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Patterns of Deindustrialization: Are Countries Converging?

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Abstract

During the last decades, the share of manufacturing in aggregate output (and employment) has declined in almost all advanced and emerging economies. In this paper, we investigated the patterns of deindustrialization in a sample of 117 (low-, middle-, and high-income) countries from 1995 to 2018. To this aim, we applied the nonlinear time-varying factor model, initially proposed by Phillips and Sul, to identify potential clubs wherein groups of countries converge toward a similar manufacturing share of GDP. Furthermore, we estimated an ordered logit model to assess the impact of economic globalization and technological revolution on the probability of falling into a particular club. Our results did not provide any support for the hypothesis of global convergence. However, the clustering algorithm successfully identified four strong final clubs, where the share of manufacturing on GDP ranges, on average, from 6% to 18%. Finally, the logit model indicated that as the *R&D* expenditures and the technological content of manufactured goods increased, so did the likelihood of belonging to a club with a high share of manufacturing value-added on GDP.

Keywords: convergence, clubs, deindustrialization, manufacturing, ordered logit model

1. Introduction

One of the most common 'stylized facts' that characterize a growing economy is the changing composition of its productive structure (Pasinetti, 1983). Historical data on the sectoral composition of output (and employment) typically show a process of structural transformation (Islam & Iversen, 2018; Alcorta, Foster-McGregor, & Verspagen, 2021). An initial stage of industrialization, wherein production shifts from agriculture to manufacturing, is usually followed by a period in which production tends to shift from manufacturing to services (Atolia et al., 2018). As a result, the bivariate relationship between income per capita and the share of manufacturing on total output (or employment) follows an inverted U-shaped pattern (Dosi, Riccio, & Virgillito, 2021). This widespread empirical regularity can be observed across countries and over time (Tregenna & Andreoni, 2020). The term deindustrialization—defined as the systematic and irreversible decrease in the share of manufacturing in a country's economy—is thus currently used to refer to the historical experience of high and middle-income countries that have long entered into a post-industrial phase of their capitalist development (Blackaby, 1979; Haverkamp & Clara, 2019).

Given the considerable economic, social, and environmental impacts, a large and growing body of literature has investigated the causes and consequences of deindustrialization (Warren et al., 2021; Kollmeyer, 2009). So far, however, to the best of our knowledge, there has been no empirical study based on convergence analysis. In this brief research paper, we attempt to fill this gap. Specifically, we utilize data on a sample of 117 countries worldwide, over the period 1995-2018, to analyze club convergence in the weight of the manufacturing sector on the overall economic activity. Our main goal is to document whether or not countries experiencing deindustrialization tend to reach a similar economic structure (i.e., around the same share of manufacturing on aggregate output). To this aim, the methodology developed by Phillips and Sul (2007, 2009) is applied to the manufacturing value-added—measured as a share of the Gross Domestic Product (GDP)—in order to cluster countries into groups (or clubs) according to their tendency to convergence toward a common 'steady state' (i.e., around the same long-term value of the manufacturing share of total output). Furthermore, an ordered logit model is estimated to identify potential factors driving club formation. For this purpose, we primarily focus on the role of the two main competitive forces that have shaped the worldwide manufacturing landscape during the last two decades: globalization and the latest wave of technological revolution (Felipe & Mehta, 2016; Popkova et al., 2019; Bryson et al., 2022).

2. Brief Literature Review

In economics (and sociology), the concept of deindustrialization first appeared in the middle of the twentieth century, when scholars began to predict the onset of post-industrial societies (Clark, 1940). In a post-industrial society, economic activity is no longer based on manufacturing; employment and output mainly come from the production of intangible goods (by the service sector) rather than physical goods (produced by the manufacturing industries). During the sixties and the seventies, the contraction of the manufacturing sector was indicated as responsible for the sluggish growth rate of the U.K. economy (Kaldor, 1966) and for the productivity slowdown affecting other advanced economies that started experiencing the first adverse economic shocks after the second world war (Bell, 1973). Deindustrialization has eventually become a very popular term throughout the ensuing decades in almost every western economy, where the delocalization of production (especially in labor-intensive industries) has represented a key feature of the globalization processes (Dunning 1993; Kollmeyer, 2009).

