00224)	(0.00233)	(0.00253)	(0.00288)	(0.00363)	(0.00456)	(0.00521)	(0.00671)	(0.00883)
GFCF	0.00268**	-0.000133	0.00284***	0.00282***	0.00280***	0.00277***	0.00273***	0.00268**	0.00260*	0.00254	0.00245	0.00321***
	(0.00116)	(0.000761)	(0.000806)	(0.000805)	(0.000823)	(0.000870)	(0.000974)	(0.00117)	(0.00156)	(0.00183)	(0.00234)	(0.00106)
Trade	-0.00222***	-0.000281*	-0.00189***	-0.00193***	-0.00198***	-0.00203***	-0.00211***	-0.00222***	-0.00240***	-0.00252***	-0.00272***	-0.00243***
	(0.000260)	(0.000171)	(0.000180)	(0.000180)	(0.000185)	(0.000195)	(0.000219)	(0.000262)	(0.000349)	(0.000411)	(0.000524)	(0.000292)
LABFPR	0.0102***	0.00310***	0.00657***	0.00700***	0.00753***	0.00816***	0.00905***	0.0103***	0.0122***	0.0135***	0.0157***	0.0107***
	(0.000888)	(0.000582)	(0.000612)	(0.000613)	(0.000629)	(0.000669)	(0.000752)	(0.000914)	(0.00120)	(0.00140)	(0.00179)	(0.000917)
Urbpop	-0.00581***	-0.00193***	-0.00354***	-0.00381***	-0.00414***	-0.00453***	-0.00508***	-0.00583***	-0.00707***	-0.00786***	-0.00924***	-0.00535***
	(0.000500)	(0.000328)	(0.000344)	(0.000345)	(0.000354)	(0.000377)	(0.000424)	(0.000517)	(0.000677)	(0.000790)	(0.00101)	(0.000609)
MineralR	0.0224***	0.00414	0.0175***	0.0181***	0.0188***	0.0197***	0.0208***	0.0225***	0.0251***	0.0268***	0.0298***	0.0221***
	(0.00429)	(0.00282)	(0.00298)	(0.00298)	(0.00305)	(0.00322)	(0.00361)	(0.00433)	(0.00576)	(0.00678)	(0.00864)	(0.00394)
Constant	0.309***	0.372***	-0.129***	-0.0777*	-0.0134	0.0619	0.168***	0.314***	0.552***	0.706***	0.972***	0.296***
	(0.0679)	(0.0445)	(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	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

Notes: *** 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-val for weak instrument identification.

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 Figure 3. Overall, results support our baseline estimation, as the mitigating effect of technological innovation on PDI remains negative and statistically significant in all regressions

Figure 3: Robustness to alternative measures of technological innovations regression coefficients (Dependent variable: Premature Deindustrialization). All regression models include baseline control variables

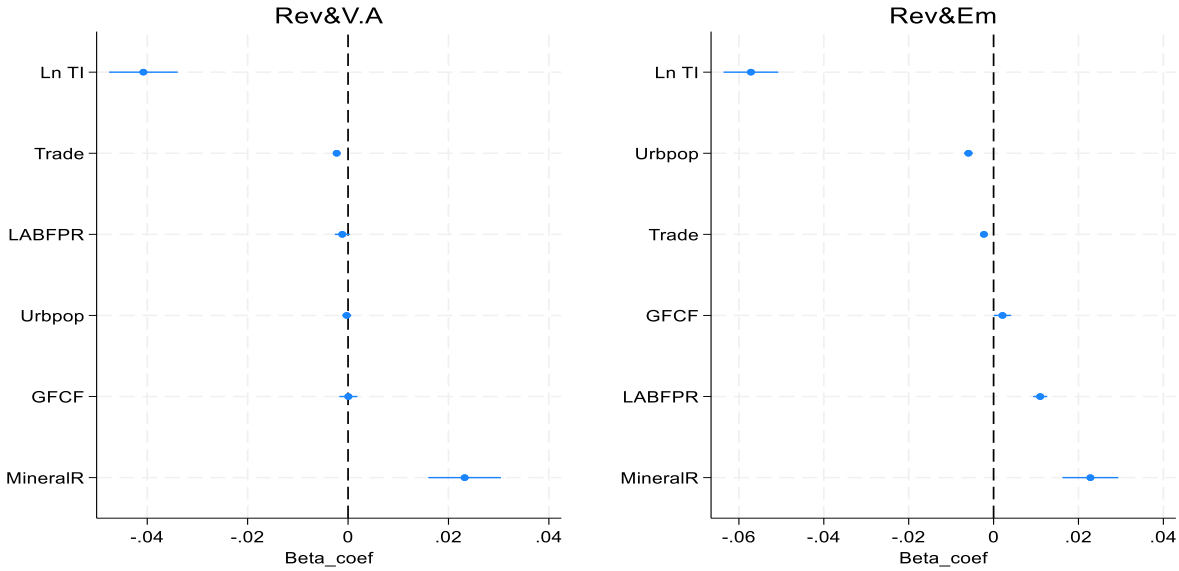


4.3.4. Robustness to alternative Dependent Variable.

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 Rodrick (2016). While only revenue

