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Manufacturing in Structural Change in Africa

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Abstract

This paper investigates the scale, causes, and timing of significant episodes of industrialization and deindustrialization in Sub-Saharan Africa. Recent studies have argued that the turning point of manufacturing output and employment shares tends to occur prematurely in this region. The analysis is performed using panel data methods for fractional responses and data from a variety of sources for a panel of 41 African countries. The results overwhelmingly do not support the common finding that Sub-Saharan African countries have begun to deindustrialize. Moreover, the study documents meaningful heterogeneity across Sub-Saharan Africa subregions, with the Southern region being the only subregion to have witnessed deindustrialization. However, this deindustrialization of the Southern subregion does not appear to be occurring prematurely. The study also explores the potential role of the Dutch disease and resource curse hypotheses in understanding Sub-Saharan Africa's manufacturing experience in resource rich countries.

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1 Introduction

It is commonly agreed among economists that industrialization is the cornerstone of economic development (Kaldor 1966, 1967). In advanced economies, industrialization enabled sustained productivity growth as well as economic convergence among both the western and European countries such as the United States and Great Britain as well as non-western countries like Japan, China, South Korea and Taiwan (Rodrik 2009). Defined as the share of manufacturing in economy-wide output or employment, the level of industrialization is known to typically follow an inverted U-shaped path over the course of development, where the turning point corresponds to the threshold at which manufacturing exhausts its function as the main driver of economic growth (Rodrik 2012). Recent studies have documented that the turning point of manufacturing output and employment shares tends to occur "prematurely" in certain developing countries. In this vein, deindustrialization is said to have occurred prematurely if manufacturing shrinks at levels of income that are much lower than those at which the advanced economies started to deindustrialize. While Rodrik (2016) documents premature industrialization in sub-Saharan Africa (SSA) and Latin America, he concludes that high-income countries have not suffered the same fate. However, given that Rodrik (2016)'s sample includes a limited number of sub-Saharan African countries, it is quite possible that these conclusions do not apply to many or even most countries of the region, or that they are missing some of the specific characteristics of individual countries.

In this paper, we study cross-country patterns and trends in the share of manufacturing in national output and employment among sub-Saharan African countries. We investigate the extent to which countries differ in terms of the timing, causes, and consequences of industrialization or "deindustrialization." Indeed, the fact that development policies are always framed, implemented and evaluated at the subregional and/or country levels suggests that the questions raised in this paper should also be addressed at finer geographic (aggregate) levels. Moreover, since countries are heterogeneous in terms of regional trade clusters, availability of skills, and natural resource endowment, it is important to exploit such richness and nuances to draw conclusions accordingly. More specifically, the analysis in this paper is organized around the following questions. (i) What are the main cross country patterns and trends in the share of manufacturing in national output and employment? Do these patterns suggest a process of industrialization or de-industrialization in specific countries, in specific sub-regions, or at the regional level? (ii) What are the main determinants of the observed outcomes of de-industrialization in these locations, and what are their quantitative effects? (ii) Are there other channels that might have led to the observed (de)industrialization patterns? This means, for example, looking at whether there are evidence on the implication of the Dutch disease and resource-curse hypotheses to the outcome of industrialization in resource rich countries.

Manufacturing has been touted as a key driver for economic development, especially for developing countries (Kuznets 1953, Matsuyama 1992). Jones & Olken (2008) examines the allocation of resources underlying economic growth, documenting that movements into and out of the labor force in manufacturing tend to coincide with accelerations and decelerations in the growth rate. In examining the constraints for sustained growth in Africa based on a comparison to benchmark countries (e.g., Indonesia and Thailand), Johnson, Ostry & Subramanian (2007) finds that, in almost all cases, these benchmark countries have escaped poverty through manufacturing exports, and posits that the manufacturing sector may be crucial for sustained growth in Africa. A small but growing literature documents the manufacturing experience of developed and developing countries with particular emphasis on the evolution of manufacturing output and employment shares. Dasgupta & Singh (2007) examines data for a set of 14 developing countries for the period 1986-2000, and finds evidence of deindustrialization, that is, manufacturing tends to monotonically increase with per capita income until it peaks and begins to decline.[1] They also note that such deindustrialization appears to occur at lower levels of income than developed countries. Similar findings have emerged for Indian states, where Amirapu & Subramanian (2015) document premature deindustrialization and reports that by 2010, manufacturing employment shares peaked at about 45 percent of the corresponding 1988 turning point value. To our knowledge, the only study examining deindustrialization in SSA is Rodrik (2016), which uses a larger set of countries (albeit only 11 African countries are included) and comes to a similar premature deindustrialization for Sub-Saharan Africa and Latin America.