In the current literature, there is no generally accepted definition of deindustrialization. However, in its simplest meaning, the term is usually utilized to refer to an absolute or relative decline of the manufacturing sector, measured either in terms of value-added or employment (Blackaby, 1979). Conversely, research has identified at least two main hypotheses to explain deindustrialization (Alford, 1997). The first is the so-called 'mature hypothesis' that relies upon differences in income elasticity and labor productivity between the manufacturing and services sectors. In a mature economy, on the one hand, according to Engel's Law, an increasing share of per capita income is spent on services rather than physical goods. On the other hand, technical change (e.g., automation) promotes continuing increases in manufacturing labor productivity, which tends to grow faster than in other sectors. In this view, deindustrialization is an inevitable consequence of the economic structural changes that characterize economic development. Conversely, deindustrialization represents a negative phenomenon in the 'failure hypothesis' when a declining manufacturing sector is the result of poor macroeconomic performances due to a lack of competitiveness (i.e., manufacturing production shifts to other countries as a result of a domestic non-competitive economic and social environment), (Rowthorn & Wells, 1987). Premature deindustrialization (Rodrik, 2016) and deindustrialization by the Dutch disease (Palma, 2005) are examples of these pathological declines in the manufacturing sector. In the former case, deindustrialization begins before the country's economy has reached a mature state undermining the development process. In contrast, in the latter, the discovery of some natural resources generates an appreciation of the real exchange rate, rising wages, and a reallocation of the labor force from the secondary to the primary sector.

3. Method

So far, a large number of studies have used the concept of convergence to examine the long-term evolution of several economic indicators, such as income per capita, health care expenditures, labor productivity, etc. (Baumol, 1986; Barro & Sala-i-Martin, 2003; Nghiem & Connelly 2017). In this literature, the empirical investigation is usually based on the nonlinear time-varying factor model developed by Phillips and Sul (2007, 2009) to represent the behavior of economies in transition. In their work, Phillips and Sul (2007, 2009) provide a framework to test the null hypothesis of convergence between countries for a given variable of interest. Furthermore, if in the set under study there is no general convergence towards a common value, the model allows for identifying patterns of convergence among specific subsets (i.e., clubs) of countries.

In this paper, we investigate the evolution of deindustrialization in a sample of 117 countries worldwide to assess whether or not the structure of their economy, in terms of manufacturing share of aggregate output, tends to converge over time. In order to briefly outline Phillips and Sul's methodology (2007, 2009), we first denote with MVA_{it} the manufacturing value added (as a percent of GDP) in country i and year t. Then, let us assume that MVA_{it} is the sum of a common (g_{it}) and an idiosyncratic (a_{it}) component (hence, $MVA_{it} = g_{it} + a_{it}$). We aim to focus on the behavior of the idiosyncratic component over time. To this end, MVA_{it} can be transformed, as described in Equation 1), such that the common and idiosyncratic components are separated as follows:

$$MVA_{it} = \left(\frac{g_{it} + a_{it}}{\mu_{it}}\right)\mu_t = \delta_{it}\mu_t \tag{1}$$

In this equation, the variables μ_t and δ_{it} denote the common trend component across countries and a time-varying heterogeneous component measuring the heterogeneous distance between μ_t and MVA_{it}, respectively (Kasman & Kasman, 2020). Put differently, δ_{it} measures the deviation of the manufacturing value added in country i from the common path (that is, the trend component, μ_t). Next, to remove the common factor, the relative transition parameter (h_{it}) and its cross-sectional variation (H_{it}) are defined as follows:

$$h_{it} = \frac{MVA_{it}}{N^{-1}\sum_{i=1}^{N} MVA_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}} \tag{2}$$

$$H_{it} = N^{-1} \sum_{i=1}^{N} (h_{it} - 1)^2 \rightarrow 0, as\ t \rightarrow \infty. \quad (3)$$

Although their paths may differ significantly, this methodology assumes that, at some future point in time, all countries will converge to a long-term steady-state (i.e., $\lim_{t\to\infty}\delta_{it} = \delta_i = \delta$, for all i = 1,..., N). As a result, if the time-varying heterogeneous component δ_{it} tends to converge towards δ, there is evidence in favor of the convergence hypothesis. In such situations, h would tend to 1 and H_{it} to 0, as time tends to reach infinity (González-Álvarez et al., 2020). Finally, to test the convergence hypothesis, Phillips and Sul (2007, 2009) suggest using a simple time-series regression defined as:

$$log\frac{H_1}{H_t} - 2log[log(t)] = \alpha + \beta log(t) + v_t, \qquad t = [rT] + 1,\ldots,T. \quad (4)$$

In equation 4), the so-called log-t regression, r is usually set to 0.3. The convergence test is based on the conventional t-statistic. The null hypothesis H_0: $\delta_i = \delta$ (i.e., $\beta = 0$) is rejected if the t-statistic takes values lower than -1.65 (data on *MVA* are detrended using the Hodrick-Prescott filter (Hodrick & Prescott, 1997) by adjusting the standard smoothing parameter of 1600 according to Backus and Kehoe (1991)).

