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FOUR SHADES OF DEINDUSTRIALIZATION

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Four shades of deindustrialization

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1. Introduction

Industrialization, defined as an increase in the share of manufacturing in a country's economy, has long been considered the key feature of the economic success of high-income countries in Europe and the US, which are commonly referred to as industrialized countries. Similarly, the more recent development of the Asian Tigers and other Newly Industrialized Countries (NICs) is often related to the growth of strong manufacturing sectors in the 1960s and 1970s.

As countries grow richer, however, the pace of industrialization eventually fizzles out: the US, the majority of European countries and even some of the NICs have deindustrialized with the growth of the services sector. This phenomenon has raised concerns among voters and policymakers. It could be argued that deindustrialization is the natural continuation of the process of an economy's structural transformation, i.e. the shift of productive resources from lower- to higher value-added sectors, and hence a development that all countries eventually experience as their income per capita increases (Rowthorn & Coutts, 2004). Against this backdrop, the manufacturing sector's significance follows an inverted U-shaped pattern: it first grows as a share of the total economy; it then settles at a peak and ultimately beings to decline.

In recent years a growing debate among policymakers has emerged voicing concern that the manufacturing sector's peak is being reached at increasingly lower levels of income per capita and at a too low share of the total economy. The manufacturing sectors of a number of developing countries, especially in sub-Saharan Africa and Latin America, have been shrinking at income levels that are much lower than those achieved by industrialized countries several decades earlier. Such "premature deindustrialization"[1] is particularly worrisome if one believes that the development of manufacturing activities is not simply associated with economic growth itself, but is actually one of its key sources.

Leaving the issue of causality aside, the debate about premature deindustrialization centres around the existence and location of the peak. As we will show below, identifying the peak of the inverted-U shaped curve is not a simple feat. Borrowing the conceptual framework developed by Dani Rodrik, this paper tests the premature deindustrialization hypothesis using a larger sample of countries. We aim to provide policymakers with a practical tool to determine whether their country is indeed experiencing premature deindustrialization.

Before proceeding to do so, we would like to remind readers that not everyone considers deindustrialization to be a noteworthy phenomenon. Section 2 provides a brief literature review

[1] The term is often credited to Dasgupta and Singh (2006).

of two approaches to development and will help the reader trace the argument within these two schools of thought. The remainder of the paper is structured as follows. Section 3 presents the variables we use as proxies to analyse the relationship between the size of a country's manufacturing sector and its income level. This is followed by a brief definition of deindustrialization and how we chose to measure it. Section 5 presents preliminary results based on descriptive statistics as well as individual country paths.

These results will help the reader understand that simple descriptive statistics do not suffice to identify a specific pattern and that a more sophisticated econometric model is necessary to make an informed decision. Our model—which is essentially the same as that popularized by Dani Rodrik—as well as the panel data analysis and country fixed effects are discussed in Section 6. Using this model, we create a fourfold classification of different types of deindustrialization in Section 7. Policymakers can apply this classification to assess whether their country's process of deindustrialization is occurring at a premature or a legitimate level. Section 8 reviews this assessment in greater detail for selected cases before Section 9 concludes.

2. Literature review

This section serves as an entry point for policymakers to understand the basic arguments of two major strands of economics and their divergent perspectives of the relevance of a strong manufacturing sector. This is because many economists do not regard the concept of deindustrialization—let alone premature deindustrialization—as an issue that policymakers should be concerned about. Within the academic debate, the significance of the manufacturing sector in the process of economic development is by no means undisputed. We therefore introduce the main aspects of both structuralism and neo-classical growth theory to help readers position themselves within this academic debate.

2.1. Early structuralism

The structuralist school of thought first developed as an explanation for the lack of development in Latin America during the post-war period[2]. Its proponents viewed development not simply as economic growth but as a transformation of the structure of the economy. In its simplest form, structural transformation is a change in the composition of the economy (traditionally divided between the primary sector, i.e. mining and agriculture, the secondary sector, i.e. industry, and

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[2] Notable early contributions to the structuralist school of thought can be found in Clark (1957), Chenery (1960), Kuznets (1966) and Syrquin (1988). Arguments for the importance of the industrial sector relative to agriculture for economic growth based on the idea of economies of scale within manufacturing can be found in Kaldor (1967) and Chenery *et al.* (1986).

the tertiary sector, services). Structuralist thought builds on Lewis's two-sector model (1954): underdeveloped countries are characterized by vast differences in the labour productivity of different sectors of their economy (Furtado, 1964). Economic development, in turn, can be fostered by introducing new combinations of production factors that lead to an increase of labour productivity.

Structuralist theory attributes low levels of income to an economy's underlying structural features, such as the sectoral composition of output and employment, heavy reliance on a traditional sector (usually subsistence farming) with low levels of productivity and a much smaller modern (manufacturing) sector that relies on a significant amount of capital and advanced technology (Hunt, 1989). The modern sector is usually established by foreign capital and engages in primary exports. Additionally, this modern sector is often characterized by trade openness, where a large share of its output is exported while most capital equipment and manufactured consumption goods are imported. This implies that employment in the modern sector is typically low in relation to the total labour force, as underdeveloped countries lack the capacity to manufacture the capital goods a modern sector requires. These characteristics prevent the generation of internal growth dynamics as market prices fail to adequately reward investors, resulting in a vicious poverty trap. Furthermore, the low elasticities of supply and labour create tendencies towards inflation and balance of payment deficits, as the country needs to import manufactured products it cannot produce at home.

The policy recommendations that arise from the above analysis are that governments should address the structural characteristics of their economies by introducing incentives for investors. Import substitution is recommended for some countries as is the establishment of common markets for underdeveloped countries to develop key industrial sectors, create final stage products and increase domestic demand. The main policy instruments to achieve this include a reduction of tariffs and quotas, the rationing of foreign exchange, the introduction of low interest rates for the formal sector and a privileged tax regime for industrial investors (Hunt, 1989).

2.2. Neo-classical growth theory

Without denying the importance assigned by structuralists to long-term changes in the composition of an economy, advocates of neo-classical growth theory focus on what can be done in the short-run to achieve the same objective. They promote efficient allocation of labour and capital based on the given economy's comparative advantage. This builds on the assumption that prices for goods and services (as determined by the law of supply and demand) provide—in most cases—guidance in resource allocation.

Early contributions of the neo-classical growth model can be found in Solow (1956) and Swan (1956). This model, sometimes also referred to as the Solow-Swan model states that sustained growth is related to incentives to save and invest. As long as the rate of savings and investment exceeds the rate required for capital replacement and the necessary resources to achieve increases in the labour force, output per worker will continue to grow. Furthermore, when a country's per capita growth rate is negatively related to its initial income level (Barro, 1991), a convergence in the levels of per capita income across countries should be perceptible.

The main conclusion of the neo-classical growth approach is that a distortion of prices leads to an inefficient allocation of resources and, as a consequence, a reduction of welfare, both in the short and long term. As a result, the main policy recommendation of this approach is to remove market distortions, which lies in stark contrast to the policy recommendations of the structuralist school of thought. The policy recommendations of neo-classical economists aim at improving short-term efficiency and resolve the pricing distortions caused by taxes, subsidies, trade restrictions and exchange rate rigidities (Khan & Knight, 1981).

The focus of international development practice shifted to neo-classical growth theory with the structural adjustment programmes introduced in sub-Saharan Africa and gained further traction in the academic debate with the World Bank's publication 'Accelerated Development in Sub-Saharan Africa' (1981). The report identified reduced government intervention and effective pricing policies as the key drivers of economic growth in Africa. A further elaboration of the 'getting the prices right' argument can be found in Lal (1983).

2.3. New structuralist economics

Recently, there has been a revival of structuralist approaches to economic development, often combined with aspects of capital accumulation and technological advancements drawn from the neo-classical growth model. In their pioneering work, McMillan and Rodrik (2011) explore patterns of structural change and labour productivity growth. They decompose labour productivity (economy-wide) into productivity growth within sectors (which resembles a neo-classical approach) and the productivity effect of labour reallocation across different sectors (in line with the arguments of structural change).

Their results indicate that unlike in East Asia, the contribution of structural change to labour productivity in Latin America and sub-Saharan Africa has impeded growth since the 1990s. Rodrik (2013) emphasises the manufacturing sector's relevance for economic development by illustrating that a (unconditional) convergence in labour productivity between countries is only exhibited by manufacturing industries. He finds that low-income countries actually did not converge at the aggregate level due to their low share of manufacturing employment in contrast to the postulations of pure neoclassical growth models.

Box 1 New structuralist economics

Interested readers may refer to the following sources as an introduction to the academic contributions of New Structuralist Economics: De Vries, Timmer and de Vries (2014) extend McMillan and Rodrik's model and conclude that workers in sub-Saharan Africa have moved into lower productivity activities within the services sector since the 1990s. Other studies by Diao, McMillan and Rodrik (2017) and McMillan, Rodrik and Verduzco-Gallo (2014), however, find that structural change has positively contributed to the increase of labour productivity in sub-Saharan Africa since 2000. A number of individual country-based case studies on structural change can be found in Rodrik, McMillan and Sepúlveda (2016). Lin (2012) provides a useful overview of the differences between traditional structuralist approaches and more recent conceptualizations.

2.4. Premature deindustrialization

One topic that has gained prominence in the academic debate in recent years is premature deindustrialization as a special form of structural change (Rodrik, 2016; Palma, 2014). Deindustrialization is linked to the hump-shaped relationship between industrialization and income level, which—in line with structuralist thinking—documents a positive correlation between higher incomes and higher levels of manufacturing output and employment. This correlation eventually turns negative when workers move out of the industrial sector and into the services sector and other non-manufacturing activities (Rowthorn & Coutts, 2004). The term 'premature' deindustrialization was first used by Dasgupta and Singh (2006) to describe what many developing countries are experiencing today, namely falling manufacturing shares at income levels that are much lower than those of developed countries in the past.