Thus, there is a dearth of literature focused on sub-Saharan Africa's manufacturing experience, and those that do have utilized a limited number of SSA countries due to data inadmissibility. This paper attempts to fill this void by assembling data on 41 sub-Saharan African countries from multiple sources including the Groningen Growth and Development Center 10-sector Database, the Maddison Project Database, the World Development Indicators, and the International Labor Organization's ILOSTAT database. Our data spans 1960-2016, which is the longest panel data on output and employment shares on Sub-Saharan African countries to our knowledge. If sub-Saharan African countries are experiencing prematurely deindustrialization, this has potentially negative ramifications for the region's economic development.

[1] See also Dasgupta & Singh (2005).

Our main dependent variable of interest at any level of aggregation is the level of industrialization defined as the share of manufacturing in economy wide GDP or in economy wide aggregate employment. To adjust for possible resource boom, we also consider the manufacturing's percentage contribution to non-oil GDP for the restricted set of oil-exporting countries. Given that these variables are bounded (i.e. these are fractional response variables) we perform our analysis using both the linear fixed-effects panel data model - which is subject to pitfalls similar to linear probability models - as well as the "fixed-effects fractional logit" model recently developed by Hardin, Hardin, Hilbe & Hilbe (2007). Our results overwhelmingly do not support the finding that SSA countries have began to deindustrialize prematurely. Moreover, we document meaningful heterogeneity across SSA subregions. The Southern region is found to be the only subregion to have witnessed deindustrialization. However, we are unable to confirm that this deindustrialization in the Southern region of SSA is premature. The rest of the paper is organized as follows. Section 2 presents the data. Section 3 discusses the relevant methodological issues. Section 4 presents the main results. Section 5 explores geographic heterogeneity. Section 6 considers potential hypotheses and Section 7 concludes.

2 Data and Descriptive Analysis

This section describes the data sources used for the analysis and provides summary statistics as well as trend analysis of our main indicators.

2.1 Data Sources and Measurements

The data for this study come from a variety of sources. The data for manufacturing valued added and manufacturing employment come from the Groningen Growth and Development Center 10-sector Database (Timmer, de Vries & de Vries 2015). The GGDC Database collects time series data on value added and employment for ten broad sectors of the economy for 42 countries (both developed and developing) spanning 1950 through 2012.[2] The advantage of the GGDC is that it provides a long-run series of sectoral productivity that is internationally comparable across a broad range of countries. However, the GGDC's Africa Sector Database (ASD) only includes eleven sub-Saharan African countries.[3] Thus, for other sub-Saharan African countries, we collect manufacturing value added and GDP time series from

[2]This period of data availability is as of September, 2017.

[3]The Sub-Saharan African countries in the ASD are Botswana, Ethiopia, Ghana, Kenya, Malawi, Mauritius, Nigeria, Senegal, South Africa, Tanzania, and Zambia.

the World Bank's World Development Indicators (WDI). The income and population data for all countries come from the 2018 version of the Maddison Project Database, which provides historical income statistics for 169 countries through 2016 (Bolt, Robert Inklaar & van Zanden 2018). The income figures are at constant 2011 US dollars. Our main analysis sample is an unbalanced panel of 41 sub-Saharan African countries over the period 1960 through 2016.