In order to assess the impact of globalization and technological revolution on the probability of falling within a given cluster—that is, within a given club of countries—we estimate the following ordered logit model:

$$logit\ MVA_{ct} = \alpha_c + \beta_1 GDPPE_i + \beta_2 TRADE_i + \beta 3FIN_i + \beta 4TECH_i + \beta_5 R\&D_i \text{ and } c = 1, 2,\ldots, C\text{-}1 \quad (5)$$

In Equation 5), *MVA* is an ordinal response variable, with *C* categories ranked in descending order, according to the different clubs identified by Phillips and Sul's (2007, 2009) methodology. The regression model is thus defined by a set of *C*-1 equations, where the parameters α_c are the thresholds (or cut-points) levels. About the independent variables: 1) *GDPPE* is the GDP per person employed (measured in constant 2017 PPP dollars); 2) *TRADE* and *FIN* are the indexes of trade and financial globalization computed by the Swiss Economic Institute (Savina et al., 2019) within the KOF Globalisation Index (a project that aims to measures and tracks the economic, social and political dimensions of globalization in the world economy); 5) *TECH* denotes the medium and high-tech manufacturing value-added, as a percent of the total manufactured value-added; and finally, 6) *R&D* is the overall research and development expenditure, in percent of GDP.

All data come from the World Bank Open Data repository (World Bank, 2022), except for the variables *TRADE* and *FIN*, provided by the KOF – Swiss Economic Institute (Savina et al., 2019). Our sample is a panel data composed of 117 countries—43 high-income countries, 33 and 31 upper-middle and lower-middle-income countries, and ten low-income countries (according to the World Bank countries classification system in 2018)—and it covers a 24-years period (from 1995 to 2018). A short description of each variable and some basic descriptive statistics are shown in Table 1. The full dataset is included in Supporting Information File S1. Dataset (.xlsx). Finally, the econometric analyses were performed in Stata version 16.1 (Stata Corp LLC, Texas, USA). Specifically, we use the software package 'psecta,' developed by Du (2017), and the corresponding algorithm added by Phillips and Sul (2007, 2009).

4. Results

During the last two decades, the relative decline of manufacturing has characterized the development of more than two-thirds (90/117) of the sample of countries under study. As shown in Figure 1—where the shares of manufacturing on GDP in 1995 and 2018 are measured on the horizontal and vertical axes, respectively—economies with an increasing trend in *MVA* (i.e., the dots lying above the 45° line) can be found mainly among a small subset of lower-middle and upper-middle-income countries.

Figure 2 reports the result of a simple test for beta convergence. The percent change in manufacturing value-added on GDP from 1995 to 2018 ($\%\Delta MVA^{95\text{-}18}$) is plotted against its initial level in 1995 (MVA^{95}). The extent of deindustrialization seems to be greater for countries with a higher starting value of *MVA* (and vice-versa, for countries experiencing positive changes in the share of manufacturing on GDP). This intuition is confirmed by the regression analysis results, showing that the initial value of *MVA* can be regarded as a predictor of its changes over time. The following estimated equation describes the regression line:

$$\%\Delta MVA_i^{95\text{-}18} = 36.5 - \underset{\substack{(0.63)\\ t\,=\,-4.78}}{3.0} MVA_i^{95} \quad (6)$$

$$N = 117 \text{ and } \bar{R}^2 = 0.16$$

where the negative β coefficient is statistically significant at the .01 level, although the proportion of the variance of $\%\Delta MVA^{95\text{-}18}$ explained is less than one-fifth.

Table 1. Summary of variables and descriptive statistics

Variable	Description	Mean	Std. Dev.	Min	Max	N. of obs.
MVA	Manufacturing, value added (% of GDP)	14.56	5.85	0.65	36.76	2,808
GDPPC	GDP per person employed (constant 2017 PPP $)	48,982.83	42,420.86	1,031.43	279,441.80	2,777
TRADE	KOF Index of trade globalization	55.16	18.72	15	100	2,808
FIN	KOF Index of financial globalization	61.12	19.93	7	100	2,784
TECH	Medium and high-tech manufacturing value added (% manufacturing value-added)	26.62	17.11	0.25	88.04	2,640
R&D	Research and development expenditure (% of GDP)	1.05	0.97	0.01	4.94	1,663

Note. KOF – Swiss Economic Institute (Savina et al., 2019).

