MPRA
Munich Personal RePEc Archive

Premature deindustrialization, global value chains, and Dutch disease in Asian latecomer economies

Taguchi, Hiroyuki and Lar, Ni

Saitama University

April 2025

Online at https://mpra.ub.uni-muenchen.de/124311/
MPRA Paper No. 124311, posted 10 Apr 2025 14:13 UTC

Premature Deindustrialization, Global Value Chains, and Dutch Disease in Asian Latecomer Economies

Hiroyuki Taguchi, Saitama University
Ni Lar, Saitama University

Abstract

This study examines premature deindustrialization in Asian latecomer developing economies and its affecting factors from the perspectives of participation in global value chains (GVC) and the Dutch Disease. We first show the degree of deindustrialization according to country-specific fixed effects in estimating the manufacturing-population-income relationships. Second, we reveal the contributions of GVC participation and the Dutch Disease effects to the country-specific fixed effect by replacing the fixed effect with these factors in the estimation. The econometric empirical estimations yielded several findings. First, the fixed-effect model estimation results suggested the existence of deindustrialization and its risk in all Asian latecomer economies, with China, Japan, and Korea as benchmark cases. Second, the factor analyses revealed that the lack of GVC participation in Asian latecomer economies contributes to their country-specific deindustrialization by around 40% on average; and as for the Dutch Disease effects, its contributions to deindustrialization is around 10% on average, although the resource-rich developing economies have relatively larger contributions to their deindustrialization.

Keywords: Premature deindustrialization, Global value chains, Dutch Disease, Asian latecomer economies, Fixed effect model
JEL Classification Codes: O14, O53

1. Introduction

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

Rodrik (2016) refined the arguments on premature deindustrialization, positing that it refers to the early shrinking of manufacturing regarding employment and output in developing countries. It also argued that countries in Latin America and sub-Saharan Africa have been severely affected by premature deindustrialization, whereas Asian countries, having comparative advantages in manufacturing, have managed to avoid this trend. Since the seminal work of Rodrik (2016), numerous empirical studies have been conducted to identify the existence of premature deindustrialization in certain countries. Most of these empirical studies have considered Asian economies outside the scope of premature deindustrialization, as Dasgupta and Singh (2007) and Rodrik (2016) argued, although individual Asian countries remain at significantly diverse stages of development.

Taguchi and Tsukada (2022) examined the risk of premature deindustrialization in Asian latecomer developing economies. Diverging from the literature that treats Asian economies as a group with comparative advantages in manufacturing, their empirical analysis focused on individual Asian economies and compared the deindustrialization processes between the forerunners and latecomers in economic development. They found that the premature deindustrialization risk was higher for manufacturing trade-deficit and South Asian countries and suggested the need to participate in global value chains (GVC) to avoid premature deindustrialization in Asian latecomer developing economies.

Extending Taguchi and Tsukada (2022), our study conducts a factor analysis of premature deindustrialization in Asian latecomer developing economies. We assume that two factors affect premature deindustrialization: the degree of GVC participation and the Dutch Disease effect.[1] The GVC participation can be a factor candidate because its quantitative linkage with premature deindustrialization was identified by Taguchi and Tsukada (2022). The Dutch Disease effect can be another factor as natural resource development and dependence are considered to crowd out manufacturing activities (see, e.g., Corden and Neary, 1982; Sachs and Warner, 1995 and 2001; Rodrik, 2016). The empirical analysis in this study takes the following two steps. First, to show the degree of premature deindustrialization, we examine the country-specific fixed effect in estimating the relationship among manufacturing, population, and income, as in the framework of Rodrik (2016). Second, we reveal the contribution of the factors above (the degree of GVC participation and the Dutch Disease effect) to the country-specific fixed effect by

[1] There might be other variables affecting deindustrialization such as human capitals and institutional qualities. However, this study does not apply them due to their data constraint and their collinearity with income levels.

replacing the fixed effect with these factors in the estimation.

The remainder of the paper proceeds as follows. Section 2 provides a literature review focusing on hypotheses of premature deindustrialization and its linkage with GVC participation and the Dutch Disease effect and clarifies this study's contributions. Section 3 describes the empirical analyses performed to examine premature deindustrialization in Asian latecomer developing economies and the factors that caused this deindustrialization. Section 4 concludes the paper.

2. Literature Review and Contributions

This section provides literature related to the hypotheses of premature deindustrialization and its linkage with GVC participation and the Dutch Disease effect and clarifies this study's contributions.

Dasgupta and Singh (2007) coined the premature deindustrialization hypotheses. However, they focused only on employment, excluded output, and argued that the decline in manufacturing is not necessarily a pathological phenomenon. Rodrik (2016) described premature deindustrialization as the early shrinking of manufacturing in employment and output in developing countries by constructing a simple two-sector theoretical model with manufacturing and non-manufacturing sectors. His model demonstrated that developing countries that liberalize trade tend to be price-takers in the global manufacturing markets. Those that lack a strong comparative advantage in manufacturing must become net importers of manufactured products because of the decline in relative price of manufacturing and the rise of Chinese manufacturing, thereby leading to deindustrialization in manufacturing employment and output. Rodrik (2016) also provided the following empirical evidence for these affirmations: late industrializers attain peak levels of industrialization lower than those of early industrializers at lower income levels (post-1990 peak incomes are approximately 40% of pre-1990 peak incomes).

Since the seminal works of Dasgupta and Singh (2007) and Rodrik (2016), numerous empirical studies have been conducted to identify the existence of premature deindustrialization in multiple countries, including: Sato and Kuwamori (2019) in non-OECD countries, Nayyar et al. (2021) in lower-income developing countries, Daymard (2020) in Latin American and African countries, Caldentey and Vernengo (2021) in Latin American countries, Ssozi and Howard (2018) in Sub-Saharan African countries, and Taguchi and Tsukada (2022) in Asian latecomer economies.

Among these previous studies, the contributions of Taguchi and Tsukada (2022) are worth noting. First, they targeted Asian latecomer developing economies, whereas the majority of other studies considered Asian economies outside of the scope of premature deindustrialization. Second, they found the quantitative linkage between the degree of GVC participation and premature deindustrialization in the context of avoiding premature deindustrialization.