We also contrast our main results with the analysis of the evolution of manufacturing in non-oil GDP series for a smaller subset of countries. For 38 countries in our main sample (excluding Equitorial Guinea, Sudan, and Swaziland), we collect data on real growth rates of non-oil GDP, oil revenues as a percent of GDP, and real effective exchange rates from the International Monetary Fund (IMF)'s Africa Regional Economic Outlook (AFRREO) Fall 2018 database for the period 2004 through 2016. The AFRREO Fall 2018 database is in turn based on the statistical appendix of the Regional Economic Outlook (Sub-Saharan Africa) of the Fall 2018 World Economic Outlook (WEO).[4] We utilized the real growth rates of non-oil GDP data series to recover estimates of the manufacturing output shares in non-oil GDP. Finally, for the purpose of testing the implications of the Dutch Disease for countries with significant oil-exporting and agricultural sectors, we collect data on the monthly minimum wages from the International Labor Organization's ILOSTAT Database for Cameroon, Ghana, Nigeria, and South Africa.

Three measures of industrialization are commonly employed in the literature, namely the share of manufacturing valued added in GDP at constant prices (RMVA), the share of manufacturing valued added in GDP at current prices (CMVA), and the share of manufacturing employment in economy-wide employment (EMP). We focus on RMVA and EMP for our substantive statistical analysis since the trend in the share of manufacturing valued added in GDP at current prices derives from movements in both price and quantity that are indistinguishable to the researcher. While the manufacturing share at current prices conflates price and quantity, the real manufacturing output share adjusts for general movements in prices over time, and thus, is more reliable for understanding structural changes in industrialization and the economy. The real manufacturing output shares are at constant 2005 national prices. Also, since WDI does not include data on manufacturing employment, our employment analysis is limited to the aforementioned eleven countries in the GGDC's Africa Sector Database. To account for possible natural resource boom, we also examine the trends and patterns of the share of manufacturing value added in non-oil GDP (RMVA-NOIL). This could be important in separating the

[4]As of January 2019, the AFRREO Fall 2018 Database is accessible at https://www.imf.org/external/datamapper/datasets/AFRREO.

trends in manufacturing output shares that may arise from the sheer increase in GDP due to the oil boom as discussed in Fardmanesh (1991). Put differently, by subtracting oil's contribution from GDP, it is possible to isolate the manufacturing sector's true trajectory as a country develops.

2.2 Trends and Patterns at Country Levels

We explore the trends and patterns of these industrialization measures across Sub-Saharan Africa countries, alongside other factors. We begin our analysis by summarizing manufacturing and employment shares for the sub-Saharan African countries for which data are available. The Appendix Tables A.1 and A.2 present the means of the share of manufacturing value added in GDP (constant prices) and the manufacturing employment shares, respectively, for each country in our sample across the six decades for which data are available. As one would expect, these tables reveal significant heterogeneity in the trends of all three measures with some countries experiencing increasing, decreasing, or stable trends while others witnessed a mixed combination of trends across the decades. By eyeballing the means in Table A.1, a majority of seventeen countries appear to have a relatively stable share of manufacturing value added in GDP. Ten countries appear to have experienced declines while seven countries show an increasing trend in RMVA over the decades. Also, five countries seem to be consistent with an inverted U-shaped trend while the remaining two countries show an initial rising trend that stabilized in latter decades. The manufacturing employment shares exhibit similar heterogeneity in trends (Table A.2).

To motivate our analysis, we depict the evolution of deindustrialization with respect to per capita income. Figures 1 and 4 display scatter plots of the shares of manufacturing output in GDP and non-oil GDP, respectively, as functions of GDP per capita (with fitted quadratic trends). While the fitted quadratic trend in manufacturing output shares in Figure 1 shows a weak semblance of an inverted U-shaped relationship, the scatter plot for manufacturing output shares in non-oil GDP in Figure 2 is suggestive of a rather U-shaped relationship with respect to per capita income. While this exercise is purely descriptive, it is also suggestive of plausibly different trajectories for manufacturing trends depending on whether one examines GDP versus non-oil GDP. In particular, this contrast is more obvious for our four countries with significant oil-exporting sectors (Cameroon, Ghana, Nigeria, and South Africa) displayed in Figure 3. Mechanically, the manufacturing output shares in GDP versus non-oil GDP mirror each other but Figure 3 shows that while the former is stable for Cameroon, it is increasing for Nigeria, and decreasing for Ghana and South Africa. Again, the goal here in examining the time series in Figure 3 is to illustrate the point that manufacturing output shares