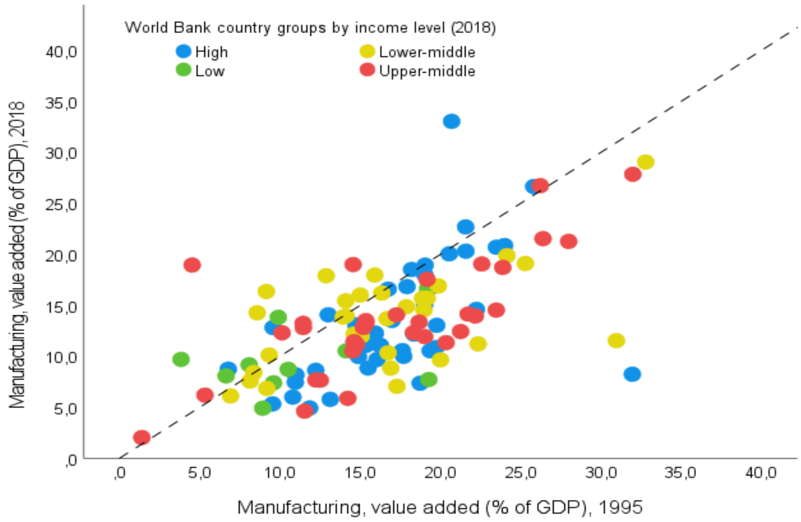

Figure 1. Manufacturing value-added as a % of GDP, 1995 vs. 2018

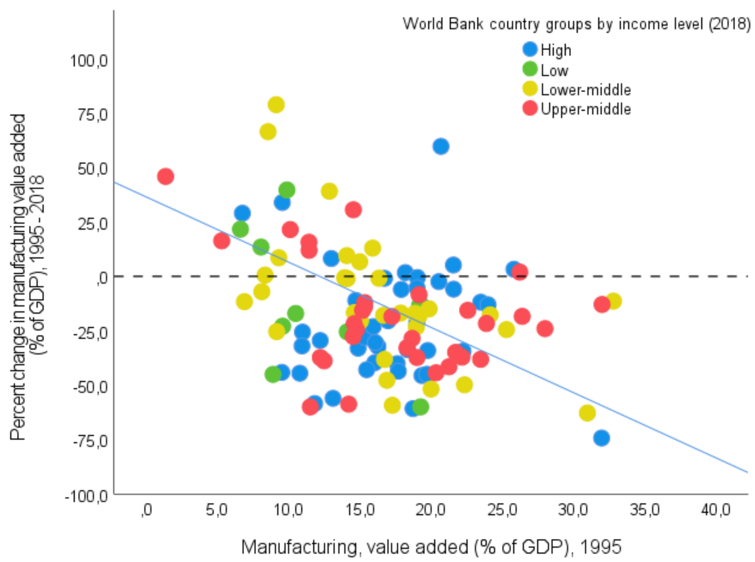

Figure 2. A simple test of beta convergence (117 countries, increasing and decreasing *MVA*)

In this paper, however, we focus mainly on the phenomenon of deindustrialization. Figure 3 shows the evolution of *MVA* in the subset of 90 countries that have experienced a declining share of manufacturing output on GDP (once again, countries are classified according to their income level in 2018). Despite a common declining trend from 1995 to 2018, there is no evidence in favor of global convergence.

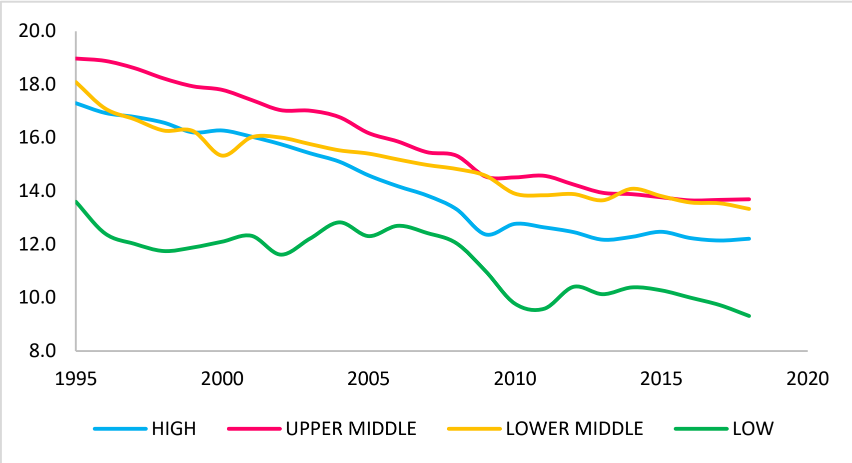

Figure 3. The decline in the share of manufacturing value-added (as % of GDP), 1995-2018