Another argument related to premature deindustrialization is the Dutch Disease hypothesis specific to resource-rich economies. The *Economist* coined the Dutch Disease in a November 1977 issue inspired by the repercussions of natural gas discoveries in the Netherlands in the late 1950s. Corden and Neary (1982) provided the theoretical grounds for this hypothesis by illustrating the resource reallocation from the tradable sector to the non-tradable sector caused by innovation from the natural resource sector. Rodrik (2016) also illustrated the Dutch Disease in the context of premature deindustrialization: a resource boom denotes an increase in productivity growth and/or prices in the non-manufacturing sector, so the Dutch Disease magnifies the deindustrializing consequences in countries with a comparative advantage in the resource sector. Many quantitative studies verified empirically the existence of Dutch Disease in resource-rich economies (e.g., Edwards, 1986; Harding and Venables, 2013; Ismail, 2010; Sachs and Warner, 1995 and 2001).

This study's contribution to the literature above is to conduct a factor analysis of premature deindustrialization in Asian latecomer developing economies, focusing on two factors: the degree of GVC participation and the Dutch Disease effect, based on Taguchi and Tsukada (2022) that identified the quantitative linkage between the degree of GVC participation and premature deindustrialization, and the literature of the Dutch Disease effect (e.g., Corden and Neary, 1982; Sachs and Warner, 1995 and 2001; Rodrik, 2016).

3. Empirical Analysis

This section describes the empirical analyses performed to identify premature deindustrialization in Asian latecomer developing economies and the factors that caused this deindustrialization. The section starts with a descriptive analysis overviewing the manufacturing-income nexuses of selected Asian economies.

3.1 Descriptive Analysis

Figure 1 displays the trends in manufacturing as a percentage of gross domestic product (GDP) along with GDP per capita in terms of constant prices in 2015 for 1990-2021[2] in selected 15 Asian economies: Bangladesh, Cambodia, China, India, Indonesia,

[2] The data are retrieved from UNCTAD Stat. See Section 3.3 and Table 1.

Japan, Kazakhstan, Korea, Laos, Malaysia, Myanmar, Nepal, Philippines, Thailand, Viet Nam. These economies are selected to easily visualize the different trends in their manufacturing-income nexus by removing the economies with similar trends, while the subsequent analysis targets 23 Asian economies (explained later). The trajectories show an inverted U-shaped curve. However, their locations are observably different: the curves of China, Korea, and Japan, that have been successful in their industrialization, are located at high positions; meanwhile, those of the other latecomers' economies are positioned downwards. It suggests the existence of premature deindustrialization in Asian latecomer developing economies, with China, Korea, and Japan being a benchmark.

The followings are simple depictions between manufacturing-GDP ratios and the indexes that are supposed to affect premature deindustrialization: the degree of GVC participation and the Dutch Disease effect. Figure 2 roughly shows a positive correlation between manufacturing-GDP ratios and GVC participation indexes[3] in 2017, with the total 23 Asian economies[4] (Afghanistan, Brunei, Iran, Kyrgyzstan, Mongolia, Pakistan, Sri Lanka, and Uzbekistan are added to the sample economies in Figure 1). Figure 3 exhibits a negative association between manufacturing-GDP ratios and natural resource rents that represent the abundance of natural resources.[5] These results align with our hypotheses of GVC participation and Dutch Disease based on the reviewed literature.

In the subsequent section, these observations should be statistically evaluated using an econometric method because the variables interact and should be controlled by income and demographic trends.

3.2 Econometric Analysis: Methodology

Regarding the empirical specification in the premature deindustrialization hypothesis, this study applies the equation presented by Rodrik (2016) as baseline regressions, namely, the inverted U-shaped manufacturing-income nexus. Using the Rodrik specification, we first examine the country-specific fixed effect to represent the volume of deindustrialization in Equation 1. Then, we investigate the contributors to deindustrialization by replacing the fixed effect with the degree of GVC participation and the Dutch Disease effect in Equation 2.

---

[3] The data are from the UNCTAD-Eora Global Value Chain database. See Section 3.3, Table 1, and the Appendix.

[4] Regarding the area definition of Asia, we follow the database of UNCTAD Stat. We exclude from the samples the following economies with small size and data constraint: Bhutan, Hongkong, Macao, Maldives, Singapore, Tajikistan, and Turkmenistan.

[5] The data are from the World Bank Open Data database, See Section 3.3, and Table 1.

$$man_{it}=\alpha_0+\alpha_1\ln pop_{it-1}+\alpha_2(\ln pop_{it-1})^2+\alpha_3\ln ypc_{it-1}+\alpha_4(\ln ypc_{it-1})^2+f_i+f_t+\varepsilon_{it} \quad (1)$$

$$man_{it}=\beta_0+\beta_1 lnpop_{it-1}+\beta_2(\ln pop_{it-1})^2+\beta_3\ln ypc_{it-1}+\beta_4(\ln ypc_{it-1})^2+\beta_5 gvc_{it-1}+\beta_6 nrr_{it-1}+f_t+\varepsilon_{it} \quad (2)$$

where the subscripts *i* and *t* denote the country (23 Asian countries) and year (1990-2021 in Equation 1 and 1990-2017 in Equation 2), respectively; *man* represents the manufacturing-GDP ratio in 2017 constant prices in USD; *pop* and *ypc* represent the country's population size and GDP per capita in 2015 constant prices in USD; f_i and f_t are a time-invariant country-specific fixed effect and a country-invariant time-specific fixed effect, respectively; *gvc* denotes the degree of GVC participation; *nrr* represents the natural resource rents as a percentage of GDP for materializing the Dutch Disease effect; ε represents a residual error term; $\alpha_{0\ldots4}$, and $\beta_{0\ldots6}$ are the estimated coefficients. ln represents the logarithm form, which we set to avoid scaling issues. The explanatory variables in Equations 1 and 2, ln*pop*, ln*ypc*, *gvc*, and *nrr* are lagged by one year. This helps avoid reverse causality in the model specifications, including the endogenous interaction between the dependent and independent variables. The data sources are explained later in Section 3.3 and Table 1.

In terms of the specifications of the estimation models, all the equations are controlled by the variables for a country's population size and real GDP per capita. The ordinary hypothesis of premature deindustrialization proposed by Rodrik (2016) postulates an inverted-U-shaped path between a country's manufacturing-GDP ratio, and population size and real GDP per capita. This hypothesis would be verified if α_1, α_3, β_1, and $\beta_3 > 0$ and α_2, α_4, β_2, and $\beta_4 < 0$ are significant.

Equation 1 applies a fixed-effect model represented by f_i for the panel estimation to examine the degree of deindustrialization in the sample Asian countries. The estimation sets China, Japan and Korea as the benchmark countries for estimating a country-specific effect because they successfully achieved a manufacturing-driven development. The significantly negative coefficient of the country-specific effect would suggest a lower manufacturing-GDP ratio in an Asian latecomer developing economy relative to benchmarks at their same development stages, implying the existence of premature deindustrialization.