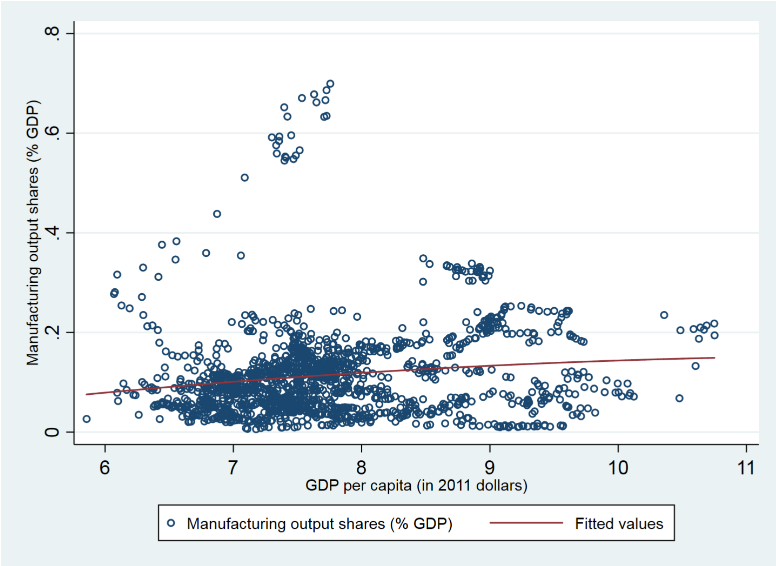


Figure 1: Manufacturing output shares (% GDP) and GDP per capita

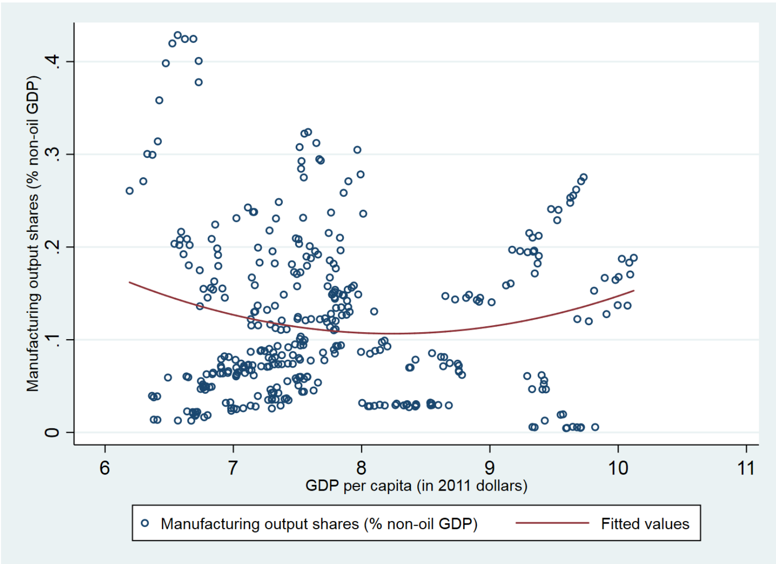
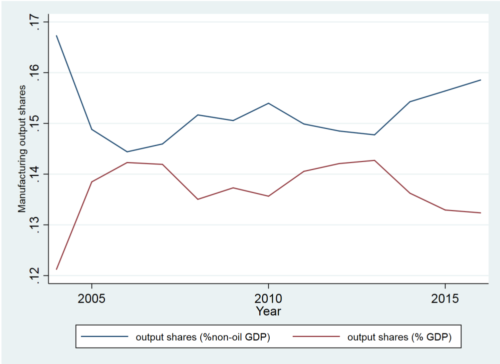