Note. Ninety countries (decreasing *MVA*). World Bank country groups by income level in 2018.

This intuition is confirmed by equation (7) which collects the results of the same regression model displayed in Equation (6) but by using data only for the subset of 90 countries with a decreasing value of *MVA* during the period 1995-2018:

$$\%\Delta MVA_i^{95\text{-}18} = -26.0 - \underset{(0.35)}{0.07} MVA_i^{95} \tag{7}$$

$$t = -0.20$$

$$N = 90 \text{ and } \bar{R}^2 = 0.01$$

where the β coefficient is not statistically significant (that is, there is no beta convergence), and the goodness-of-fit of the regression line is close to zero.

On this point, Table 2 reports the results of Phillips and Sul's (2007, 2009) log-t regressions, where the difference between δ_{it} and δ_i is assumed to decline over time. The t-statistic is less than -1.65. Thus, the null hypothesis of convergence is rejected at a 5% significance level. This result further supports the hypothesis that the share of manufacturing does not tend to converge towards a common level among the sample of 90 countries where *MVA* declined from 1995-2018.

Table 2. Results of the overall log-t test for convergence analysis

Variable	Coeff.	S.E.	t-stat	N. of countries	N. of years
log(t)	-0.9627	0.0249	-38.6579	90	24

Among the 90 countries experiencing a declining share of manufacturing on GDP, there is no evidence to suggest a general convergence toward a common value. This result, however, does not preclude the possibility of convergence within one or more specific subsets of countries. The semi-parametric clustering algorithm developed by Phillips and Sul (2007, 2009) enables the endogenous determination of clubs by clustering those countries that tend to converge toward the same steady-state. According to the clustering algorithm, we identified four strong clubs. Figure 4 shows the final clubs, grouped from highest to lowest manufacturing share on GDP (along with their respective mean value). Detailed results of the log t regressions and a list of countries composing each club are provided in the Appendix (Table 1A).

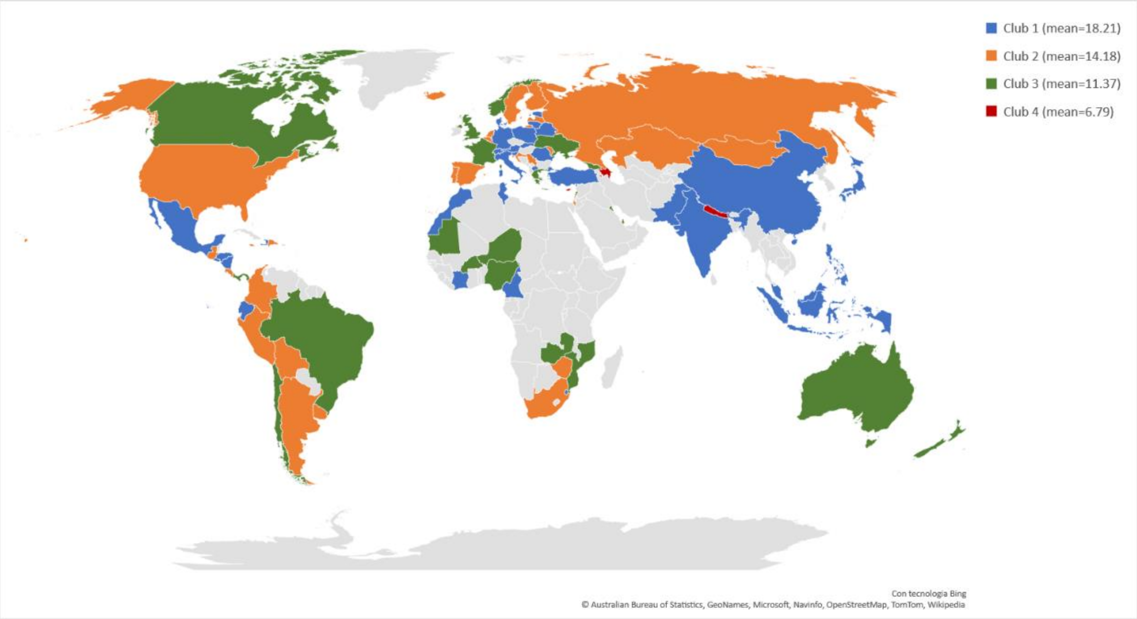

Figure 4. Map of club composition and average manufacturing value added (as a % of GDP) in each club.