Rodrik (2016) finds that the turning point of the relationship between manufacturing employment or output shares and levels of per capita income has dropped in the past five decades. This can be observed both in terms of manufacturing employment as well as manufacturing value added (MVA) shares in current and constant prices. Similarly, Palma (2014) finds increasing deindustrialization at greater degrees than expected, which he identifies as a specific case of the 'Dutch disease' phenomenon.[3]

Despite this re-emergence of structuralist approaches and the popularization of the concept of premature deindustrialization, the healthy debate on the turning point in the trajectory of development considered 'normal' deindustrialization as opposed to 'premature' deindustrialization continues unabated. Rodrik identifies peak industrialization in Western European countries at US$ 14,000 (at constant 1990 dollars) compared to many low-income countries today that reach their peak at an income of only US$ 700. Palma (2014) finds a similar, albeit less severe drop in the level of income per capita at which manufacturing employment starts to decrease.

These numbers were only identified visually by looking at individual countries (Rodrik, 2016, p. 15). Haraguchi and Rezonja (2011) explore the evolution of production structures at different levels of income, thus providing a reference point for a country's specific comparative advantage at different stages of development. However, none of the mentioned studies provides policymakers practical guidance on whether or not their country is under-industrialized.

This brief literature review aims to help readers better understand the key features of structuralism and of neo-classical growth theory and how these two approaches differ. The two approaches would draw very different conclusions and policy recommendations on the issue of deindustrialization and premature deindustrialization.

3. A look at the available evidence

The previous section touched upon the intricacy of settling the debate between structuralism and neo-classical growth theory on purely theoretical grounds. To gain a better understanding of the potential relationship between the manufacturing sector and a country's overall development, one has to examine the empirical relationship between the two. Yet, even the way we measure the empirical relationship between the manufacturing sector and a country's overall development is

[3] The 'Dutch disease' refers to an appreciation of the real exchange rate, often resulting from a boom in commodity exports, such as oil or other natural resources, and the resulting crowding out of the manufacturing sector. See Corden and Neary (1982) or van Wijnbergen (1984) for an elaboration on this phenomenon.

not undisputed. This section outlines our choice of variables and explains the basic concepts behind them.

Box 2 Measurement of a country's level of industrialization

There are a number of ways to measure a country's level of industrialization. The size of its manufacturing sector can, for instance, be measured in terms of manufacturing employment (in relation to total employment) or manufacturing output (usually measured as the share of manufacturing value added (MVA) in GDP). The latter approach can be further differentiated by measuring MVA shares in either constant or in current prices. Some studies have pointed out that the share of manufacturing employment is a much better predictor for a country's development (Felipe, Mehta, & Rhee, 2014). However, due to better data availability, especially for the period before 1990, we focus only on MVA shares and exclude any measure for the level of manufacturing employment.

We use both MVA shares in current as well as in constant 2010 prices and compare the results to each other. MVA shares in current prices as a measure for a country's level of industrialization has higher statistical significance and is therefore chosen as the more suitable measurement. This is in line with Lavopa and Szirmai (2015), who find that changes in the global structure of production and deindustrialization only become perceptible in current prices. The authors explain this with the differences in sectoral price trends and the phenomenon that over time, the price of services increases in relation to the price of manufactured goods. Based on these findings, we only present our results for MVA shares in current prices.

Throughout the remainder of this paper, we use the share of manufacturing value added (MVA) in the total economy and the size of the manufacturing sector interchangeably. To compare the level of industrialization to the level of income, we will use per capita output-side real GDP at chained PPPs (in 2011 US$).

Box 3 Measurement of MVA

We use output-side real GDP at chained PPPs for the following reasons. Firstly, output-side GDP measures value added, i.e. the difference between total revenue minus total costs of inputs purchased from other businesses of each industry in the economy. As opposed to the expenditure-side approach, which sums up consumption by households, investment by businesses, government spending as well as net exports, thus capturing differences in living standards, the output-based approach is more suited for comparisons of productive capacity across countries. Secondly, real rather than nominal values for the measure of per capita income means that the values are adjusted for inflation and therefore makes a comparison across time possible. Thirdly, using purchasing power parity- (PPP) adjusted numbers accounts for differences in price levels across countries.

4. A practical definition of deindustrialization

Having discussed the rationale behind structuralism and how to measure the size of a country's manufacturing sector, the reader should have an intuitive understanding of what deindustrialization means.

In its simplest form, deindustrialization is a consistent decrease in the size of a country's manufacturing sector in the total economy. Using this simple intuition, we identify countries whose manufacturing sectors have registered a negative average growth rate over the last decade. Table 1 presents all countries that have experienced deindustrialization ranked according to decrease in annual percentage.

The table below includes countries such as Belgium, Denmark or Japan where deindustrialization should be anything but surprising given the high income level they had already achieved at the beginning of the decade. To identify cases of problematic premature deindustrialization, i.e. cases that divert from the trajectory of the inverted U-shaped relationship, it is necessary to first identify the threshold at which deindustrialization can be considered normal.

An intuitive way to do so is to look at the data to identify the "normal" trajectory that countries follow as they become richer and use that as the reference point. Premature deindustrialization thus means a decrease in the size of the manufacturing sector that occurs too early compared to the 'normal' progress of development. However, if a peak cannot be identified, it is difficult to assess whether any process of deindustrialization is premature or in fact legitimate.

Table 1 Level of deindustrialization in different countries (in %)

Country	Annual Growth	Country	Annual Growth	Country	Annual Growth
Hong Kong SAR	-8.25%	Colombia	-2.23%	United States	-0.83%
Lesotho	-7.72%	Trinidad and Tobago	-2.21%	Ecuador	-0.83%
Ghana	-7.19%	Norway	-2.20%	Belarus	-0.78%
Burkina Faso	-6.31%	Sweden	-2.10%	India	-0.74%
Mozambique	-5.02%	Algeria	-2.10%	Slovenia	-0.72%
Sierra Leone	-4.85%	Mauritius	-2.08%	Denmark	-0.68%
Australia	-4.79%	Malawi	-2.05%	Japan	-0.67%
Azerbaijan	-4.72%	Kenya	-2.04%	Uganda	-0.67%
Canada	-4.36%	France	-1.96%	Morocco	-0.64%
Benin	-3.90%	Panama	-1.93%	Lao People's DR	-0.64%
Singapore	-3.86%	Netherlands	-1.91%	Thailand	-0.58%
Dominican Republic	-3.79%	Cambodia	-1.89%	Georgia	-0.56%
Brazil	-3.67%	Moldova	-1.88%	Mauritania	-0.52%
Finland	-3.61%	Senegal	-1.87%	Estonia	-0.46%
Zambia	-3.60%	Uruguay	-1.87%	Ireland	-0.44%
Ukraine	-3.25%	Indonesia	-1.67%	Austria	-0.42%
South Africa	-3.20%	El Salvador	-1.60%	Guinea-Bissau	-0.39%
Costa Rica	-3.19%	Peru	-1.56%	Mexico	-0.38%
Chile	-3.17%	Philippines	-1.46%	Lithuania	-0.30%
Nepal	-2.91%	Israel	-1.45%	Switzerland	-0.28%
Viet Nam	-2.86%	Spain	-1.42%	Greece	-0.28%
Malaysia	-2.74%	United Kingdom	-1.37%	Slovakia	-0.28%
New Zealand	-2.53%	Madagascar	-1.26%	Gambia	-0.19%
Ethiopia	-2.51%	Swaziland	-1.24%	Jamaica	-0.15%
Venezuela	-2.51%	Italy	-1.24%	Namibia	-0.10%
U.R. of Tanzania	-2.45%	Paraguay	-1.21%	Guatemala	-0.05%
Kazakhstan	-2.44%	Croatia	-1.06%	Tunisia	-0.04%
Argentina	-2.42%	Iran	-1.03%	Togo	-0.04%
Bolivia	-2.42%	Latvia	-1.03%	Botswana	-0.03%
Belgium	-2.32%	Honduras	-0.99%	Turkey	-0.01%
Armenia	-2.29%	Portugal	-0.95%		
Russian Federation	-2.25%	Sri Lanka	-0.92%		

To help the reader identify a 'normal' trajectory that can be used as a benchmark, we log-transformed per capita income (on the horizontal axis). This is a common statistical practice to rescale the units of a variable and make the visual interpretation of a graph easier.

Figure 1 Scatterplots with non log-transformed and with log-transformed income data

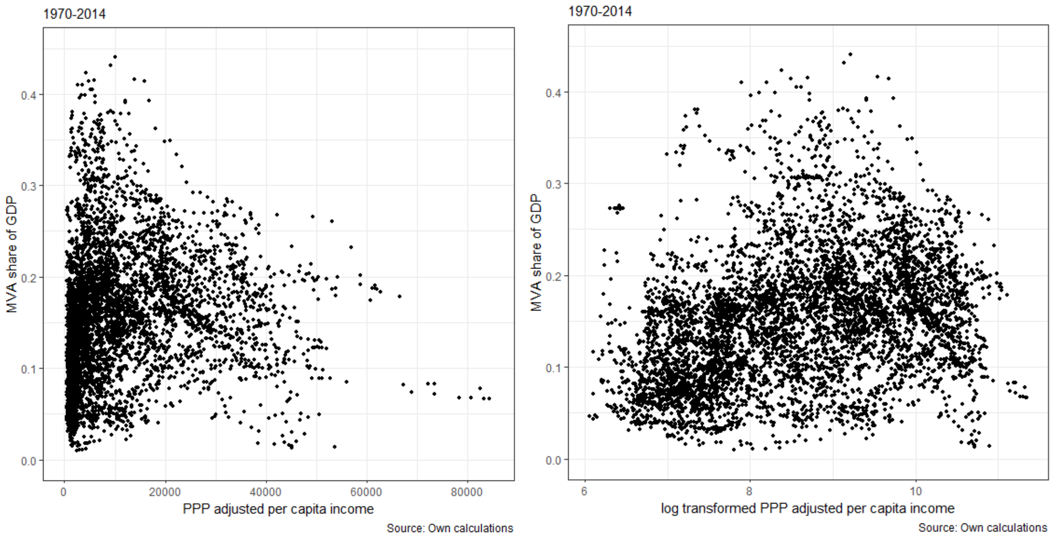


Figure 1 compares the difference between log-transformed and non-transformed data. The graph on the right is more suitable for identifying any trend within the data since the observations are less clustered to the left of the graph. The transformation reduces data variance. As a result, the levels of income must, however, be interpreted differently. For example, a log-transformed per capita GDP of 6 to 6.5 equals an actual per capita income of US$ 400 to US$ 700, one of 9 equals around US$ 8,100 and one of 10 just over US$ 22,000. No clear pattern emerges from the data even after the log-transformation. It remains difficult to determine where this trend peaks and when the relationship between the manufacturing sector's size and per capita income turns negative.