In Equation 2, we replace the country-specific fixed effect above with the possible industrialization-related factors contributing to the fixed effect. We employ the degree of GVC participation (*gvc*) and the Dutch Disease effect (*nrr*) as industrialization-related factors. Following Taguchi and Tsukada (2022), that identified a positive linkage between industrialization and GVC participation, we expect the coefficient of *gvc* to be significantly positive ($\beta_5 > 0$). The Dutch Disease factor means that a boom in the natural resource sector reduces manufacturing (Corden and Neary, 1982); thus, we expect a significantly negative coefficient of *nrr* ($\beta_6 < 0$).

Regarding the estimation technique, this study applies the ordinary least squares (OLS) estimator and the Poisson pseudo maximum likelihood (PPML) estimator. The reason for applying the PPML estimator is that the sample data, including those of developing countries, would be plagued by heteroskedasticity and autocorrelation; in which cases, the OLS estimator leads to bias and inconsistency in estimates. The PPML estimator corrects for heteroscedastic error structure across panels and autocorrelation with panels, as Silva and Tenreyro (2006) and Kareem et al. (2016) suggest. Therefore, these two estimators are applied to ensure the robustness of the estimations. We used EViews (version 12) for processing the data and estimations.

3.3 Econometric Analysis: Data

The data sources for the variables and the sample sizes for the estimation are as follows. The data for the manufacturing-GDP ratio (*man*), population size (*pop*) and real GDP per capita (*ypc*) are retrieved from the UNCTAD Stat database.[6] The data for GVC participation (*gvc*) are from the UNCTAD-Eora Global Value Chain database[7], and those for natural resource rents (*nrr*)are from the World Bank Open Data database.[8]

The sample targets 23 economies, as shown in Section 3.1, and the sample period is 1990–2021 for Equation 1 and 1990–2017 for Equation 2 due to the data constraints of the GVC participation index. We then construct a panel data set of the sample economies and periods. We present the variable list in Table 1 and report the descriptive statistics for the variables in Table 2.

For the subsequent estimation, we investigate the stationary property of the constructed panel data by employing panel unit root tests: the Levin, Lin, and Chu test (Levin et al., 2002) as a common unit root test; and the Fisher-ADF and Fisher-PP tests (Choi, 2001; Maddala & Wu, 1999) as individual unit root tests. The common unit root test assumes a common unit root process across cross-sections, and the individual unit root test allows for individual unit root processes that vary across cross-sections. We run these tests based on the null hypothesis that a level of panel data has a unit root by including "individual intercept" and "individual intercept and trend" in the test equations. Table 3 shows that the Levin, Lin, and Chu test results reject the null hypothesis of a unit

[6] See the website: https://unctadstat.unctad.org/EN/.
[7] See the website: https://worldmrio.com/unctadgvc/. The compilation of GVC participation index is described in Appendix.
[8] See the website: https://data.worldbank.org/.

root at the conventional significance level for all variables in both test equations. The individual unit root tests do not necessarily reject the null hypothesis in all cases; however, the Fisher–PP test rejects the null hypothesis at the conventional level for all variables. Therefore, we assume there is no serious issue with unit roots in the panel data, allowing us to use the panel data in levels for subsequent estimations.

We next check the possible existence of a multicollinearity problem among the explanatory variables in Equation 2 by applying the variance inflation factors (VIF), a method of measuring the level of collinearity between regressors, where a multicollinearity problem is identified if the factors are beyond ten points. Table 4 reveals that the VIF in the estimation with four variables have collinearity in population size and real GDP per capita, with their VIF values being far beyond ten points, whereas the estimation with three variables produces no multicollinearity problem. However, the population size and real GDP per capita are incorporated in Rodrik's estimation model (2016). Thus, the subsequent estimations in this study explore two aspects: the estimation with four variables and that with three variables.

3.4 Econometric Analysis: Estimation Results

Tables 5 and 6 report the estimation results of the country-specific fixed effect model in Equation 1 and the alternative model containing GVC participation and the Dutch Disease effects in Equation 2, respectively, with each result including OLS and PPML estimations. We summarize the results as follows.

First, regarding the control variables for a country's population size and real GDP per capita across all estimation results in Tables 5 and 6 (estimation i, iii, v, and vii), α_3 and $\beta_3 > 0$ and α_4 and $\beta_4 < 0$ in the coefficients of real GDP per capita hold significantly, whereas the opposite signs in the coefficients of population size (α_1 and $\beta_1 < 0$ and α_2 and $\beta_2 > 0$) are estimated. It suggests that an inverted-U-shaped path postulated by Rodrik is verified between a country's manufacturing-GDP ratio and real GDP per capita and not between the ratio and population size. Considering the results and the multicollinearity problem in population size and real GDP per capita shown in Section 3.3, we add the estimation containing only real GDP per capita as a control variable in Tables 5 and 6 (estimation ii, iv, vi, and viii). The turning points in real GDP per capita (computed using $-\alpha_3/2\alpha_4$ in Equation 1 and $-\beta_3/2\beta_4$ in Equation 2) fall within the reasonable ranges of real GDP per capita, namely between 2,747 and 14,705 USD. However, the main research focus in this study is the position of a country's manufacturing–income curve, not its shape.

Second, focusing on the fixed-effect model in Table 5, the coefficients of the country-specific dummies are significantly negative for all 20 economies (except three benchmark countries) in any case (though the coefficient of Thailand is insignificant only in the estimation i). Among the 20 economies, focusing on estimation iv, the ones with a larger magnitude of the dummy coefficient are resource-rich economies such as Mongolia, Laos, Uzbekistan, Kazakhstan, Iran, and less-developed economies such as Nepal, Pakistan, Afghanistan, Myanmar, and Cambodia. Thus, all Asian latecomer economies have lower manufacturing GDP ratios than the benchmark countries of China, Japan, and Korea in their same development stages, thereby suggesting deindustrialization in this set of economies. From the perspective of the premature deindustrialization hypothesis, a lower manufacturing-income path could indicate the existence of premature deindustrialization and its future "risk" because the lower country's manufacturing ratio will peak out at a lower ratio and a lower income level, thereafter, compared with those in benchmark countries.