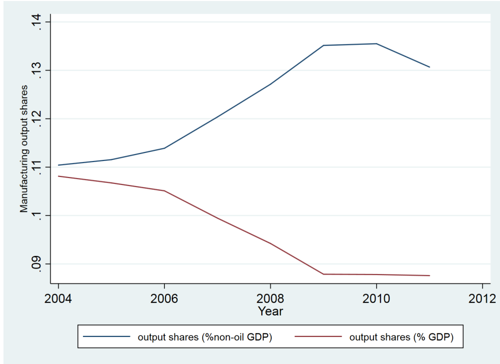
Figure 2: Manufacturing output shares (% non-oil GDP) and GDP per capita

can potentially take a different trajectory when we take into account oil resources.

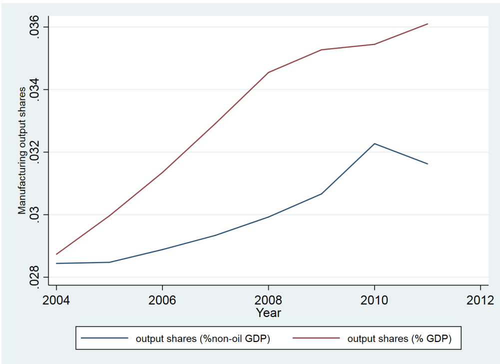
Turning our attention to manufacturing employment shares, Figure 4 depicts an increasing trend with the level of per capita income. Again, these observations are descriptive and only serve to foreshadow our main statistical analysis.



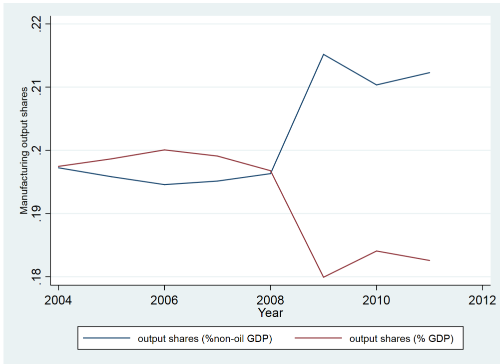
(a) Cameroon



(b) Ghana



(c) Nigeria



(d) South Africa

Figure 3: Evolution of manufacturing output shares (% GDP and % non-oil GDP) for selected African countries (2004-2016)

2.3 Trends and Patterns at Subregional Levels

We now present regional summaries of the share of manufacturing valued added in GDP in Table 1. For the remainder of this paper, subregional analysis are only performed for RMVA (and not EMP) due to the limited availability of employment shares data as noted previously. We follow the geographic SSA subregions of the African Union, namely West Africa, East Africa, Central Africa, and Southern Africa (for the manufacturing output shares only).[5] Table 1 reveals a more consistent pattern at the subregional level; that is, the share of manufacturing value added in GDP (constant prices) appears to follow an inverted U-shape. For West Africa, RMVA rises from 0.08 to 0.12 and declines to 0.07 by the 2010s. The other

[5]See Table A.3 for a list of sub-Saharan African countries in our sample and their respective geographic subregional groups.