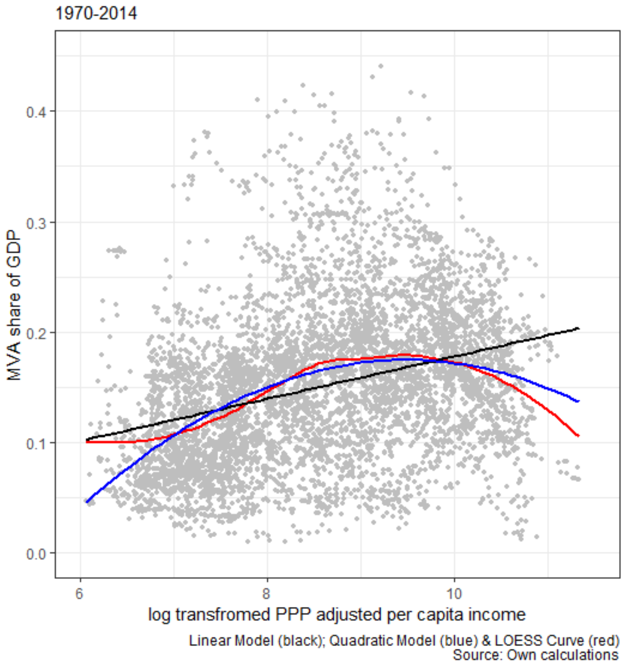
Before setting out on our quest to find this peak, it is worth pointing out some problems with the very idea of identifying a clear pattern, let alone a turning point, for the relationship between the size of the manufacturing sector and a country's level of development in cross-country studies. Reporting a point estimate of a turning point can be problematic when the precision of this estimate is not assessed. There is a wealth of literature and empirical research on identifying and locating a turning point based on regression functions, i.e. on the Environmental Kuznets Curve. The focus of the literature has moved further and further away from the concept of identifying a clear point estimate of a turning point because the relationship between environmental degradation and GDP displays more complex patterns than the 'inverted-U' of the well-known Kuznets Curve. To account for a more complex relationship and to ensure that the model is not mis-specified, some studies have turned to nonparametric approaches with fewer restrictions (Azomahou, Van Phu, & Laisney, 2006). Building on this approach, the next section introduces a nonparametric method that helps us assess the suitability of a quadratic regression function.

5. Some simple descriptive statistics

Simple statistical methods can help us identify data patterns. The first part of this section presents different types of fitted lines that can help us do so. We then address the data spread, which is quite large, even when we divide the dataset into different subgroups.

Figure 2 uses the same scatterplot with the log-transformed data from the right figure of Figure 1 and plots three different lines to identify a data trend. The black line is obtained by using a simple linear regression which resembles the direct relationship between the share of MVA and per capita income.

Figure 2 Identification of data trends based on a simple linear regression



A line is rarely suited for analysing the relationship between these two variables, as most countries with a rising per capita income eventually start to deindustrialize. To account for this change in the relationship as countries become richer, a quadratic regression function that includes GDP/capita^2 as a further explanatory variable is applied. The use of a squared variable can capture how the relationship changes when GDP/capita rises. To identify the most suitable type of regression, we include a *locally estimated scatterplot smoothing* (LOESS) curve[4]. The LOESS curve in Figure 2 is similar to the maximum along the blue line of the quadratic model. This

[4] A LOESS curve is a nonparametric approach that fits multiple regression models to different subsets of the data and can thereby capture any changes in the relationship. This technique can be used to visually identify the best model (linear, quadratic, exponential, etc.).

corresponds to the notion that countries start to deindustrialize as they become richer and eventually move into other sectors of the economy.

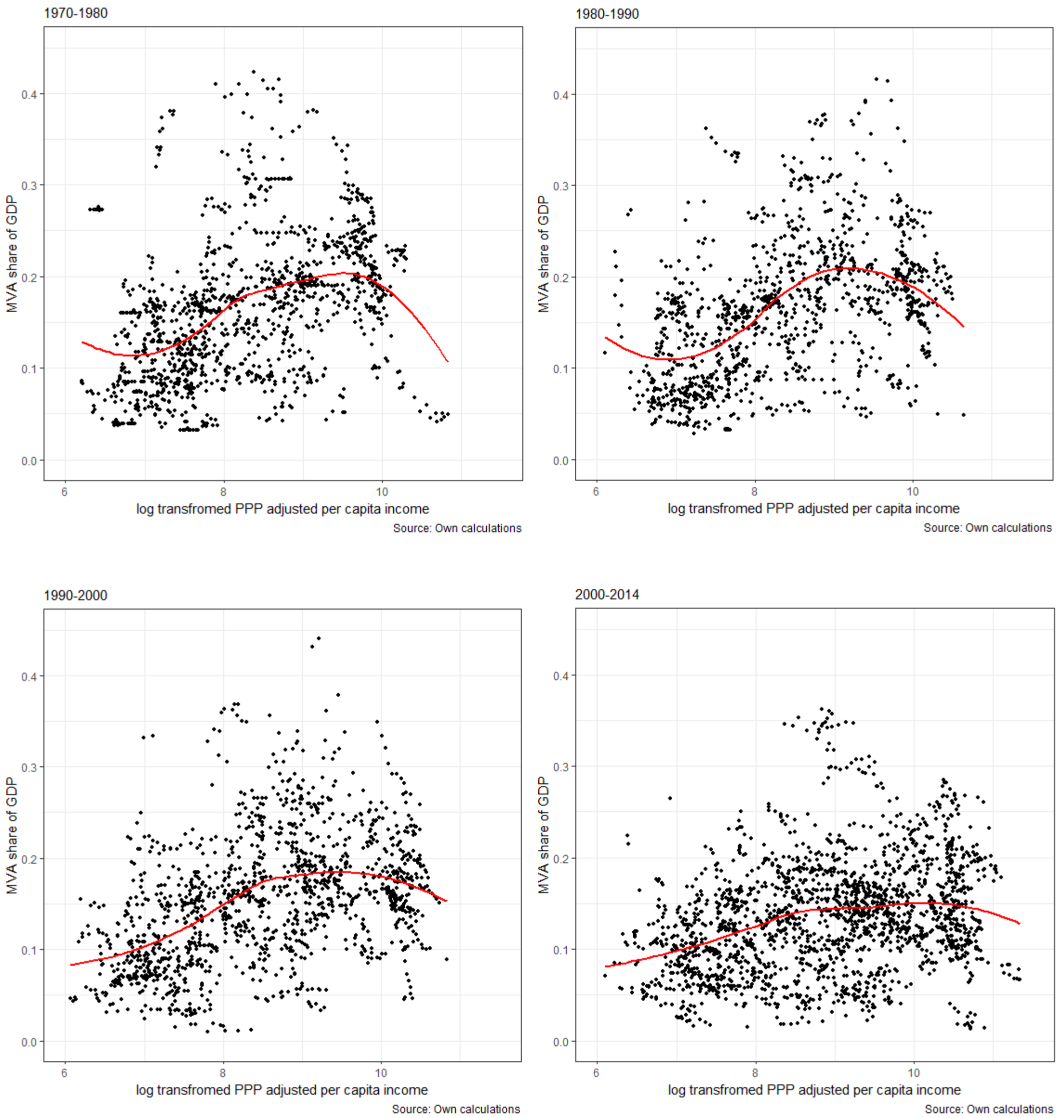
As the different shapes of both the linear and the quadratic regression illustrate, the type of regression used has very different policy implications. The upward sloping line and the absence of a turning point in the linear regression imply that deindustrialization is not a relevant feature in the course of a country's development. The use of a quadratic function allows us to identify a turning point which serves as a threshold for premature or legitimate deindustrialization. Any decrease in the share of MVA in GDP to the right of this turning point can be regarded as legitimate deindustrialization, while a decrease to the left of this threshold is an indication of premature deindustrialization.

What is more important than the shape of the best fit, however, is the spread of the data points in Figure 2. Although we can use different methods to identify data patterns, the scatterplot clearly illustrates the substantial variance across countries. Section 6 introduces econometric methods that can be applied to control for individual country effects. For now, the most relevant finding is that such a data spread makes it difficult to identify a clear pattern that applies to all countries. Finding a suitable comparator or defining a threshold at which deindustrialization can be considered premature is therefore not as straightforward as one might intuitively expect.

Based on the widespread claim in the literature that the nature of deindustrialization is changing, we divided our sample into four different subgroups according to decades (1970-1980; 1980-1990; 1990-2000; and 2000-2014). This might help reduce the variance across time and make trends more visible.

To identify data patterns for each subgroup, we again fitted a LOESS curve. A comparison of the four different curves in Figure 3 reveals a downward shift of the curve's turning point over time. This might be an indication that the average size of the manufacturing sectors of our sample has been decreasing since the 1970s. This might also suggest that late industrializers today reach peaks of industrialization at much lower income levels compared to countries that industrialized in the past. On the other hand, the level of per capita income at which the different curves reach their maximum seems to have changed only marginally. As our dataset includes countries with varying income levels, the absence of a leftward shift of the curve should not be over-interpreted. The most relevant finding here is that the data spread continues to be substantial, even when it is split into different decades.

Figure 3 Scatterplots by decade



To further explore the variance across countries and explain the difficulties that arise from this variance, it is worth looking at some descriptive statistics of the dataset. Table 2 presents basic descriptive statistics for the full dataset as well as for different subgroups based on decade or income decile. Table 2 clearly shows that the data spread is unaffected, regardless of any division of the sample into subgroups. The mean, i.e. the average share of MVA in GDP, generally lies around 15 per cent in each decade. The picture looks slightly different when we compare income groups in which the mean of the share of MVA in GDP changes from 10 per cent in the 1st income decile (namely the lowest 10 per cent per capita income) to 18 per cent in the 9th decile. This implies that the size of the manufacturing sector as a share of GDP is, on average, larger in countries with a higher per capita income.