Third, the alternative models in which we replace the country-specific dummies with the variables representing GVC participation and the Dutch Disease effects in Table 6 produce the expected results. The degree of GVC participation (*gvc*) has significantly positive coefficients in all the cases from the estimation v to viii, while the Dutch Disease indicator (*nrr*) has significantly negative ones. These results suggest that the degree of industrialization is affected by the degree of GVC participation and the Dutch Disease effect. The joint estimation outcomes of the country-specific fixed effect and the possible industrialization-related factors (GVC participation and the Dutch Disease effects) raise the question of the degree of contributions of the industrialization-related factors to the country-specific deindustrialization in the sample Asian latecomer economies.

3.5 Factor Analysis

The final step is to clarify the contributions of the less degree of GVC participation and the Dutch Disease effects to the country-specific deindustrialization in the Asian latecomer economies. We apply the combination of the two estimations: estimation iv in the fixed-effect model in Table 5 and viii in the alternative model in Table 6 because the PPML estimator is more sophisticated than the OLS one in correcting heteroskedasticity and autocorrelation (discussed in Section 3.2) and the exclusion of population size avoids multicollinearity problem (shown in Section 3.3). Tables 7 and 8 show factor analyses on GVC participation (*gvc*) and the Dutch Disease (*nrr*) effects, respectively, and Figure 4 displays both of their contributions.

In Tables 8 and 9, Column (a) shows the coefficients of dummies in the estimation iv in Table 5; Columns (b) presents the sample-period-average values of the GVC participation and the Dutch Disease indicators (*gvc*, and *nrr*); Columns (c) computes their deviations from the average of those of China, Japan, and Korea (the benchmark countries); and Columns (d) reports the contributions of GVC participation and the Dutch Disease indicators after multiplying their indicators' deviations by their estimated coefficients in the estimation viii of Table 6. Column (e) computes the contribution ratios of the lower degree of GVC participation and the Dutch Disease effects to the country-specific deindustrialization fixed effects by dividing (d) by (a). Figure 4 visualizes the contributions of the less degree of GVC participation and the Dutch Disease effects in Column (d) against the country-specific deindustrialization fixed effects in Column (a), shown by white dots on the bar graphs.

We can summarize the analytical results as follows. Regarding the GVC participation effect in Table 7 (Column (e)) and Figure 4, lower GVC participation in Asian latecomer economies contributes to their country-specific deindustrialization by around 40% on average, except in Malaysia and the Philippines. As for the Dutch Disease effects in Table 8 (Column (e)) and Figure 4, its contributions to deindustrialization are around 10% on average. However, resource-rich economies such as Brunei, Iran, Kazakhstan, Mongolia, and Uzbekistan have relatively larger contributions to their deindustrialization. The verified contributions of the lack of GVC participation and the Dutch Disease effect to the country-specific deindustrialization in the sample Asian latecomer economies are in line with the arguments of Taguchi and Tsukada (2022), Corden and Neary (1982), Rodrik (2016), and Sachs and Warner (1995) and (2001).

These factor analyses point toward policy implications for mitigating and avoiding premature deindustrialization and its risk. For the less-developed Asian economies that have faced premature deindustrialization and its associated risk, it would be of significance to participate in GVC activities that the forerunners such as China, Japan, and Korea have experienced. Their GVC participation facilitates the recovery of their deindustrialization by approximately 40%. Numerous reports by international organizations (e.g., UNCTAD 2013; World Bank 2020) have recommended developing GVC participation strategies, such as strategies related to infrastructure and human resource development, institutional improvements, and policy frameworks to create industrial clusters and networks. For resource-rich developing economies, the Dutch disease effect may accelerate premature deindustrialization. Thus, to offset the disease effect, resource revenues should be mobilized for productive uses, such as infrastructure development, to activate manufacturing activities (e.g., Coutinho, 2011; Sachs, 2007).

4. Summary and Conclusion

This study examined premature deindustrialization in Asian latecomer developing economies and investigated the factors affecting deindustrialization from the perspectives of GVC participation and the Dutch Disease. We first showed the degree of deindustrialization according to country-specific fixed effects in estimating the manufacturing-population-income relationships. Second, we revealed the contributions of the factors above (GVC participation and the Dutch Disease effects) to the country-specific fixed effect by replacing the fixed effect with these factors in the estimation.

The empirical estimations yielded several findings. First, the fixed-effect model estimation results suggested deindustrialization and its risk in all 20 sample Asian latecomer economies, with China, Japan, and Korea being benchmark economies. Second, the outcomes of the factor analyses revealed that the lack of GVC participation in Asian latecomer economies contributed to their country-specific deindustrialization by about 40% on average, except in Malaysia and the Philippines; the contribution of the Dutch Disease effect to deindustrialization were around 10% on average, although the resource-rich developing economies have relatively larger contributions to their deindustrialization.

The policy implications in this study are the following. For the less-developed Asian economies that have faced premature deindustrialization and its risk, it would be useful to participate in GVC activities so that their GVC participation can facilitate the recovery of their deindustrialization; for resource-rich developing economies to offset the Dutch Disease effect, resource revenues should be mobilized for productive uses, such as infrastructure development, to activate manufacturing activities.

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

References

Caldentey, E.P., and Vernengo, M. 2021. Financialization, premature deindustrialization, and instability in Latin America. *Review of Keynesian Economics*, 9(4): 493–511.

Casella, B., Bolwijn, R., Moran, D., and Kanemoto, K. 2019. Improving the Analysis of Global Value Chains: The UNCTAD-Eora Database. *Transnational Corporations*, 26(3):115–142.

Choi, I. 2001. Unit root tests for panel data. *Journal of International Money and Finance*, 20(2), 249–272.

Coutinho, L. 2011. The resource curse and fiscal policy. *Cyprus Economic Policy Review*, *5*(1): 43–70.

Corden, W.M., and Neary, J.P. 1982. Booming sector and de-industrialization in a small open economy, *Economic Journal*, 92: 825–848.

Dasgupta, S. and Singh, A. 2007. Manufacturing, Services, and Premature Industrialization in Developing Countries: A Kaldorian Analysis. In Mavrotas, C. and Shorrocks, A. (eds.), *Advancing Development*, New York: Palgrave-Macmillan.

Daymard, A. 2020. Agricultural productivity as a prerequisite of industrialization: Some new evidence on trade openness and premature deindustrialization. *THEMA Working Papers*, No. 2020-07.

Edwards, S. 1986. A commodity export boom and the real exchange rate: The money-inflation link. In J. P. Neary and S. van Wijnbergen (Eds.), *Natural resources and the macroeconomy*. MIT Press.

Islami, M.I., and Hastiadi, F.F. 2020. Nature of Indonesia's deindustrialization. *Economics Development Analysis Journal*, 9(2), 220–232.