Note. Ninety countries (decreasing *MVA*). Countries in light grey are included in the subset with increasing *MVA* or are countries with no data.

Turning to the ordered logit model, estimations results (reported in Table 3) indicated a positive and statistically significant impact of the variable *TECH* and *R&D* on the likelihood of being in clubs with a higher manufacturing share of GDP. Specifically, this means that one unit increase in the percentage of medium and high-tech products on the total manufacturing value-added and the share of research and development expenditures on GDP is associated with a 13% (0.87 – 1) and 7% (0.93 – 1) decrease in the odds of being in a higher club (i.e., in a club with a lower level of manufacturing on total output).

Table 3. Results of the ordered logit model

	Logit Coeff.	Odds ratio
GDPPE	0.00001***	1.0000***
	(0.00001)	(0.00001)
TRADE	-0.02945***	0.97098***
	(0.00326)	(0.00317)
FIN	0.05562***	1.05720***
	(0.00524)	(0.00553)
TECH	-0.06989***	0.93249**
	(0.00507)	(0.00473)
R&D	-0.13879**	0.87040**
	(0.08024)	(0.06983)
N. of obs. = 1,320		
Wald Chi-Square = 381.74, prob. 0.0000		
Pseudo R-squared = 0.17		

Note. Robust standard errors in parentheses.

Ninety countries (decreasing *MVA*).

*** $p < 0.01$ ** and $p < 0.1$.

5. Discussion

A large number of studies have addressed the issue of deindustrialization from different perspectives (Szirma et al., 2013). However, no previous work has analyzed the convergence process in the share of manufacturing on GDP. Using data from 117 (low-, middle-, and high-income) countries worldwide, we examined the evolution of the manufacturing sector (measured by the manufacturing's share of total value-added) from 1995 to 2018. The paper's primary purpose was to test the hypothesis of convergence (that is, we aimed to answer the following research question: will the share of manufacturing on aggregate output reach a similar level across countries?). To this end, we applied Phillips and Sul's (2007, 2009) time-varying factor model. The econometric analysis indicated that the null hypothesis of global convergence was rejected. However, the clustering algorithm successfully identified four final clubs (specifically, three clubs plus one composed of four small countries). Furthermore, we investigated globalization and new technology's impact on the convergence process. Using an ordered logit model, we found that more trade globalization, high-tech manufacturing, and *R&D* expenditures increased the likelihood of being in clubs with a higher manufacturing share of GDP.

Although the relative decline of manufacturing is a "stylized fact" of many world economies, regardless of their stage of development, our analysis reveals three main patterns of deindustrialization. In the long run, the share of manufacturing on GDP tends to converge toward a mean value greater than 18% in the largest club (i.e., club 1 in Figure 4), including advanced economies (such as Italy, Germany, and Japan) and major emerging countries (e.g., China and India). This value decreases to 14% in club 2 (the second largest club, composed of countries such as Spain, Sweden, and the USA) and 11% for countries such as Australia, Canada, and the U.K., collected in the third club. Even within the European Union, countries tend to converge toward three different long-run levels of *MVA*. About the determinants of club composition, the share of manufacturing appears to be positively affected by the level of innovation (as captured by the share of high-tech products in total manufacturing output and *R&D* activity on total GDP) and, to a lesser extent, by the degree of trade globalization. Conversely, labor productivity (captured here by the GDP per person employed) and the degree of financial globalization seem to have a negligible impact on club formation.