Table 2 Descriptive statistics of the full dataset and of subgroups

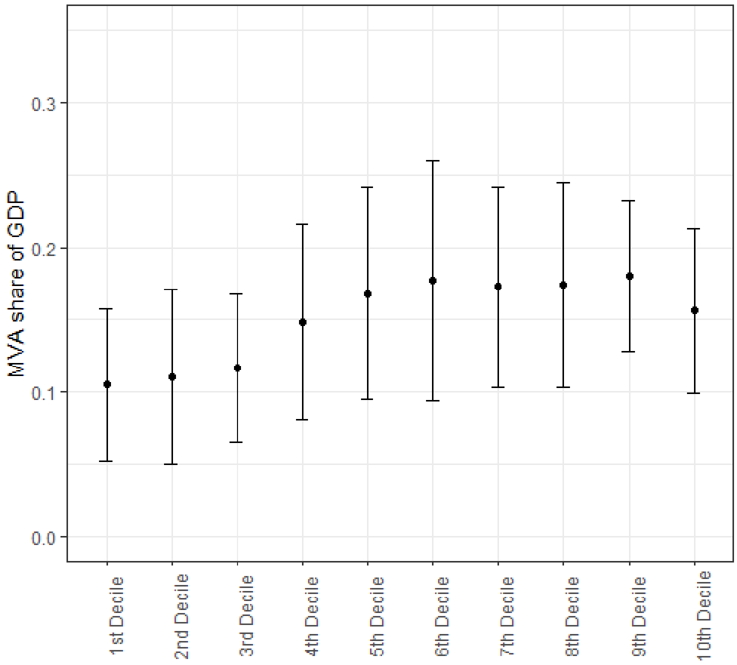
	Number of Obs.	Minimum MVA Share	Maximum MVA Share	Mean	Median	Standard Deviation
Full Sample	5,807	1.00%	44.02%	15.09%	14.87%	7.04%
1970-1980	1,287	3.24%	42.30%	16.22%	16.23%	7.74%
1980-1990	1,193	2.81%	41.63%	16.20%	16.29%	7.42%
1990-2000	1,390	1.00%	44.02%	15.35%	15.36%	6.90%
2000-2014	1,937	1.23%	36.25%	13.46%	13.09%	6.03%
1st Decile	581	2.42%	33.20%	10.48%	9.18%	5.29%
2nd Decile	581	1.52%	38.09%	11.07%	9.56%	6.05%
3rd Decile	580	1.64%	35.25%	11.66%	11.46%	5.13%
4th Decile	581	1.00%	40.98%	14.86%	14.75%	6.77%
5th Decile	581	1.13%	42.30%	16.78%	16.22%	7.33%
6th Decile	580	1.93%	41.52%	17.74%	17.37%	8.29%
7th Decile	581	2.68%	44.02%	17.24%	17.27%	6.96%
8th Decile	580	2.15%	41.63%	17.40%	16.67%	7.11%
9th Decile	581	4.02%	36.25%	18.03%	18.07%	5.20%
10th Decile	581	1.23%	29.22%	15.60%	15.43%	5.71%

As both the minimum and maximum values as well as the standard deviation around the mean indicate, there is a considerable difference between the countries that make up each subgroup, including the different income deciles. Even in the 9th decile, where the average share of MVA in GDP is highest, there are still some cases in which the manufacturing sector only accounts for 4 per cent of GDP. At the other end of the spectrum, the lowest income decile includes countries with MVA shares in GDP of over 30 per cent. The standard deviation[5] in our dataset ranges from 0.05 to 0.08, depending on which subgroup of the data we look at. This is quite high when compared to the mean's average value.

Figure 4 illustrates this range in data. The graph plots the means for each income decile together with the variation of two standard deviations in each direction. With this spread in mind, the question arises what scenarios would qualify as 'premature' deindustrialization.

[5] In statistics, the standard deviation is a typical measure for the spread of data. A low standard deviation (in relation to the mean) indicates that most data points are close to the average value.

Figure 4 **Means of MVA share for each income decile with two standard deviations**



Source: Own calculations

As mentioned above, some researchers—for example, Palma (2014) or Tregenna (2015)—use the regression line of a quadratic or polynomial model as an indicator where any country that falls below the curve (indicating that the size of their manufacturing sector is lower than would be expected at their level of income per capita) is considered a premature 'deindustrializer'. These studies acknowledge the shortcomings of cross-sectional pooled data regressions[6] and only use them as an empirical benchmark rather than a 'prediction' of future developments. However, with the data spread in mind, this does not hold much value for policymakers, considering that the size of a country's manufacturing sector could fall anywhere within the range of almost zero to 30 per cent of GDP.

5.1 A look at the performance of a few countries

To help the reader understand the different paths countries' manufacturing industries and levels of income have taken, we look at selected countries in the scatterplot. Figures 5(a)(d) highlight the BRICS, selected countries in Latin America and in SSA as well as the Asian Tigers. A clear inverted U-shaped pattern is only identifiable for Mauritius, Taiwan, Province of China and China (although China's manufacturing sector seems to have recovered following a phase of moderate

[6] For a further elaboration, see Section 6 on 'Panel Analysis and Country Fixed Effects'.

deindustrialization during the 1980s). The per capita income of countries such as India or Botswana increased at constant levels of industrialization. In others, for instance in the Republic of Korea, the share of MVA in GDP continued to increase, even after reaching high-income status. A few countries, most notably South Africa and several Latin American countries, indicate what seems to be strong signs of deindustrialization at income levels, which could potentially be considered ‘premature’.

Figure 5(a) Scatterplot of BRICS

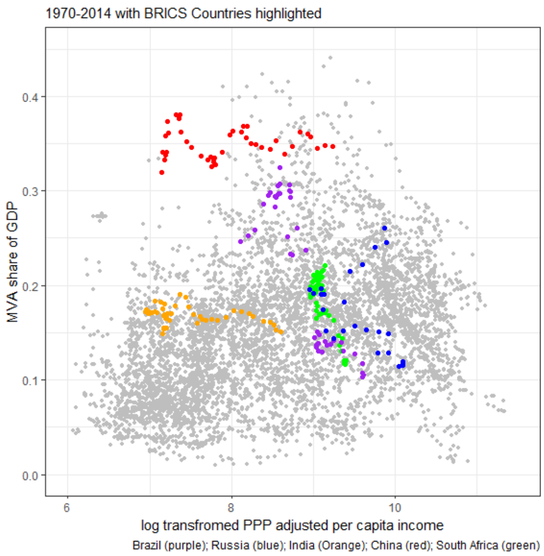


Figure 5(b) Scatterplot of Latin American countries

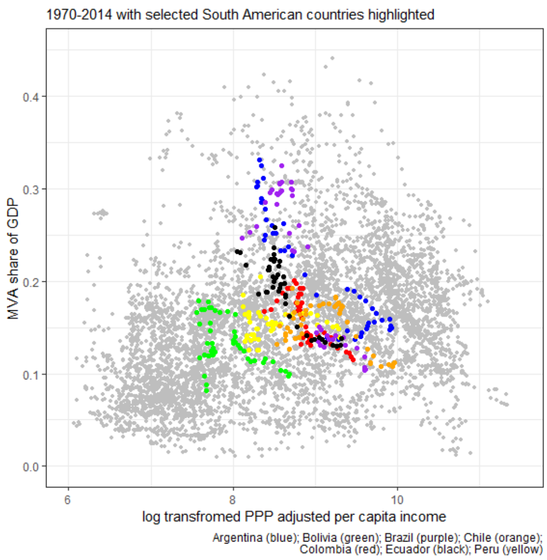


Figure 5(c) Scatterplot of SSA countries

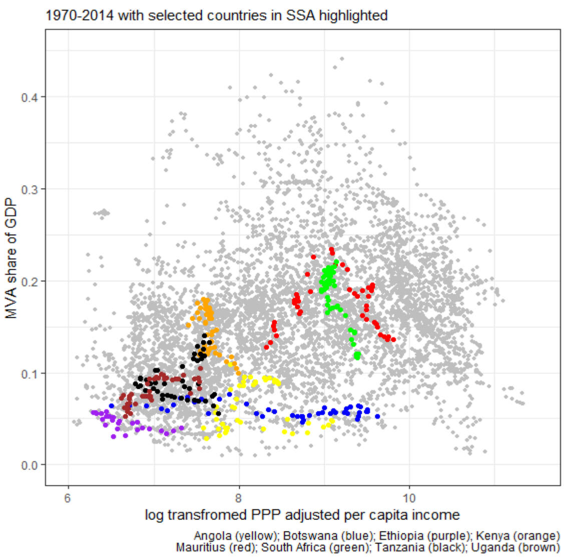
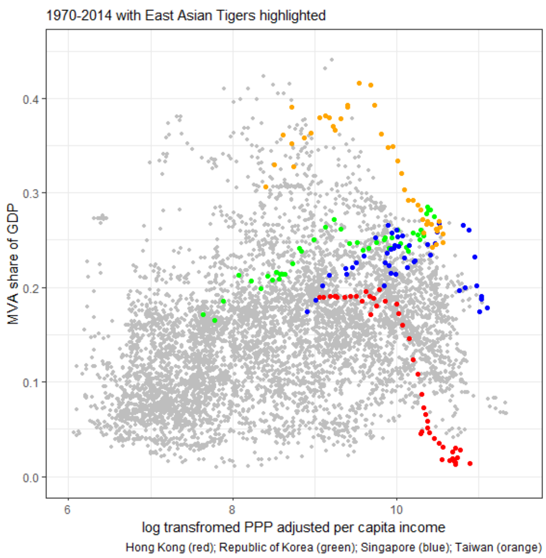


Figure 5(d) Scatterplot of East Asian Tigers



To validate a claim of premature deindustrialization, a more complex model that provides a suitable counterfactual for each country is needed. The following section introduces common econometric robustness measures that can help us control for other variables that might affect the size of a given country's manufacturing sector.