Harding, T., and Venables, A.J. 2013. The implications of natural resource exports for nonresource trade. *Research Paper*, No. 103. OxCarre (Oxford Centre for the Analysis of Resource Rich Economies).

Kareem, F.O., Martinez-Zarzoso, I., and Brümmer, B. 2016. Fitting the Gravity Model When Zero Trade Flows are Frequent: A Comparison of Estimation Techniques Using Africa's Trade Data. *Global Food Discussion Papers*, No. 77.

Kimura, F. 2006. International Production and Distribution Networks in East Asia: Eighteen Facts, Mechanics, and Policy Implications. *Asian Economic Policy Review*, 1: 326–44.

Koopman, R., Powers, W., Wang, Z., and Wei, S.J. 2010. Give Credit Where Credit Is Due: Tracing Value Added in Global Production Chains. *NBER Working Paper*, No. 16426.

Levin, A., Lin, C. F., and James Chu, C. 2002. Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, 108(1), 1–24.

Maddala, G.S., and Wu, S.A. 1999. A Comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, 61(S1), 631–652.

Rodrik, D. 2016. Premature Deindustrialization. *Journal of Economic Growth*, 21: 1–33.

Sachs, J.D. 2007. How to handle the macroeconomics of oil wealth in escaping the resource curse. In Hamphreys, M., Sachs, J.D., and Stiglitz, J.E. (eds.). New York: Columbia University Press.

Sachs, J.D., and Warner, A.M. 1995. Natural resource abundance and economic growth, *National Bureau of Economic Research Working paper*, No. 5398, Cambridge, MA.

Sachs, J.D., and Warner, A.M. 2001. Natural Resources and Economic Development: The Curse of Natural Resources, *European Economic Review*, 45: 827–838.

Sato, H. and Kuwamori, H. A Note on Premature Deindustrialization. *IDE Discussion Paper*, No. 763, Institute of Developing Economies, Japan External Trade Organization (IDE-JETRO).

Silva, J.M.C.S., and Tenreyro, S. 2006. The log of gravity. *The Review of Economics and Statistics*, 88: 641–658.

Ssozi, J., and Howard, E. 2018. The Non-Classical Structural Economic Transformation of Sub-Saharan Africa: Urbanization with Premature Deindustrialization. *Africa growth Agenda Journal*, 15(1): 8–12.

Taguchi, H., and Tsukada, Y. 2022. Premature Deindustrialization Risk in Asian Latecomer Developing Economies. *Asian Economic Papers*, 21(2): 61–77.

United Nations Conference on Trade and Development (UNCTAD) 2013. *World investment report 2013 – global value chains: Investment and Trade for Development*. UNCTAD: Geneva.

World Bank 2020. *World Development Report—Trading for Development in the Age of Global Value Chains*. Washington, DC: The World Bank.

Appendix GVC Participation Index

This appendix illustrates the compilation of the GVC participation index using the UNCTAD-Eora Global Value Chain database. Regarding GVC forms, Koopman et al. (2010) presented the following two types of participation in a vertical specialization chain:

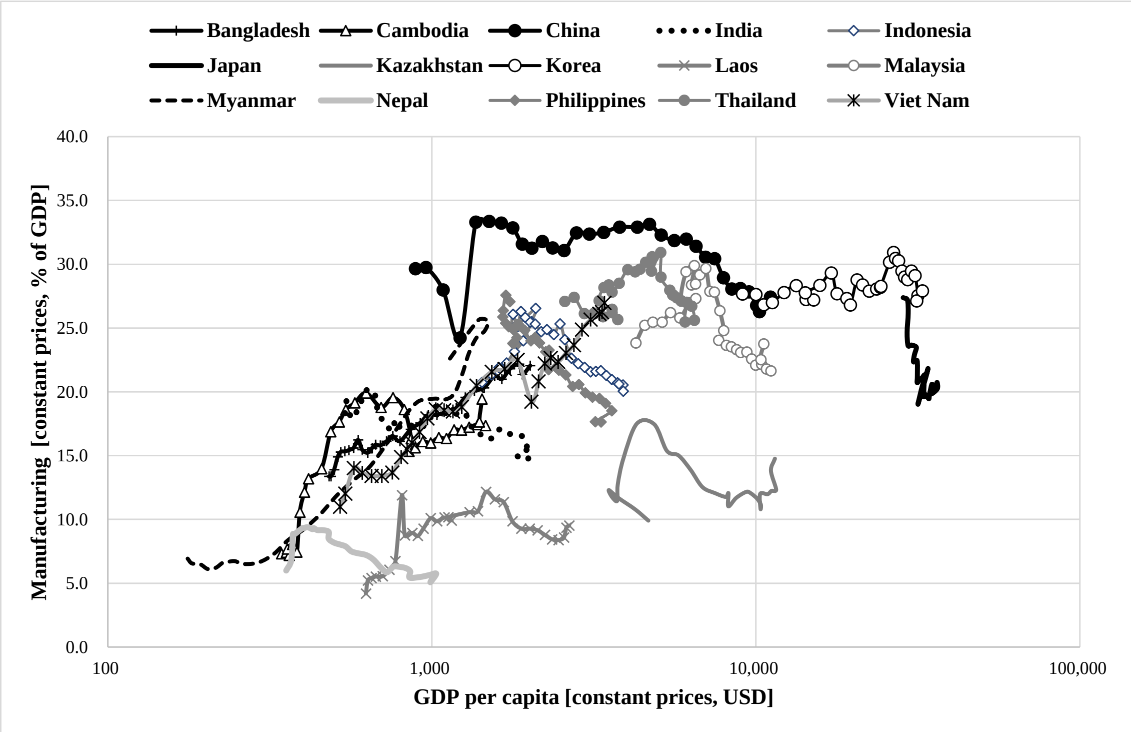
GVC Participation = FV/E + IV/E

where FV, IV, and E represent "foreign value-added embodied in gross exports", "domestic value-added embodied as intermediate inputs in other countries' gross exports", and "gross exports", respectively. The first item (FV/E), representing downstream GVC participation, corresponds to GVC backward participation, while the second item (IV/E), showing upstream GVC participation, is called GVC forward participation, following, for example, the World Bank (2020).

This study compiles the GVC participation index based on the forward participation form in the machinery sectors of manufacturing industries. The reason for focusing on "forward" participation is that it is strongly linked to a sustainable increase in manufacturing activities through industrial upgrading. Advanced manufacturing makes it possible to provide sophisticated intermediate inputs for exporters. The World Bank (2020) argued that forward GVC participation tends to increase along with innovative manufacturing activities. The reason for targeting machinery sectors is that GVC activities with many multilayered vertical production processes are typically observed in machinery sectors, as Kimura (2006) argued.