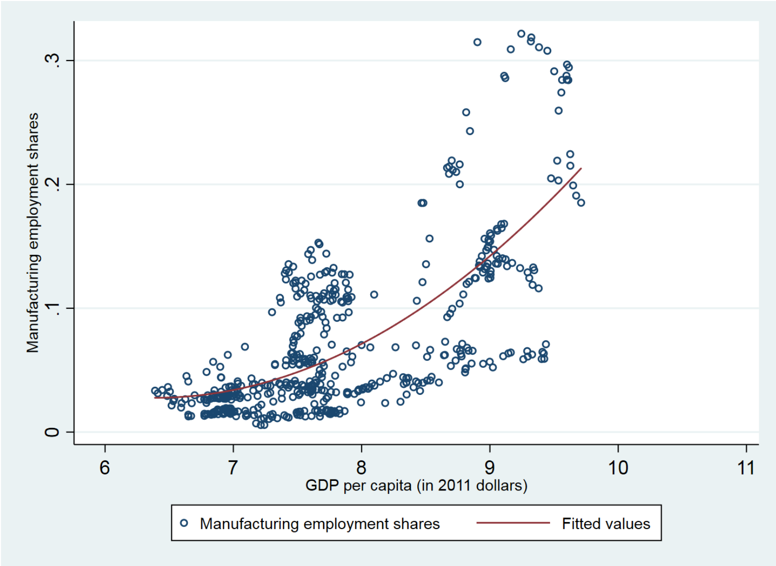


Figure 4: Manufacturing employment shares vs GDP per capita

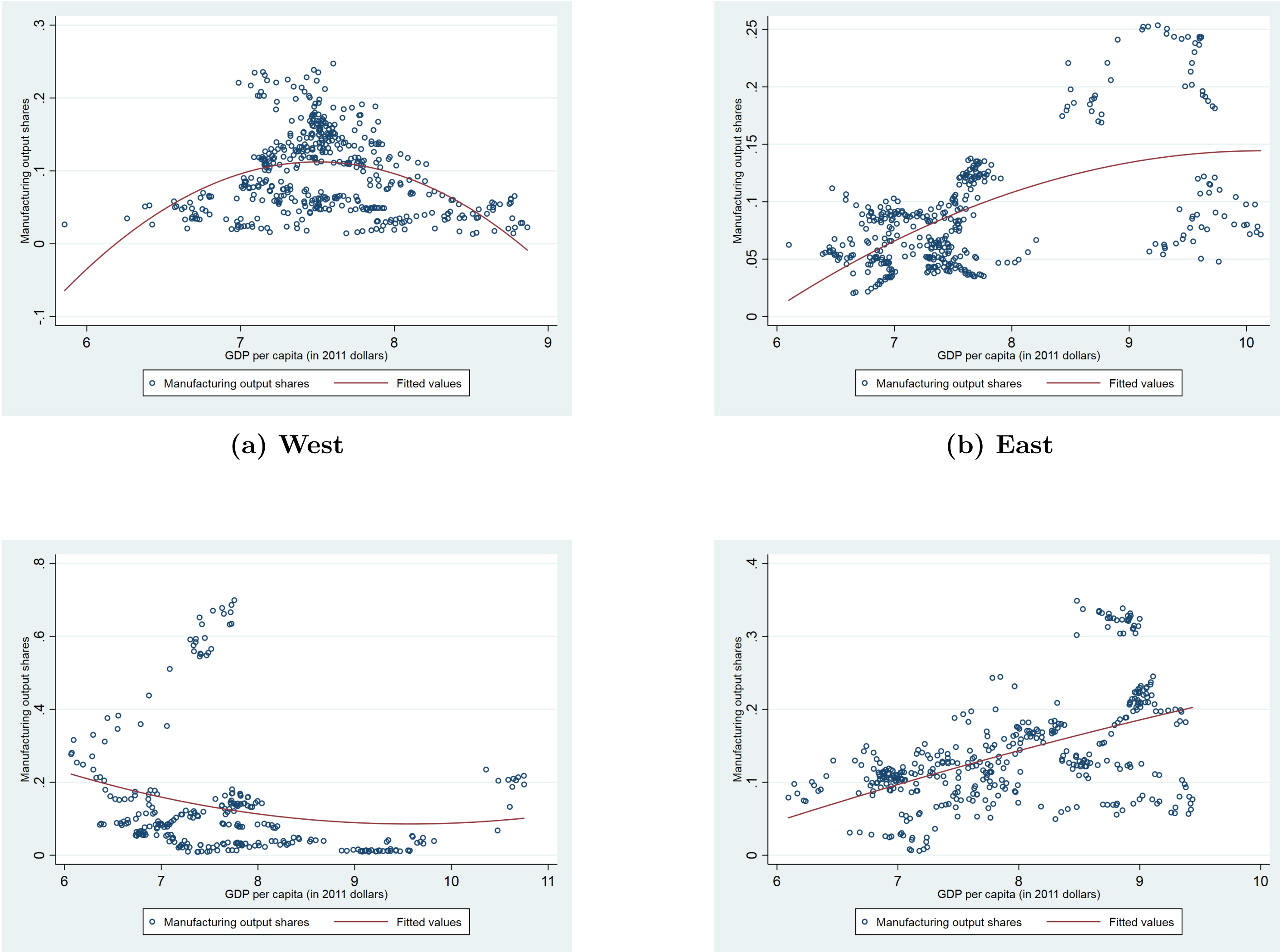
regions follow a similar pattern with East Africa rising from 0.07 through 0.09 to 0.08; Central Africa moving from 0.16 to a high of 0.25 before declining to 0.09; and Southern Africa increasing from 0.11 through 0.15 to 0.14. For all countries, Table 1 unsurprisingly shows that the same inverted U-shape persists with RMVA beginning from 0.10 in the 1960s, reaching a high of 0.15 in the 1970s and declining afterwards to 0.10 in the 2010s.