6. Econometric model

The visual analysis of the individual paths of different countries revealed that very few countries closely followed the path of the estimated LOESS curve from Figure 2. This is contrary to the claim that virtually all countries roughly follow a similar trajectory in terms of economic development and the role of the manufacturing sector (Rowthorn & Coutts, 2004).

We therefore turn to the seminal work of Rodrik (2016) and repeat substantial parts of his analysis with a much larger sample of 139 countries compared to the 42 he used. The first part of this section introduces the basic model, which we subsequently extend with decade dummies and country fixed effects.

Box 4 Simple regression model

One way to test the relationship between the size of the manufacturing sector and per capita income is to include the population number as a robustness check which accounts for demographic trends. By including additional variables in the regression analysis, we can check for any omitted variable bias by testing whether the coefficients of per capita income change. We use the following baseline regression to determine the correlation between the size of the manufacturing sector (denoted by MVA share in GDP) and income level (denoted by GDP/capita).

$$MVA\ share = \beta_0 + \beta_1 \ln\left(\frac{GDP}{capita}\right) + \beta_2(\ln GDP/capita)^2 + \beta_3 \ln Population + \beta_4(\ln Population)^2 + \epsilon$$

where β_0 is the intercept; β_1 and β_2 denote the coefficients that describe the associated effect of a change in per capita income and in per capita income^2, respectively, and β_3 and β_4 report the same for a change in population size.

The results of column (1) in Table 3 show that there is a significant positive correlation (positive estimate for β_1) between the size of the manufacturing sector and income. As data for income is in a natural logarithm, a 1 per cent increase in per capita income is associated with a 0.2 percentage point increase in the share of MVA in GDP. At higher income levels, this relationship eventually turns negative as signified by the negative estimate of β_2. The results remain robust, i.e. do not change significantly, when population is included in the model as a further explanatory variable (second column in the table).

Table 3 Regression analysis

	Dependent variable:	
	Share of MVA/GDP	
	(1)	(2)
Intercept	-0.813^{***} (0.048)	-0.712^{***} (0.092)
ln GDP/capita	0.208^{***} (0.011)	0.216^{***} (0.011)
ln GDP/capita^2	-0.011^{***} (0.001)	-0.011^{***} (0.001)
ln Population		-0.028^{***} (0.009)
ln Population^2		0.001^{***} (0.0003)
Number of Countries	139	139
Observations	5,807	5,807
Adjusted R^2	0.142	0.206
Note:		*p<0.1; **p<0.05; ***p<0.01

As with any econometric analysis, these results should be treated with caution considering that only correlations have been analysed, which does not imply any causality. Another reason for caution is the low adjusted R^2 of 0.142, which means that only 14 per cent of the variance can be explained by the regression. The adjusted R^2 continues to remain relatively low when the population variable is included. The overall low R^2 together with the individual country paths highlighted in Figures 5(a)-(d) shows how important it is for such an analysis to take individual country characteristics into account. This is particularly the case when plotting a regression line as the benchmark based on which cases of premature deindustrialization can be identified whereby countries lie below the curve or conversely above the curve.

To better understand the problem of analysing the type of data we have obtained, it is important to understand the statistical methods that are being used.

Box 5 Panel data

The type of data we analyse here is commonly referred to as panel or longitudinal data. In panel analysis, the same units—in our case individual countries—are followed over a given period of time (1970-2014). In pooled cross-sectional data analysis, on the other hand, each observation of a given country in a given year is treated independently from all other observations relating to that particular country or year. Treating panel data as pooled cross-sectional data is not necessarily wrong. This is what we did for the scatterplots in Figures 1-5 as well as in the regression analysis of Table 3. However, certain questions cannot be answered by simply viewing each observation independently. Given the spread of the data shown above, a simple ordinary least square regression to estimate data trends does not yield satisfactory results.

By using panel analysis, we can track individual countries over time and thereby control for unobserved characteristics. Rodrik (2016) uses a model that not only accounts for changes in demographics and income level, but further includes country fixed effects which account for the characteristics of panel data. He uses the model to document the changing nature of deindustrialization, namely that countries are starting to deindustrialize at much lower levels of income compared to early industrializers. Contrary to his analysis, we are less interested in the changing relationship between the size of the manufacturing sector and level of income – we want to test whether panel analysis is a suitable tool for identifying cases of under-industrialization or premature deindustrialization.

Following Rodrik's model, we include country fixed effects as well as decade dummies in the regression. Fixed effects are an econometric method to explore the relationship between dependent and independent variables within a country. In other words, by including country fixed effects, we can account for individual country heterogeneity and country-specific features such as geography, climate, endowments or history. The rationale behind this approach is that each country has individual characteristics that impact its share of MVA in GDP, which must be accounted for to establish an unbiased estimation of the relationship between the size of their manufacturing sector and their level of per capita income.

Fixed effects remove the effect of country-invariant characteristics. A further advantage of using this model is that these characteristics are unique for each country and are not correlated with other individual characteristics. Should this not be the case, i.e. should the individual error terms of each country be in fact correlated with the others, fixed effects would not be suitable and another method (such as random effects) would have to be used to obtain correct inferences. To account for this possibility, we perform a Hausman test to confirm that the unique errors are not correlated.

Box 6 Regression model with fixed effects and decade dummies

Essentially, the fixed effect method entails including a dummy variable for each country in the dataset, which takes on a value of 1 for all observations of a specific country and 0 for all remaining countries. We thereby capture a different intercept for each country while the slope of each curve continues to stay the same. This leaves us with 139 identically shaped curves which only vary according to their intercept on the Y-axis. As this would be too many intercepts to report in the regression output tables, the use of country fixed effects is only indicated at the bottom of the table. The actual country-specific coefficients can be found in Appendix B.

The use of decade dummies follows a similar rationale as that for the use of country fixed effects. By including a different intercept for each decade, we can gauge the changing relationship between the size of a country's manufacturing sector relative to its economy and level of income. Hence, the coefficients of these decade dummies can be regarded as a parametric test of the curve from Figure 3. Regardless of the magnitude of each coefficient, the effects of either a country or decade dummy should not be viewed in isolation. It is crucial to view the effects of a specific country within a specific decade, as the two effects add up and thus both affect the intercept of a given country. The extension of our original model with country fixed effects as well as with decade dummies provides the following equation:

$$MVA\ share_{it} = \beta_1 \ln \frac{GDP}{capita}_{it} + \beta_2 \left(\ln \frac{GDP}{capita}_{it}\right)^2 + \beta_3 \ln Population_{it} + \beta 4\ (\ln Population_{it})^2 + \sum_i \alpha_i + \sum_T \gamma_T PER_T + \varepsilon_{it}$$

where α_i denotes the different country-specific intercepts as a result of the use of fixed effects and PER_T is the decade-specific period dummy.

Table 4, column (4) presents the results of this model. Column (1) only includes quadratic measures for income per capita and decade dummies, while column (2) includes country fixed effects. Columns (3) and (4) repeat this analysis by including population as a further explanatory variable. The results for income per capita are similar to the results of Table 2 and across the four different model specifications, both in terms of significance as well as magnitude. As explained above, due to the use of decade dummies and country fixed effects, the regression results table no longer reports an intercept but rather the sum of the coefficient of each period. Moreover, the country fixed effect becomes the respective intercept for each country.

Table 4 Regression analysis including country fixed effects and decade dummies

	Dependent variable:			
	Share of MVA/GDP			
	(1)	(2)	(3)	(4)
ln GDP/capita	0.191*** (0.011)	0.220*** (0.010)	0.200*** (0.010)	0.169*** (0.011)
ln GDP/capita^2	−0.010*** (0.001)	−0.013*** (0.001)	−0.010*** (0.001)	−0.010*** (0.001)
ln Population			−0.015* (0.009)	0.150*** (0.020)
ln Population^2			0.001*** (0.0003)	−0.003*** (0.001)
1970s	−0.738*** (0.046)	−0.742*** (0.046)	−0.755*** (0.089)	−2.169*** (0.175)
1980s	−0.743*** (0.046)	−0.744*** (0.046)	−0.762*** (0.089)	−2.183*** (0.175)
1990s	−0.749*** (0.046)	−0.748*** (0.045)	−0.769*** (0.089)	−2.200*** (0.175)
2000s+	−0.777*** (0.046)	−0.765*** (0.045)	−0.799*** (0.089)	−2.229*** (0.175)
Fixed effects	No	Yes	No	Yes
Number of Countries	139	139	139	139
Observations	5,807	5,807	5,807	5,807
Adjusted R^2	0.856	0.955	0.869	0.958
Note:				*p<0.1; **p<0.05; ***p<0.01

In all four regressions, the estimated coefficient for the decades become increasingly negative, thus indicating that countries that industrialize today do not reach the same level of industrialization as early industrializers. This confirms the visual identification of a downward moving curve in Figure 3, which is in line with the findings of Rodrik (2016). Lastly, the substantial increase in the adjusted R^2 is worth noting. This, however, should be interpreted with caution as it is not necessarily surprising that we can explain much of the variation in the share of MVA in GDP with the use of decade and country dummies which, in turn, drives the adjusted R^2 to be unusually high[7].

The inclusion of country fixed effects has reproduced the quadratic line from Figure 2 for each of the 139 countries of our dataset with the exact same slope but with different intercepts by country. Comparing this to the individual country trajectories highlighted in Figures 5(a)-(d) reveals that not too much emphasis should be placed on the high adjusted R^2 as a measure for goodness of fit. That being said, the high adjusted R^2 together with the magnitude of the sum of country fixed and decade effects indicates the possibility of significant model misspecifications. The use of fixed effects (both for countries and decades) allows us to exclude any country-specific or time- (decade-) specific effects and analyse the relationship between the manufacturing sector's size and the per capita income level *ceteris paribus*.

[7] It should be noted that the computation of the model for estimating the slope parameters does not necessarily require the inclusion of individual dummy variables in the matrix of explanatory variables. It is possible to replace accumulated dummies through a 'within operator' so that individual observations are measured as deviations from individual means (over time). However, as we are interested in the actual magnitude of each country-specific effect, we include a dummy variable for each country.