However, these results need to be interpreted with caution because they are subject to at least three main limitations. First, structural changes in GDP sectoral composition are long-run phenomena that take place over decades. Our analysis is limited to a relatively short period (23 years, starting from the latest wave of globalization). Second, the same manufacturing share of GDP may hide a very different sectoral composition. Our results suggest the need to disaggregate *MVA* by industry (i.e., by manufacturing sub-sectors, such as foods, chemicals, machinery, etc.) to analyze patterns of convergence between the same manufacturing sub-sectors across countries and time. Third, a complex set of forces affect the rise and fall of manufacturing in national economies. By focusing only on two dimensions (globalization and technological innovation), we failed to address this complexity. These main limitations provide some insights for future research. Besides using a more extended time series, a natural progression of this work is to analyze the main manufacturing subsectors by using both data on value-added and employment. Finally, a natural progression of this work is to improve the ordered logit model by looking at more dimensions of the manufacturing environment, such as overall industry policy and regulations, tax policy, energy and transportation costs, workforce availability and quality, and the country's overall level of infrastructure.

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References

Alcorta, L., Foster-McGregor, N., & Verspagen, B. (Eds.). (2021). *New perspectives on structural change: Causes and consequences of structural change in the global economy*. Oxford, U.K.: Oxford University Press. https://doi.org/10.1093/oso/9780198850113.001.0001

Alford, B. (1997). *De-industrialisation* (Refresh. Autumn, 25). London, U.K.: Economic History Society.

Atolia, M., Loungani, P., & Marquis, M. et al. (2018). Rethinking development policy: Deindustrialization, servicification, and structural transformation. *IMF Working Paper No. 223*. International Monetary Fund, Washington, DC. https://doi.org/10.5089/9781484377499.001

Backus, D., & Kehoe, P. J. (1991). International Evidence on the Historical Properties of Business Cycles. *The American Economic Review, 82*(4), 864-888. https://doi.org/10.21034/sr.145

Barro, R. J., & Sala-I-Martin, X. I. (2003). *Economic growth* (2nd ed.) Cambridge, Mass.: The MIT Press.

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: what the long-run data show. *The*

American Economic Review, 76(5), 1072-85. http://www.jstor.org/stable/1816469

Bell, D. (1973). *The Coming of Post-industrial Society: A Venture in Social Forecasting*. New York: Basic Books.

Blackaby F. (Ed.). (1979). *Deindustrialization*. National Institute of Economic and Social Research, London, UK: Heinemann Educational Books.

Bryson, J. R., Billing, C., & Graves, W. et al. (2022). *A research agenda for manufacturing industries in the global economy*. London, UK: Edward Elgar publishing. https://doi.org/10.4337/9781789908510

Clark, C. (1940). *The conditions of economic progress.* London: MacMillan.

Dosi, G., Riccio, F., & Virgillito, M. E. (2021). Varieties of deindustrialization and patterns of diversification: Why microchips are not potato chips. *Structural Change and Economic Dynamics, 57*, 182-202. https://doi.org/10.1016/j.strueco.2021.01.009

Du, K. (2017). Econometric convergence test and club clustering using Stata. *Stata Journal, 17*(4), 882-900. https://doi.org/10.1177/1536867X1801700407

Dunning, J. H. (1993). *The globalization of business: The challenge of the 1990s.* London: McMillan. https://doi.org/10.4324/9781315743691

Felipe, J., & Mehta, A. (2016). Deindustrialization? A global perspective. *Economics Letters, 149*, 148-51. https://doi.org/10.1016/j.econlet.2016.10.038

González-Álvarez, M. A., Lázaro-Alquézar, A., & Simón-Fernández, M. B. (2020). Global trends in child obesity: Are figures converging? *International Journal of Environmental Research and Public Health, 17*(24), 9252. https://doi.org/10.3390/ijerph17249252

Haverkamp, K., & Clara, M. (2019). *Four shades of deindustrialization. Inclusive and Sustainable Industrial Development*. Working Paper Series. Working Paper No. 02. UNIDO, Vienna.

Hodrick, R. J., & Prescott, E. C. (1997). Postwar U.S. business cycles: An empirical investigation. *Journal of Money, Credit and Banking, 29*(1), 1-16. https://doi.org/10.2307/2953682

Islam, S. N., & Iversen, K. (2018). From structural change to transformative change: Rationale and implications. *DESA Working Paper No. 155*. U.N. - Department of Economic and Social Affairs, New York.

Kaldor, N. (1966). *Causes of the slow rate of growth in the United Kingdom*. Cambridge: Cambridge University Press.