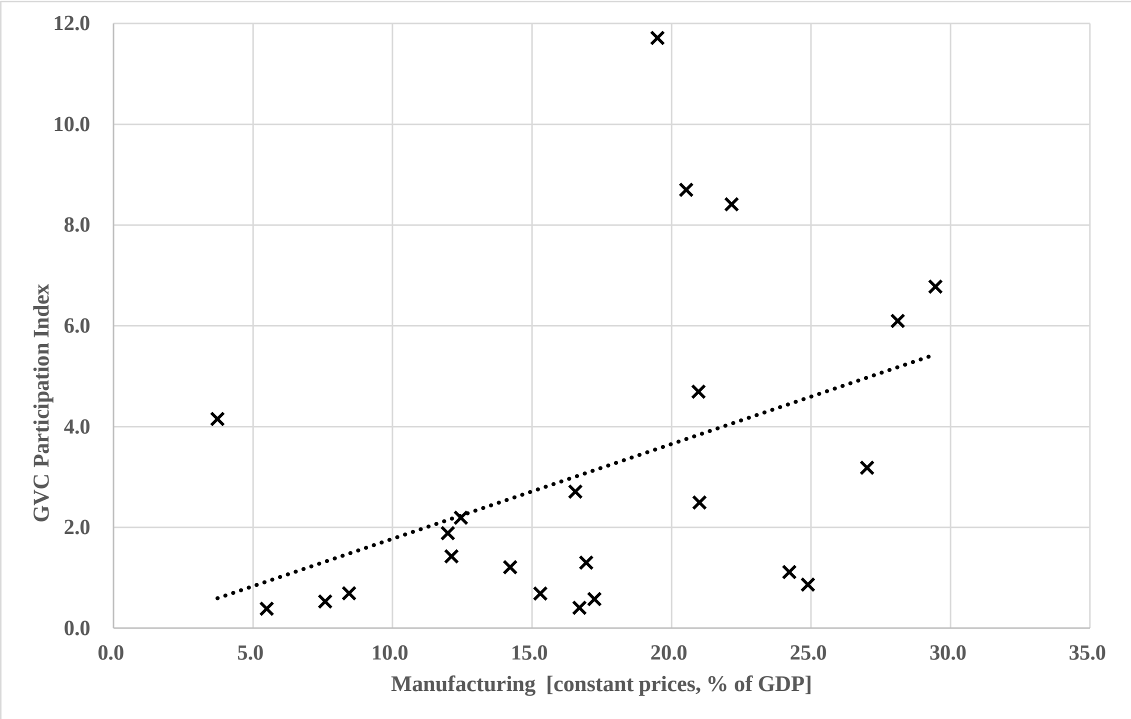
Based on the forward participation form in machinery sectors, the GVC participation index (of 23 sample economies) can be computed using the UNCTAD-Eora Global Value Chain database. Its data source is shown in Note 5 in the text, and its methodological background is described by Casella et al. (2019). The database provides the country/ sector-by-country matrix from 1990 to 2017 with global coverage (189 countries and a "Rest of World" region). It reports, for each country of exports, the value contributed by all other countries/sectors in the world, where the rows show the country/sector originating the value added, and the columns show the country exporting that value added. The GVC forward participation index in the machinery sectors of A sample economy is calculated as follows: A sample economy's domestic values in the machinery sectors embodied as intermediate inputs in all other countries' gross exports (given in the row in the matrix) are divided by A sample economy's gross exports (given in the column).

Figure 1 Trends in Manufacturing-income Nexuses in Selected Asian Economies



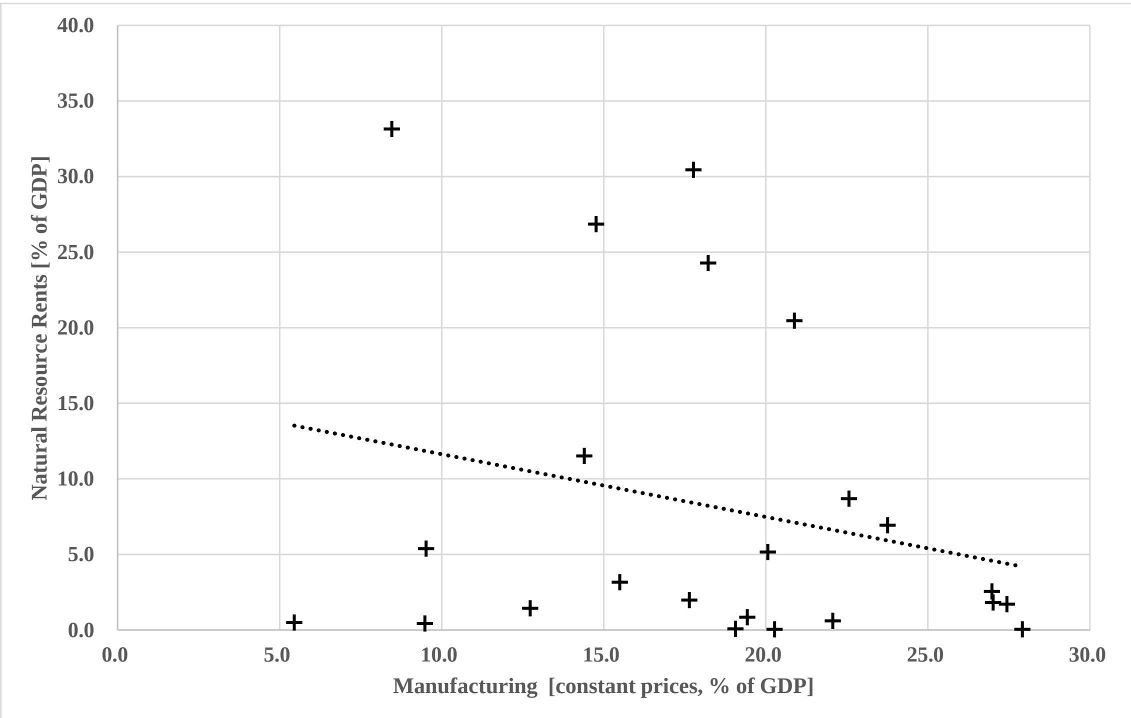
Source: Authors' description based on UNCTAD Stat.

Figure 2 Correlation between Manufacturing-GDP Ratios and GVC Participations



Source: Authors' description based on UNCTAD Stat and UNCTAD Eora Global Value Chain Database.