and manufacturing employment share (Rev&Em)[15] 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&V.A)[16] (Rekha, 2022; Ravindran and Babu, 2023). Figure 4 shows the findings with these substitute dependent variables using the same methods as the baseline regression.

Figure 4: Robustness to alternative measures of Dependent variable: Premature Deindustrialization (PDI) regression coefficients. All regression models include baseline control variables



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 premature deindustrialization 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 that the baseline

[15] Omitting value added share
[16] Omitting employment share

estimates are driven by including groups of countries with wildly disparate macroeconomic profiles (Tadadjeu et al., 2023). 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 (M.EN.A), 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 thereupon conclude that our baseline result is not driven by any specific region of our sample. These results report the healthful effect of technological innovations in downsizing premature deindustrialization.

Table 5: Robustness to alternative subsample.

	Dependent Variable: Premature Deindustrialization (PDi)					
	Without E&A	Without M.EN.A	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

Notes: *** 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-val for weak instrument identification.

5. Conclusion, policy implication, and limits of the study

This study seeks to examine the impact 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 Rodrick (2016). Based on the Ordinary Least Squares and the Instrumental Variable GMM (IV-GMM), our empirical analyses show evidence that technological innovation (TI) leads to a decrease in PDI in MICs. The obtained results were robust to additional control variables, different estimation methods (Lewbel, 2012), 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.

Premature deindustrialization has been a main concern in recent decades, with industries faced with significant challenges in adapting to the rapid pace of technological change. This phenomenon has far-reaching implications for economies, particularly in 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 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.

Governments 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. Governments should equally take effectual measures to improve social and economic freedom and carry out practical and stronger property protection that prompt the incentives and spur 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 proven detrimental to premature deindustrialization. Consequently, our empirical results strengthen the significance of the manufacturing sector in enhancing economic growth and development as well as the primal role of technological innovations in curbing premature deindustrialization 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 premature deindustrialization 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 premature deindustrialization while promoting technological innovations.

APPENDIX

Appendix 1: 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	

References

Acheampong, A. O., Opoku, E. E. O., & Dogah, K. E. (2023). The political economy of energy transition: the role of globalization and governance in the adoption of clean cooking fuels and technologies. *Technological Forecasting and Social Change*, *186*, 122156.

Acheampong, A. O., Opoku, E. E. O., Dzator, J., & Kufuor, N. K. (2022). Enhancing human development in developing regions: Do ICT and transport infrastructure matter?. *Technological Forecasting and Social Change*, *180*, 121725.

Adebayo, T. S., Akadiri, S. S., Adedapo, A. T., & Usman, N. (2022a). Does interaction between technological innovation and natural resource rent impact environmental degradation in newly industrialized countries? New evidence from method of moments quantile regression. *Environmental Science and Pollution Research*, *29*(2), 3162-3169.

Ahmad, M., & Khan, R. E. A. (2019). Does demographic transition with human capital dynamics matter for economic growth? A dynamic panel data approach to GMM. *Social Indicators Research*, *142*, 753-772.

Almeida, R., & Fernandes, A. M. (2008). Openness and technological innovations in developing countries: evidence from firm-level surveys. *The Journal of development studies*, *44*(5), 701-727.

Andreoni, A., & Tregenna, F. (2021). The middle-income trap and premature deindustrialization in South Africa. *Structural transformation in South Africa: The challenges of inclusive industrial development in a middle-income country*, 1-27.

Andriyani, V. E., & Irawan, T. (2018). Identification of premature deindustrialization and its acceleration in Indonesia (period 1986-2015). *Jurnal Ekonomi dan Kebijakan Pembangunan*, *7*(1), 78-101.

Araujo, E., Araújo, E., Peres, S. C., & Punzo, L. F. (2021). An investigation into shapes and determinants of deindustrialization processes: Theory and evidence for developed and developing countries (1970–2017). *EconomiA*, *22*(2), 129-143.

Avom, D., Keneck-Massil, J., Njangang, H., & Nvuh-Njoya, Y. (2022). Why are some resource-rich countries more sophisticated than others? The role of the regime type and political ideology. *Resources Policy*, *79*, 103067.