Kasman, S., & Kasman, A. (2020). Convergence in obesity and overweight rates across OECD countries: Evidence from the stochastic and club convergence tests. *Empirical Economics, 61*(2), 1063-96. https://doi.org/10.1007/s00181-020-01895-3

Kollmeyer, C. (2009). Explaining deindustrialization: How affluence, productivity growth, and globalization diminish manufacturing employment. *American Journal of Sociology, 114*(6), 1644-1674. https://doi.org/10.1086/597176

Nghiem, S. H., & Connelly, L. B. (2017). Convergence and determinants of health expenditures in OECD countries. *Health Economics Review, 7*(1), 29. https://doi.org/10.1186/s13561-017-0164-4

Palma, J. G. (2005). Four sources of "De-Industrialization" and a New Concept of the "Dutch Disease". In J. A. Ocampo (Ed.), *Beyond reforms - Structural dynamics and microeconomic Vulnerability.* Washington, DC: The World Bank.

Pasinetti, L. L. (1983). *Structural change and economic growth: A theoretical essay on the dynamics of the wealth of nations*. Cambridge, UK: Cambridge University Press.

Phillips, P. C. B., & Sul, D. (2007). Transition modelling and econometric convergence tests. *Econometrica, 75*, 1771-1855. https://doi.org/10.1111/j.1468-0262.2007.00811.x

Phillips, P. C. B., & Sul, D. (2009). Economic transition and growth. *Journal of Applied Econometrics, 24*, 1153-1185. https://doi.org/10.1002/jae.1080

Popkova, E. G., Ragulina, Y. V., & Bogoviz, V. (2019). *Industry 4.0: Industrial revolution of the 21st century*. Berlin: Springer Nature. https://doi.org/10.1007/978-3-319-94310-7

Rodrik, D. (2016). Premature deindustrialization. *Journal of Economic Growth, 21*, 1-33. https://doi.org/10.1007/s10887-015-9122-3

Rowthorn, R., & Wells, J. R. (1987). *Deindustrialization and foreign trade.* Cambridge: Cambridge University Press.

Savina, G., Haelg, F., & Potrafke N. et al. (2019). The KOF Globalisation Index – Revisited. *Review of International Organizations*, *14*(3), 543-574. https://doi.org/10.1007/s11558-019-09344-2

Szirma, A., Naudé, W., & Alcorta, L. (Eds.). (2013). *Pathways to Industrialization in the Twenty-First Century: New Challenges and Emerging Paradigms.* Oxford: Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199667857.001.0001

Tregenna, F., & Andreoni, A. (2020). *Deindustrialization reconsidered: Structural shifts and sectoral heterogeneity*. UCL Institute for Innovation and Public Purpose. Working Paper No. 06. (2020), University College London, London, UK.

Warren, J., Stephenson, C. ,& Wistow, J. (Eds.) (2021). *After industry – The economic and social consequences of deindustrialization*. Lausanne: Frontiers Media. https://doi.org/10.3389/978-2-88966-750-5

World Bank. (2022). *World Development Indicators Database*. Washington DC; The World Bank Open Data. Retrieved from https://data.worldbank.org/.

Appendix A

Table 1A. List of countries by club and results of the log-t test for convergence analysis

Club 1: 35 countries	Austria, Belarus, Cameroon, China, Congo Rep., Côte d'Ivoire, Denmark, Ecuador, Egypt Arab Rep., El Salvador, Estonia, Eswatini, Germany, Haiti, Honduras, India, Indonesia, Italy, Japan, Lithuania, Malaysia, Mexico, Morocco, Nicaragua, North Macedonia, Pakistan, Philippines, Poland, Romania, Singapore, Slovak Republic, Slovenia, Switzerland, Tunisia, Turkey.	Log(t) Coeff: 0.065 T-stat: 0.888
Club 2: 29 countries	Argentina, Belgium, Bolivia, Colombia, Costa Rica, Croatia, Dominican Republic, Finland, Guatemala, Iceland, Iran Islamic Rep., Israel, Jamaica, Kazakhstan, Latvia, Mauritius, Moldova, Mongolia, Netherlands, Peru, Portugal, Russian Federation, Serbia, South Africa, Spain, Sweden, United States, Uruguay, Zimbabwe.	Log(t) Coeff: 0.343 T-stat: 2.106
Club 3: 22 countries	Australia, Brazil, Burkina Faso, Canada, Chile, France, Georgia, Greece, Kuwait, Lebanon, Malta, Mauritania, Mozambique, New Zealand, Niger, Nigeria, Norway, Panama, Qatar, Ukraine, United Kingdom, Zambia.	Log(t) Coeff: 0.081 T-stat: 1.182
Club 4: 4 countries	Azerbaijan, Cyprus, Luxembourg, Nepal.	Log(t) Coeff: 0.011 T-stat: 0.025