This is legitimate from an econometric standpoint; however, from a policy standpoint, the black box, i.e. the unobserved variables captured by the fixed effects, is of great significance. This essentially means that not only the size of a country's economy but also the size of its population as well as specific country characteristics play a crucial role in explaining the relationship between the manufacturing sector's size and the level of income per capita.

7. Predictions / measurement of premature deindustrialization

Following our improved understanding of the model as well as of the regression results, we can revisit our earlier question of how to determine whether a country is under-industrialized or prematurely deindustrializing.

Firstly, we can use the output of the regression analysis to calculate a **turning point** at which level of per capita income the share of MVA in GDP begins to decrease. If the size of the manufacturing sector starts to decrease before this income level is reached, we can assume that the country is deindustrializing prematurely. Secondly, using the country- and decade-specific intercept obtained from the sum of coefficients of the specific country fixed effects together with the decade dummy allows us to ascertain whether a country is over- or under-industrialized compared to the predictions of our model for a country with the same population size, country-specific effects and within a given time period.

Using the estimated coefficients of our regression analysis, we can calculate the level of per capita income at which the predicted curve reaches its maximum and starts to decrease. As outlined above, due to the use of country fixed effects as well as decade dummies, we gain different intercepts depending on the country and the time period we choose to look at. This, however, only shifts the curve upwards or downwards and does not alter the value of income per capita on the X-axis at which each curve peaks. Using simple algebra, we can then calculate this peak by taking the derivative of our model equation. Our model predicts a turning point at ln GDP/capita of 8.45. This equals a per capita income of US$ 4,675.

This turning point should be interpreted with caution. As outlined above, the use of country fixed effects allows us to account for differences in the size of the manufacturing sector across countries by assigning a different intercept to each case, which captures the individual country characteristics. However, as this method produces a constant slope for all countries, it fails to capture country level heterogeneity. Since our sample consists of many heterogeneous countries, the estimated turning point might not be exactly the same in each scenario. Despite this, we compare this value to the actually observed value of each country's per capita income in our sample for the year 2005. The choice of the year 2005 as the base year is somewhat arbitrary, but we selected that year because it falls into a period during which many countries deindustrialized and were still unaffected by the 2008 financial crisis.

To determine whether a country is under-industrialized, we use the output of our regression analysis to calculate the **predicted** share of MVA in GDP for each country in the year 2014. We can then compare the actual size of a country's manufacturing sector and compare it to the share of MVA in GDP that our model predicts for a country with the same fixed effects, i.e. country-specific characteristics, same population size as well as same time period. If the predicted share of MVA in GDP is larger than the actual share of a given country, we can assume that this country is under-industrialized.

The two tests, premature vs. legitimate deindustrialization as well as over- vs. under-industrialization, provide us with a fourfold classification that can be applied to all countries that are currently experiencing deindustrialization as defined at the beginning of this paper. The four classifications can be summarized in a matrix:

Table 5 Four Shades of Deindustrialization

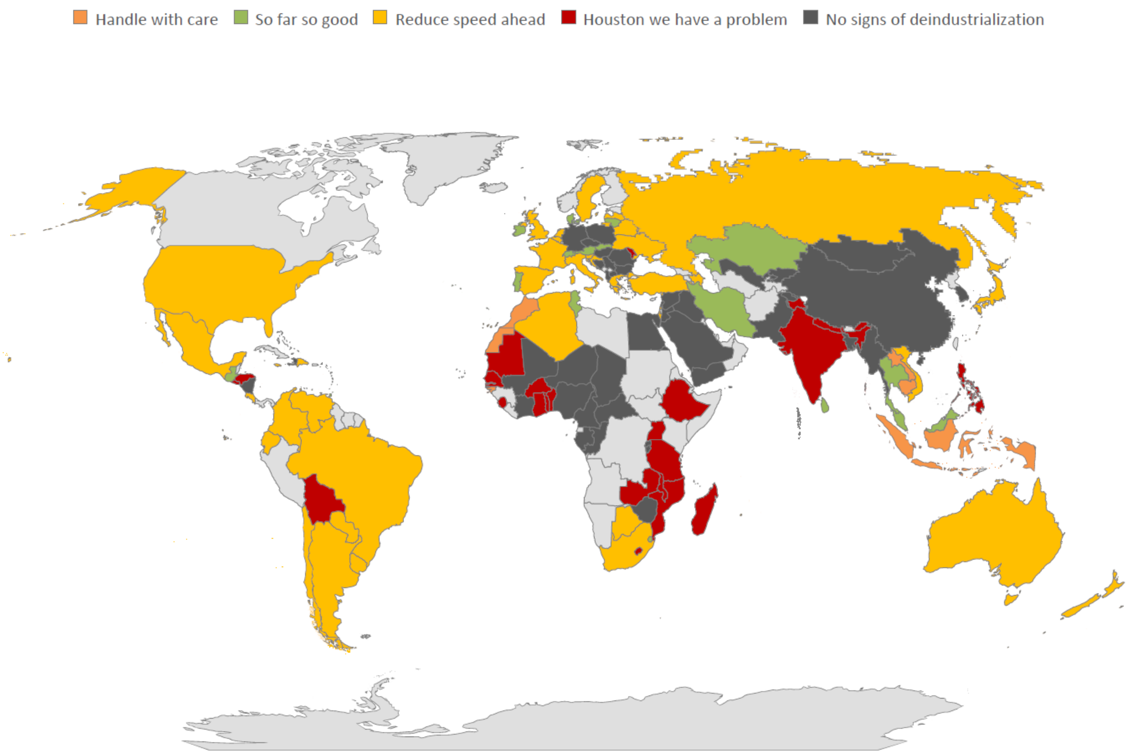
	Premature deindustrialization	**Legitimate deindustrialization**
Over-industrialized	A: Handle with care	B: So far, so good
Under-industrialized	C: Houston, we have a problem	D: Reduce speed ahead

A country that falls into group A has a manufacturing sector that is larger than we would expect based on our model, i.e. the actual share of MVA in GDP lies above our estimated curve. If the country shows signs of premature deindustrialization (defined as a decrease in the manufacturing sector over the last ten years) at a per capita income level below the threshold of US$ 4,675 in the year 2005, caution is warranted as a rapid process of deindustrialization might lead the country to move below the curve and fall into group C. A country that is both under-industrialized and is experiencing deindustrialization at premature levels applies to a country that has a smaller manufacturing sector than we would expect and is further decreasing despite its still relatively low per capita income level.

The two categories on the right of the matrix comprise countries that are deindustrializing at income levels that do not classify as premature deindustrialization. If the size of a country's manufacturing sector is larger than predicted by our model, i.e. lies above the curve, policymakers in that country need not be concerned about deindustrialization. In fact, deindustrialization in those countries is exactly what we would expect based on our model predictions (that is why group B is called 'So far, so good'). Group D comprises countries that are experiencing deindustrialization at legitimate levels, but their deindustrialization occurred too quickly and their manufacturing sector is already smaller than what we would expect based on our model. Although countries that fall into this group should be careful to prevent their manufacturing sector from decreasing further at the same speed, falling into this group does not necessarily call for drastic policy measures.

Returning back to our earlier question how to determine which countries experience deindustrialization at premature levels, we can now group all countries from Table 1 according to their classification. Figure 6 presents all countries with a manufacturing sector that had a negative moving average growth rate indicating deindustrialization as defined in Section 4, together with their classification of type of deindustrialization as outlined above.

Figure 6 **Countries that have experienced deindustrialization in the past decade**

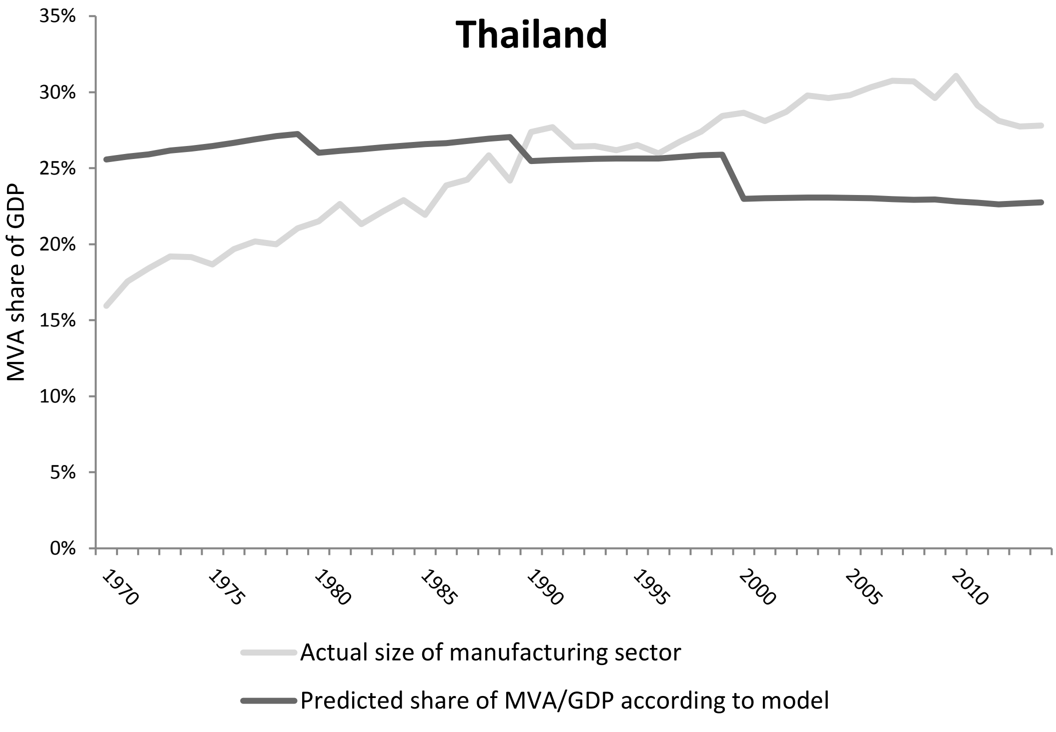


8. Illustration of the development of the manufacturing sector of selected countries

To further explain the difference between the four classifications, we present one country from each group and plot the country's respective changes in the share of MVA in GDP against the predicted size of the manufacturing sector according to our model. We obtain the predicted size of the manufacturing sector by plugging the observed values for income per capita and population size for a given country in each year into our regression model together with the country-specific fixed effect dummy. The downward shifts of the light-grey curve in Figures 7 to 10 represent the coefficients of the decade dummies from our regression analysis, which, as outlined above, decrease over time and therefore shift the curve downward each time we move into a new decade.