Baum, C. F., Schaffer, M. E., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *The Stata Journal*, *3*(1), 1-31.

Beg, M., Sertic, M. B., & Druzic, I. (2017). Determinants of deindustrialisation in developed European and post-communist countries. *Montenegrin journal of economics*, *13*(2), 93-106.

Botta, A., Yajima, G. T., & Porcile, G. (2023). Structural change, productive development, and capital flows: does financial “bonanza” cause premature deindustrialization?. *Industrial and Corporate Change*, *32*(2), 433-473.

Coccia, M. (2021). Technological innovation. *innovations*, *11*, I12.

Cruz, M. (2015). Premature de-industrialisation: theory, evidence and policy recommendations in the Mexican case. *Cambridge Journal of Economics*, *39*(1), 113-137.

Dasgupta, S., & Singh, A. (2007). *Manufacturing, services and premature deindustrialization in developing countries: A Kaldorian analysis* (pp. 435-454). Palgrave Macmillan UK.

de Oliveira, B. F., & da Fonseca Nicolay, R. T. (2022). Does innovative capacity affect the deindustrialization process? A panel data analysis. *Journal of Economic Structures*, *11*(1), 33.

Destek, M. A., Hossain, M. R., & Khan, Z. (2024). Premature deindustrialization and environmental degradation. *Gondwana Research*, *127*, 199-210.

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of economics and statistics*, *80*(4), 549-560.

Fan, S., Huang, H., Mbanyele, W., & Zhao, X. (2023a). A step toward inclusive green growth: can digital finance be the main engine?. *Environmental Science and Pollution Research*, 1-23.

Fang, M., Njangang, H., Padhan, H., Simo, C., & Yan, C. (2023). Social media and energy justice: A global evidence. *Energy Economics*, 106886.

Felipe, J., Kumar, U., & Galope, R. (2017). Middle-income transitions: trap or myth?. *Journal of the Asia Pacific Economy*, *22*(3), 429-453.

Felipe, J., Mehta, A., & Rhee, C. (2019). Manufacturing matters… but it’s the jobs that count. *Cambridge Journal of Economics*, *43*(1), 139-168.

Fujimoto, K., & Whittaker, D. H. (2021). *Premature Deindustrialization, Inter-sectoral Employment Shifts, and Accelerated Servicization*. Centre for Business Research, University of Cambridge.

Gill, I. S., Kharas, H. J., & Bhattasali, D. (2007). *An East Asian renaissance: Ideas for economic growth*. World Bank Publications.

Gollin, D., & Kaboski, J. P. (2023). New views of structural transformation: insights from recent literature. *Oxford Development Studies*, 1-23.

Grabowski, R. (2017). Premature deindustrialization and inequality. *International Journal of Social Economics*, *44*(2), 154-168.

Greenstein, J., & Anderson, B. (2017). Premature deindustrialization and the defeminization of labor. *Journal of Economic Issues*, *51*(2), 446-457.

Hamid, N., & Khan, M. (2015). Pakistan: A case of premature deindustrialization?. *The Lahore Journal of Economics*, *20*, 107.

Herrendorf, B., Rogerson, R., & Valentinyi, A. (2014). Growth and structural transformation. *Handbook of economic growth*, *2*, 855-941.

Hoyos López, M. (2017). Trade liberalization and premature deindustrialization in Colombia. *Journal of Economic Structures*, *6*(1), 30.

Itaman, R. E., & Awopegba, O. E. (2021). Finance, oil rent and premature deindustrialisation in Nigeria. *Structural Change and Economic Dynamics*, *59*, 149-161.

Jann, B. (2014). Plotting regression coefficients and other estimates. *The Stata Journal*, *14*(4), 708-737.

Kali, R., Méndez, F., & Reyes, J. (2007). Trade structure and economic growth. *The Journal of International Trade & Economic Development*, *16*(2), 245-269.

Kaplinsky, R., & Kraemer-Mbula, E. (2022). Innovation and uneven development: The challenge for low-and middle-income economies. *Research Policy*, *51*(2), 104394.

Kleibergen, F., & Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of econometrics*, *133*(1), 97-126.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, *30*(1), 67-80.

Liu, Z., Li, R., Zhang, X. T., Shen, Y., Yang, L., & Zhang, X. (2021). Inclusive green growth and regional disparities: evidence from China. *Sustainability*, *13*(21), 11651.

Machado, J. A., & Silva, J. S. (2019). Quantiles via moments. *Journal of Econometrics*, *213*(1), 145-173.

Masi, T., Savoia, A., & Sen, K. (2024). Is there a fiscal resource curse? Resource rents, fiscal capacity and political institutions in developing economies. *World Development*, *177*, 106532.