Figure 3 Correlation between Manufacturing-GDP Ratios and Natural Resource Rents



Source: Authors' description based on UNCTAD Stat and World Bank Open Data database.

Table 1 Variables and their Sources

Var.	Description	Sources
Dependent Variable		
man	*Manufacturing in US dollars at constant prices (2015), percentage of Gross Domestic Product (GDP)*	UNCTAD Stat
Explanatory Variables		
pop	*Populaiton in thousands*	UNCTAD Stat
ypc	*GDP in US dollars at constant prices (2015) per capita*	
gvc	*Forward participation in global value chains (GVC) in machinery, devided by gross export values*	UNCTAD-Eora
nrr	*Total natural resources rents, percantage of GDP*	World Bank

Source: Authors' description.

Table 2 Descriptive Statistics

Variables	Obs.	Median	Std. Dev.	Min.	Max
Dependent Variable					
man	730	17.355	7.124	3.724	33.357
Explanatory Variables					
lnpop	730	10.736	1.803	5.568	14.170
$(\ln pop)^2$	730	115.265	37.390	31.006	200.798
ln*ypc*	730	7.547	1.286	5.170	10.500
$(\ln ypc)^2$	730	56.961	21.062	26.734	110.254
gvc	644	1.173	2.637	0.228	11.709
nrr	719	3.214	8.771	0.012	42.217

Source: Authors' calculation.

Table 3 Panel Unit Root Tests

	individual intercept			*individual intercept and trend*		
	L. L. & C.	*Fisher ADF*	*Fisher PP*	*L. L. & C.*	*Fisher ADF*	*Fisher PP*
man	-2.324 **	75.187 ***	73.982 ***	-2.734 ***	65.823 **	73.833 ***
ln*pop*	-3.866 ***	96.840 ***	322.336 ***	-3.958 ***	203.084 ***	124.713 ***
$(\ln pop)^2$	-3.726 ***	70.500 **	309.183 ***	-3.981 ***	203.542 ***	106.929 ***
ln*ypc*	-3.757 ***	51.011	63.333 **	-1.749 **	51.802	75.494 ***
$(\ln ypc)^2$	-2.987 ***	48.548	59.854 *	-1.675 **	51.667	79.408 ***
gvc	-2.093 **	76.793 ***	81.202 ***	-1.742 **	48.127	68.777 **
nrr	-4.348 ***	86.576 ***	94.602 ***	-2.354 ***	74.091 ***	73.489 ***

Source: Authors' estimation.

Table 4 Panel Unit Root Tests

	4 Variables	3 Variables	
ln*pop*	18.927	-	2.733
ln*ypc*	28.170	4.068	-
gvc	2.681	2.541	2.044
nrr	2.420	2.024	1.533

Source: Authors' estimation.

Table 5 Estimation Results for Fixed Effect Model in Equation 1

	OLS		PPML	
Estimation	i	ii	iii	iv
ln *pop* $_{-1}$	-17.441 ***		-23.052 ***	
	(-4.709)		(-4.224)	
(ln *pop*)$^{2}_{-1}$	0.686 ***		0.898 ***	
	(4.541)		(3.920)	
ln *ypc* $_{-1}$	29.907 ***	31.365 ***	25.833 ***	22.443 ***
	(16.466)	(17.983)	(9.713)	(10.365)
(ln *ypc*)$^{2}_{-1}$	-1.806 ***	-1.878 ***	-1.594 ***	-1.417 ***
	(-16.125)	(-18.649)	(-9.003)	(-10.264)
Afghanistan	-16.490 ***	-11.988 ***	-19.899 ***	-16.721 ***
Bangladesh	-8.424 ***	-8.680 ***	-9.830 ***	-12.246 ***
Brunei	-38.168 ***	-7.709 ***	-48.809 ***	-7.372 ***
Cambodia	-16.023 ***	-9.468 ***	-20.378 ***	-13.766 ***
India	-9.863 ***	-9.688 ***	-10.378 ***	-12.617 ***
Indonesia	-6.185 ***	-7.298 ***	-6.206 ***	-8.467 ***
Iran	-16.148 ***	-15.890 ***	-16.482 ***	-16.111 ***
Kazakhstan	-22.583 ***	-17.843 ***	-24.466 ***	-17.767 ***
Kyrgyzstan	-21.263 ***	-10.258 ***	-26.790 ***	-13.660 ***
Laos	-29.409 ***	-19.116 ***	-34.390 ***	-21.725 ***
Malaysia	-8.408 ***	-5.330 ***	-9.712 ***	-5.120 ***
Mongolia	-35.611 ***	-20.695 ***	-41.746 ***	-21.901 ***
Myanmar	-10.038 ***	-7.960 ***	-13.702 ***	-13.770 ***
Nepal	-20.294 ***	-16.339 ***	-23.314 ***	-20.415 ***
Pakistan	-15.068 ***	-15.663 ***	-15.945 ***	-18.408 ***
Philippines	-7.862 ***	-7.770 ***	-8.549 ***	-9.023 ***
Sri Lanka	-14.088 ***	-0.817 ***	-16.361 ***	-11.006 ***
Thailand	-3.916	-3.481 ***	-4.353 **	-3.737 ***
Uzbekistan	-20.590 ***	-17.304 ***	-22.777 ***	-19.301 ***
Viet Nam	-0.072 ***	-9.724 ***	-10.492 ***	-11.351 ***
Turning point of *ypc* (USD)	3,950	4,229	3,300	2,747
Period fixed effect	Yes	Yes	Yes	Yes
Period	1991-2021	1991-2021	1991-2021	1991-2021
Country fixed effect	Yes	Yes	Yes	Yes
No. of Countries	23	23	23	23
No. of Observations	707	707	707	707

Note: ** and *** denote the rejection of the null hypothesis at the 95% and 99% levels of significance, respectively. T-statistics are shown in parentheses.

Source: Authors' estimation.