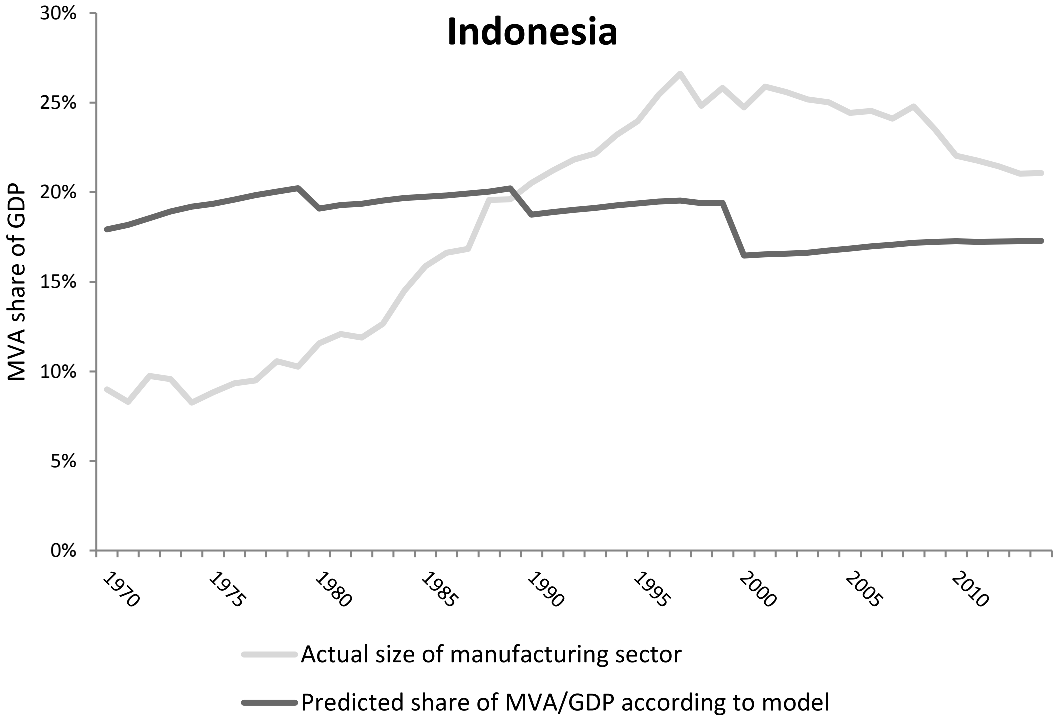
The coefficients from Table 4 together with the reported country fixed effects dummies in Appendix B allow policymakers to calculate the type of deindustrialization for any country included in our database. Below we present four countries, one from each group, and compare the development of their manufacturing sector with our model predictions for the specific country.

Figure 7 **Example of country type B (So far, so good)**



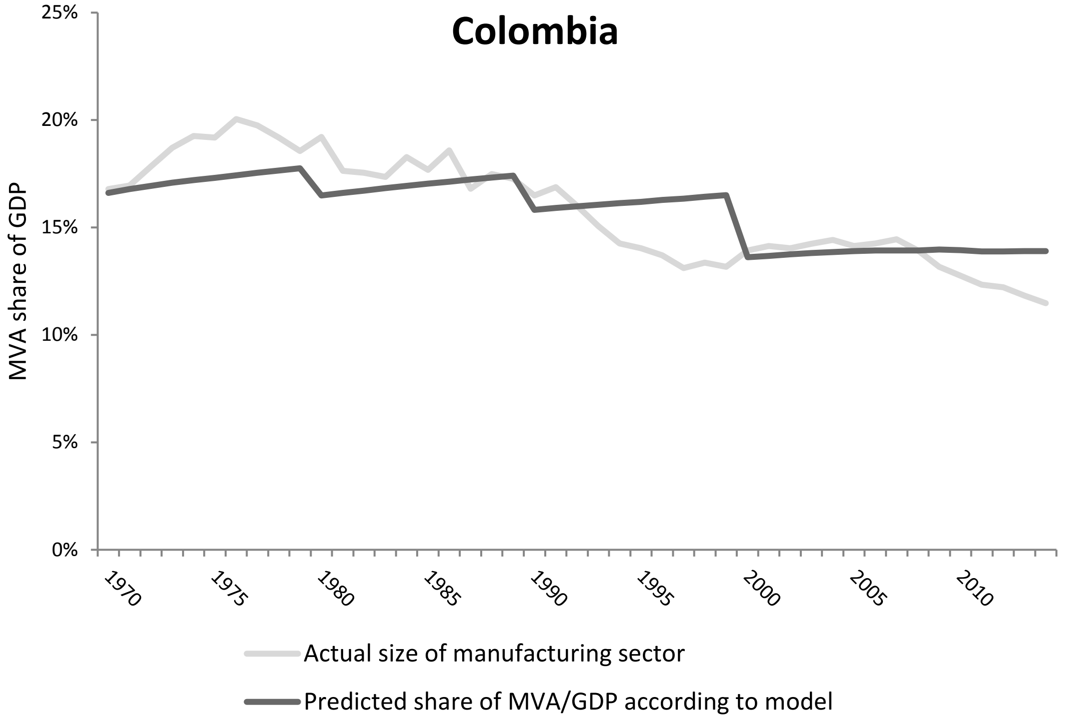
One good example of a country that experienced deindustrialization at legitimate levels according to our model (and thus policymakers in this country do not need to be concerned about this development) is Thailand. Figure 7 plots the size of Thailand's manufacturing sector over the past four decades against the level of industrialization the country should have according to our predictions. Thailand was under-industrialized in the 1970s and 1980s (dark-grey line above the light-grey line), but its manufacturing sector experienced growth in the ensuing decade. By 1990, Thailand's share of MVA in GDP was larger than the predicted value of our model. Over the last few years, Thailand's manufacturing sector has been decreasing again as the peak in the dark-grey line indicates. However, by that point, Thailand had already long passed the income threshold. Hence, Thailand's deindustrialization is a natural progression according to our model and the country is therefore grouped in the 'Nothing to worry about' quadrant of our matrix.

Figure 8 Example of country type A (Handle with care)



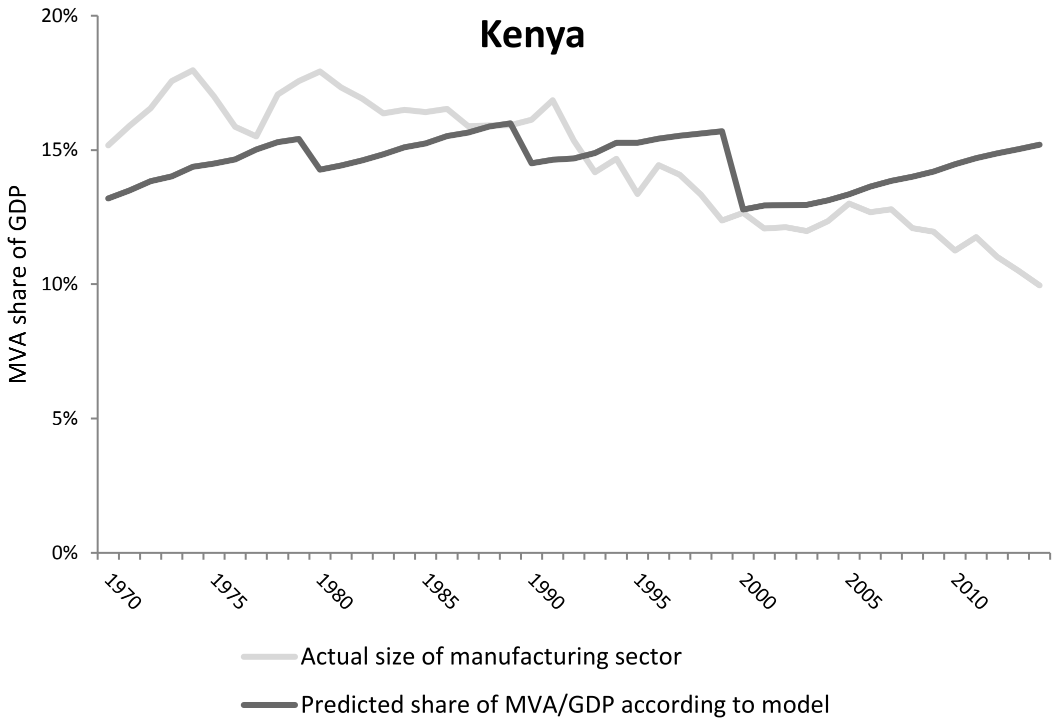
Indonesia is a country that falls into group A: 'Handle with care' according to our model, because it has a manufacturing sector that is larger than we would expect, but has started to deindustrialize at a per capita income level that classifies as premature deindustrialization. As Figure 8 shows, Indonesia experienced rapid industrialization during the 1980s and 1990s and reached a share of MVA in GDP of over 25 per cent. During the last decade, Indonesia's manufacturing sector has started to decrease. As Indonesia's per capita income reached US$ 4,089 in 2005 and was thus just below our threshold of US$ 4,675, deindustrialization in Indonesia can be considered 'premature' according to our model. In this case, policymakers should pay some attention to the process of deindustrialization to ensure that it does not progress too quickly, but do not need to be overly concerned.

Figure 9 **Example of country type D (Reduce speed ahead)**



Similarly, policymakers in Colombia need not jump to the conclusion that it is deindustrializing. Figure 9 shows that Colombia's manufacturing sector developed in line with our expectations. The country's share of MVA in GDP has decreased and is currently below the level it 'should be' according to our model. Indeed, we can classify Colombia's deindustrialization as progressing 'too fast' (hence, as falling into group D: 'Reduce speed ahead'), but the fact that Colombia is experiencing signs of deindustrialization is completely legitimate. Given Colombia's per capita income level of US$ 7,650 in 2005, it would be incorrect to claim Colombia's deindustrialization was 'premature'.