Matos, S., Viardot, E., Sovacool, B. K., Geels, F. W., & Xiong, Y. (2022). Innovation and climate change: A review and introduction to the special issue. *Technovation*, 102612.

McMillan, M. S., & Rodrik, D. (2011). *Globalization, structural change and productivity growth* (No. w17143). National Bureau of Economic Research.

Momeni, F., Fattahi, S., Najafi, S. M. S., & Moghadam, S. F. (2020). Service Sector Growth in Iran: Knowledge-based Economy or Premature Deindustrialization?.

Muluh, G. A., Dieubenit, T. M., & Gildas, N. T. (2022). Technological innovations and structural transformation in african economies. *International Journal of Innovative Technologies in Economy*, (2 (38)).

Nassif, A., & Morceiro, P. C. (2021). Industrial policy for prematurely deindustrialized economies after the Covid-19 pandemic crisis: Integrating economic, social and environmental goals with policy proposals for Brazil. *Niterói: Universidade Federal Fluminense, Faculdade de Economia, Textos para Discussão*, *351*.

Oreiro, J. L., Manarin, L. L., & Gala, P. (2020). Deindustrialization, economic complexity and exchange rate overvaluation: the case of Brazil (1998-2017). *PSL Quarterly Review*, *73*(295), 313-341.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, *37*(2), 187-204.

Palma, J. G. (2014). De-industrialisation,'premature'de-industrialisation and the dutch-disease. *Revista NECAT-Revista do Núcleo de Estudos de Economia Catarinense*, *3*(5), 7-23.

Qayyum, M., Ali, M., Nizamani, M. M., Li, S., Yu, Y., & Jahanger, A. (2021). Nexus between financial development, renewable energy consumption, technological innovations and CO2 emissions: the case of India. *Energies*, *14*(15), 4505.

Ravindran, R., & Babu, M. S. (2023). Premature Deindustrialisation and Income Inequality Dynamics: Evidence from Middle-Income Economies. *The Journal of Development Studies*, *59*(12), 1885-1904.

Rekha, R. (2022). Premature deindustrialisation and growth slowdowns in middle-income countries. *Structural Change and Economic Dynamics*, *62*, 377-389.

Rodrik, D. (2016). Premature deindustrialization. *Journal of economic growth*, *21*, 1-33.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of political economy*, *94*(5), 1002-1037.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*, *71*(1), 135-158.

Sikder, M., Wang, C., Yao, X., Huai, X., Wu, L., KwameYeboah, F., ... & Dou, X. (2022). The integrated impact of GDP growth, industrialization, energy use, and urbanization on CO2 emissions in developing countries: evidence from the panel ARDL approach. *Science of the Total Environment*, *837*, 155795.

Tadadjeu, S., Njangang, H., & Woldemichael, A. (2023). Are resource-rich countries less responsive to global warming? Oil wealth and climate change policy. *Energy Policy*, *182*, 113774.

Taguchi, H. – Elbek, A. (2022): Premature deindustrialization in post-Soviet economies. MPRA Paper. No. 114413

Taguchi, H. (2023). Premature deindustrialization: an empirical analysis in latecomer developing countries.

Tekay, B. (2018). A comparative study on Turkey under globalization: Premature deindustrialization and institutional transformations. Lund University, School of Economics and Management Master Thesis. Lund.

Tsukada, Y. (2023). Premature deindustrialization risk in Vietnam. *Journal of Asian Business and Economic Studies*, *30*(3), 226-240.

Ullah, S., Ozturk, I., Majeed, M. T., & Ahmad, W. (2021). Do technological innovations have symmetric or asymmetric effects on environmental quality? Evidence from Pakistan. *Journal of cleaner production*, *316*, 128239.

Van der Heijden, I. (2018). Deindustrialization in the globalization era: Examining the relationship between globalization and industrialization in developing economies. Lund University, School of Economics and Management Master Thesis. Lund.

Wang, Q. J., Feng, G. F., Wang, H. J., & Chang, C.P. (2021). The impacts of democracy on innovation: Revisited evidence. *Technovation*, *108*, 102333.

Weiss, M., & Clara, M. (2016). Unlocking domestic investment for industrial development. *Inclusive and Sustainable Industrial Development Working Paper Series UNIDO*, *12*, 1-54.

Xin, C., Fan, S., Mbanyele, W., & Shahbaz, M. (2023). Towards inclusive green growth: does digital economy matter?. *Environmental Science and Pollution Research*, 1-23.

Yanikkaya, H., Altun, A., & Tat, P. (2019). Openness and Deindustrialization: A Turkish Case. *Bogazici Journal, Review of Social, Economic and Administrative Studies*, *33*(2), 1-25.