Table 6 Estimation Results for Alternative Model in Equation 2

Estimation	OLS v	OLS vi	PPML vii	PPML viii
ln pop_{-1}	-2.577 ***		-2.729 ***	
	(-3.053)		(-3.391)	
$(\ln pop)^2_{-1}$	0.180 ***		0.186 ***	
	(4.633)		(4.886)	
ln ypc_{-1}	20.839 ***	23.554 ***	12.345 ***	14.249 ***
	(12.096)	(12.838)	(9.535)	(11.661)
$(\ln ypc)^2_{-1}$	-1.121 ***	-1.298 ***	-0.643 ***	-0.785 ***
	(-10.575)	(-11.747)	(-7.563)	(-10.026)
gvc_{-1}	0.557 ***	0.727 ***	0.805 ***	1.146 ***
	(5.339)	(7.047)	(7.247)	(11.729)
nrr_{-1}	-0.212 ***	-0.277 ***	-0.163 ***	-0.186 ***
	(-8.524)	(-10.702)	(-8.433)	(-9.684)
Turning point of *ypc* (USD)	10,861	8,733	14,705	8,712
Period fixed effect	Yes	Yes	Yes	Yes
Period	1991-2017	1991-2017	1991-2017	1991-2017
Country fixed effect	No	No	No	No
No. of Countries	23	23	23	23
No. of Observations	609	621	621	621

Note: *** denotes rejecting the null hypothesis at the 99% significance level. T-statistics are shown in parentheses.
Source: Authors' estimation.

Table 7 Factor Analysis: GVC Participation Effect

	Fixed Effects	*gvc*	(b) - ave. *gvc*	(c) × 1.146	(d) / (a) *100
	(a)	(b)	(c)	(d)	(e)
Afghanistan	-16.721	1.706	-4.480	-5.133	30.7
Bangladesh	-12.248	1.014	-5.172	-5.926	48.4
Brunei	-7.372	2.316	-3.869	-4.433	60.1
Cambodia	-13.766	0.524	-5.662	-6.487	47.1
India	-12.617	1.620	-4.565	-5.231	41.5
Indonesia	-8.467	4.174	-2.011	-2.304	27.2
Iran	-16.111	1.189	-4.997	-5.725	35.5
Kazakhstan	-17.767	2.156	-4.029	-4.617	26.0
Kyrgyzstan	-13.660	0.500	-5.686	-6.515	47.7
Laos	-21.725	0.646	-5.539	-6.347	29.2
Malaysia	-5.120	8.649	-	-	-
Mongolia	-21.901	0.533	-5.652	-6.476	29.6
Myanmar	-13.770	1.061	-5.124	-5.871	42.6
Nepal	-20.415	0.462	-5.724	-6.558	32.1
Pakistan	-18.408	1.154	-5.031	-5.765	31.3
Philippines	-9.023	11.174	-	-	-
Sri Lanka	-11.006	1.342	-4.844	-5.550	50.4
Thailand	-3.737	3.398	-2.788	-3.194	85.5
Uzbekistan	-19.301	0.710	-5.476	-6.274	32.5
Viet Nam	-11.351	0.790	-5.396	-6.182	54.5
Benchmark	0.000	6.185	-	-	

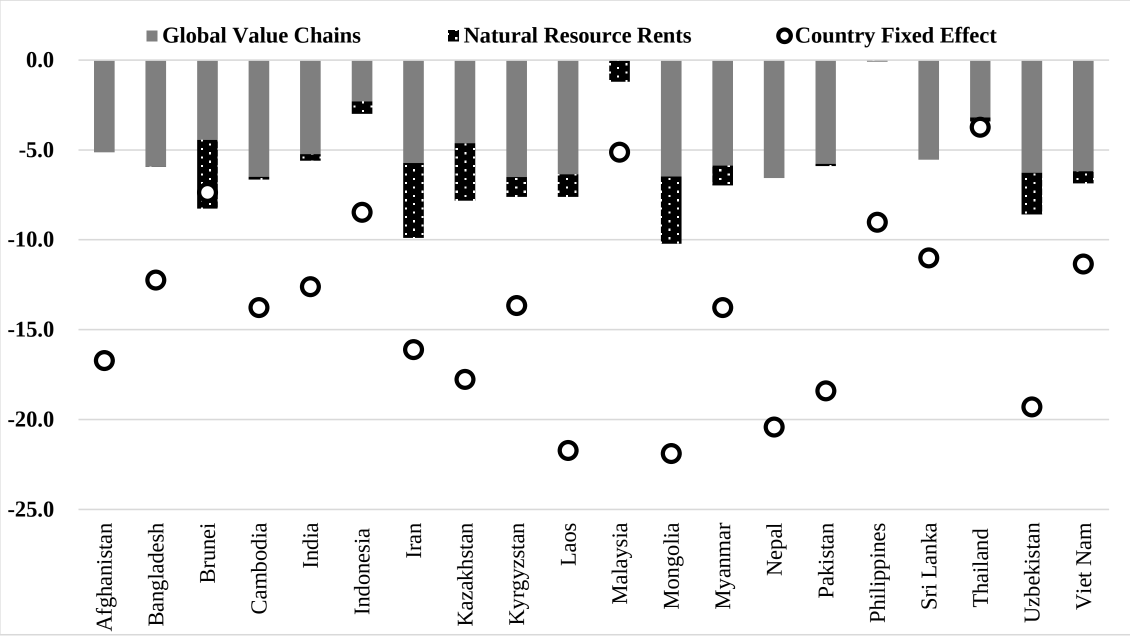
Source: Authors' calculation.

Table 8 Factor Analysis: Dutch Disease Effect

	Fixed Effects	*nrr*	(b) - ave. *nrr*	(c) × -0.186	(d) / (a) *100
	(a)	(b)	(c)	(d)	(e)
Afghanistan	-16.721	0.613	-	-	-
Bangladesh	-12.248	0.962	0.032	-0.006	0.0
Brunei	-7.372	21.518	20.588	-3.826	51.9
Cambodia	-13.766	1.791	0.860	-0.160	1.2
India	-12.617	2.920	1.990	-0.370	2.9
Indonesia	-8.467	4.642	3.712	-0.690	8.1
Iran	-16.111	23.408	22.478	-4.177	25.9
Kazakhstan	-17.767	18.218	17.288	-3.213	18.1
Kyrgyzstan	-13.660	6.830	5.899	-1.096	8.0
Laos	-21.725	7.742	6.812	-1.266	5.8
Malaysia	-5.120	7.406	6.476	-1.203	23.5
Mongolia	-21.901	21.119	20.189	-3.752	17.1
Myanmar	-13.770	6.851	5.921	-1.100	8.0
Nepal	-20.415	0.819	-	-	-
Pakistan	-18.408	1.667	0.737	-0.137	0.7
Philippines	-9.023	1.338	0.408	-0.076	0.8
Sri Lanka	-11.006	0.111	-	-	-
Thailand	-3.737	2.133	1.203	-0.224	6.0
Uzbekistan	-19.301	13.436	12.506	-2.324	12.0
Viet Nam	-11.351	4.569	3.639	-0.676	6.0
Benchmark	0.000	0.930	-	-	

Source: Authors' calculation.

Figure 4 Factor Contributions



Source: Authors' calculation.