Figure 10 Example of country type C (Houston, we have a problem)



Lastly, an example of a country for which premature deindustrialization is indeed an issue is Kenya. Kenya’s manufacturing sector has been shrinking for the past 20 years and today contributes less than 10 per cent to the country’s overall GDP. This is much lower than the predicted size of the manufacturing sector according to our model. Additionally, Kenya’s per capita income of US$ 1,976 (in 2005) is still relatively low. Having experienced this level of deindustrialization at that income level classifies Kenya as a clear example of premature deindustrialization. In this case, our model can be used by policymakers to justify the implementation of industrial policies to counter these developments and to promote the manufacturing sector.

9. Conclusion

Deindustrialization is observed in many countries. Building on the arguments of the structuralist school of thought, deindustrialization can be problematic if it occurs in countries that are still "developing" and have not yet reached the same income level as today's advanced countries when they began to deindustrialize. Premature deindustrialization has been the focus of several academic studies in recent years. However, despite the attention deindustrialization has been getting from policymakers, there is a lack of clear definitions and analyses that justify claims of premature deindustrialization. We have sought to fill this gap with this research by expanding the work of Rodrik (2016) and recreating a similar model using a larger database. This paper can be used by policymakers as an introduction to the main arguments of the structuralist school of thought and in particular to the concept of premature deindustrialization.

As we have shown above, the substantial difference in the individual paths of each country and the resulting data spread makes it difficult to identify a clear pattern in the data and to determine a point at which most countries start to deindustrialize. Using panel analysis, we developed a model that accounts for the changing relationship of per capita income and the size of the manufacturing sector over time as well as individual country characteristics. The use of country fixed effects helps us account for these individual country characteristics; however, this comes at the expense of cross-country comparisons. As we exclude any variables such as a country's history, location, climate or economic system, we can no longer compare countries that are not exactly identical without risking an omitted variable bias that might falsify our conclusion.

This paper contributes to a broader understanding of the concept of premature deindustrialization. Our detailed description of the different types of deindustrialization can be used by policymakers to assess their own economy and to justify potential claims of premature deindustrialization. Any assessment of a country's type of deindustrialization is not possible without a thorough understanding of the underlying model and concepts. Although our results proved statistically significant, policymakers should draw conclusions with care as there will surely be country cases in which a clear classification will be too close to call. We hope that with our contribution, the concept of premature deindustrialization will gain further prominence both within academic as well as in policy-related spheres.

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Appendix A – Data

The main source of sectoral value added is the United Nations' National Accounts Main Aggregates Database (United Nations Statistical Division, 2017). The database contains national accounts data on essentially all countries and their individual sectors from 1970 to 2016. Using this database has the advantage that it presents a global picture of sectoral value added and its changes over time based on consistently compiled data and not based on any estimation of the authors. Unfortunately, the database does not include any disaggregated manufacturing value added (ISIC D) data for China prior to 2004 and includes no data for Taiwan, Province of China. Given the importance of China due to its large size and the rapid growth of the Chinese manufacturing sector in the late 20th century, we substituted the data for China's economy with MVA and GDP data from the Groningen Growth and Development Centre's 10-Sector Database. This database reports MVA and GDP in current values of local currencies. However, as we only use the share of MVA in GDP and not nominal values, we deemed this to be acceptable. We further used this database to substitute for the missing data of Taiwan, Province of China, in the UNSD database. To compare the level of industrialization to levels of income, we used per capita output-side real GDP at chained PPPs (in 2011 US$) from the Penn World Table (PWT) of the Groningen Growth and Development Centre (Feenstra, Inklaar, & Timmer, 2015). The most recent PWT version 9 includes data for 182 countries between 1950 and 2014.

Small Island States and other smaller states with a population of less than one million in 2014 were excluded. Setting the cut-off year at 2014 has the important implication that countries with a population of less than one million in earlier years are still included. In the case of Mauritius, for example, the population surpassed one million inhabitants in 1984. Yet all observations for Mauritius prior to that point are still included in our sample despite the fact that the country's population is actually below one million. Additionally, countries with an MVA share of more than 50 per cent or less than 1 per cent were considered extreme outliers and subsequently dropped from the analysis. This included Turkmenistan and Tajikistan (for more than 50 per cent) as well as Liberia and Oman (for less than 1 per cent). Small oil producing countries, which include Qatar, Kuwait and the United Arab Emirates, were also considered outliers based on their large per capita GDP. Lastly, the Democratic Republic of the Congo was excluded due to conflict affected numbers.

This leaves a final database of 139 countries for a period of 45 years between 1970 and 2014 (with the exception of China and Taiwan, Province of China, for which data is only available until

2011 and 2012, respectively, as well as the former USSR and Ex-Yugoslavian countries, for which data is only available from 1990 onwards)[8]. These 139 countries account for 95 per cent of the world's population.

For comparison purposes, the same analysis was carried out using MVA share of GDP data from the UNIDO INSTAT 2 database. The regression estimates yielded similar results, but were subsequently dropped from the analysis as the INSTAT 2 database only has data from 1990 onwards.

[8] Countries covered are: Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Belarus, Belgium, Benin, Bolivia (Plurinational State of), Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Côte d'Ivoire, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, China, Hong Kong SAR, Colombia, Congo, Costa Rica, Croatia, Czechia, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Haiti, Honduras, Hungary, India, Indonesia, Iran (Islamic Republic of), Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kyrgyzstan, Lao People's DR, Latvia, Lebanon, Lesotho, Lithuania, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Republic of Korea, Republic of Moldova, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Serbia, Sierra Leone, Singapore, Slovakia, Slovenia, South Africa, Spain, Sri Lanka, State of Palestine, Sudan (Former), Swaziland, Sweden, Switzerland, Syrian Arab Republic, Taiwan, Province of China, TFYR of Macedonia, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, U.R. of Tanzania: Mainland, Uganda, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela (Bolivarian Republic of), Viet Nam, Yemen, Zambia, Zimbabwe.

Appendix B – Country fixed effects dummies

The table below reports the country fixed effects dummy for each country of our dataset. Zimbabwe does not have a coefficient as one country case has to be excluded due to singularities.

Country	FE dummy	Country	FE dummy	Country	FE dummy
Albania	-0,003144	Ghana	-0,105429	Paraguay	0,014109
Algeria	-0,152948	Greece	-0,051228	Peru	-0,074399
Angola	-0,130882	Guatemala	-0,008816	Philippines	-0,023383
Argentina	-0,032600	Guinea	-0,097221	Poland	-0,014714
Armenia	0,055737	Guinea-Bissau	0,072064	Portugal	-0,026062
Australia	-0,060632	Haiti	-0,021453	Republic of Korea	-0,011694
Austria	0,040303	Honduras	0,030054	Republic of Moldova	0,053780
Azerbaijan	-0,069103	Hungary	0,018682	Romania	0,069467
Bahrain	0,125303	India	-0,186238	Russia	-0,116010
Bangladesh	-0,137106	Indonesia	-0,128958	Rwanda	-0,066200
Belarus	0,091335	Iran	-0,140879	Saudi Arabia	-0,107365
Belgium	0,021956	Iraq	-0,145745	Senegal	-0,025792
Benin	-0,012603	Ireland	0,073261	Serbia	0,027053
Bolivia	-0,029690	Israel	0,033634	Sierra Leone	-0,065341
Bosnia and Herzegovina	-0,001757	Italy	-0,058665	Singapore	0,122436
Botswana	-0,001696	Jamaica	0,014679	Slovakia	0,083002
Brazil	-0,097186	Japan	-0,030916	Slovenia	0,155433
Bulgaria	0,014762	Jordan	0,003497	South Africa	-0,072680
Burkina Faso	-0,035075	Kazakhstan	-0,071408	Spain	-0,064614
Burundi	-0,007662	Kenya	-0,076478	Sri Lanka	-0,041905
Cote d'Ivoire	-0,037077	Kyrgyzstan	0,041387	Palestine	0,047150
Cambodia	-0,050203	Lao People’s DR	-0,058860	Sudan (Former)	-0,152995
Cameroon	-0,053351	Latvia	0,075525	Swaziland	0,227555
Canada	-0,060065	Lebanon	-0,036106	Sweden	0,036593
Central African Republic	0,078011	Lesotho	0,048358	Switzerland	0,065063
Chad	-0,048565	Lithuania	0,081015	Syria	-0,116869
Chile	-0,051038	Madagascar	-0,087195	Taiwan, Province of China	0,109793
China	-0,021018	Malawi	-0,000834	Macedonia	0,025680
Hong Kong, SAR	-0,030349	Malaysia	0,014502	Thailand	-0,019053
Colombia	-0,093080	Mali	-0,042889	Togo	-0,032642
Congo	-0,027172	Mauritania	-0,016620	Trinidad and Tobago	0,102940
Costa Rica	0,066291	Mauritius	0,124979	Tunisia	-0,029752
Croatia	0,041889	Mexico	-0,106470	Turkey	-0,066175
Czechia	0,071548	Mongolia	0,026400	Tanzania	-0,125988
Denmark	0,011665	Morocco	-0,056766	Uganda	-0,110986

Country	FE dummy	Country	FE dummy	Country	FE dummy
Dominican Republic	0,078366	Mozambique	0,015425	Ukraine	-0,028741
Ecuador	0,000178	Myanmar	-0,126575	United Kingdom	-0,097463
Egypt	-0,103250	Namibia	0,029353	United States	-0,132247
El Salvador	0,062345	Nepal	-0,132387	Uruguay	0,051854
Estonia	0,123146	Netherlands	-0,033922	Uzbekistan	-0,037413
Ethiopia	-0,176399	New Zealand	0,071155	Venezuela	-0,011802
Finland	0,079081	Nicaragua	0,019667	Viet Nam	-0,099702
France	-0,105372	Niger	-0,087506	Yemen	-0,106628
Gabon	0,009601	Nigeria	-0,224799	Zambia	-0,005278
Gambia	0,045091	Norway	0,000898		
Georgia	0,003145	Pakistan	-0,184692		
Germany	-0,030532	Panama	0,015824		