These observations are generally reflected in Figure 5, which depicts the scatter plots of the shares of manufacturing output as a function of GDP per capita (with fitted quadratic trends) for the SSA subregional groupings. Except for Central Africa, the fitted quadratic trend in Figure 5 highlights an inverted U-shaped relationship between RMVA and per capita income at the subregional level. Obviously, these eyeball tests do not accurately depict the underlying, structural aggregate trends in manufacturing output and employment shares in SSA and we conduct formal statistical tests momentarily.

Table 1: Regional variation in Manufacturing Value Added (% of GDP)

	1960s	1970s	1980s	1990s	2000s	2010s
West Africa	0.08	0.12	0.11	0.11	0.09	0.07
Observations	24	63	75	99	121	82
Number of countries	3	7	8	10	14	14
East Africa	0.07	0.09	0.09	0.09	0.09	0.08
Observations	30	62	88	90	90	38
Number of countries	4	7	9	9	9	9
Central Africa	0.16	0.25	0.17	0.13	0.1	0.09
Observations	12	32	50	53	76	61
Number of countries	3	4	5	6	9	9
Southern Africa	0.11	0.13	0.14	0.14	0.15	0.14
Observations	26	69	80	89	90	40
Number of countries	5	7	8	9	9	9
Sub-Saharan Africa (All SSA)	0.11	0.15	0.13	0.12	0.11	0.10
Observations	92	226	293	331	377	221
Number of countries	15	25	30	34	41	41

The table reports SSA regional mean shares of manufacturing output shares in GDP (constant prices) for each south-Saharan African country by decade (e.g., 1960-1969, etc) based on our main sample of 41 SSA countries. Each column represents decade-specific mean shares followed (on the corresponding rows) by the number of countries in each region as well as the number of years for which data are available. See Table A.3 for a list of the SSA countries belonging to each of the four subregional groups in our sample.



(a) **West** (b) **East**

(c) **Central** (d) **Southern**

Figure 5: Subregional scatter Plot of manufacturing employment shares as a function of GDP per capita

3 Methodological Issues

The previous section explored the trends and patterns of industrialization or deindustrialization by eyeballing the trends in the shares of manufacturing value added and employment in GDP and economy-wide employment. This section pursues various statistical approaches to provide rigorous evidence of industrialization and/or (premature) deindustrialization in Sub-Saharan Africa and studies its determinants. Several economic phenomena are non-monotonic and commonly follow either a U-shaped or an inversed U-shaped relationships. While some of these relationships are grounded in theory, others tend to the subject of much empirical investigation. Classic examples of inverted U-shapes in economics include the Laffer Curve (the relationship between the rate of taxation and the level of government revenue) and the Kuznets Curve (the relationship between income and inequality). The nature of the relationship between the shares of manufacturing in GDP (or aggregate employment) and per capita income is theoretically ambiguous and is thus an empirical question.

To investigate non-monotonic relationships, it is standard to include some polynomial (typically quadratic terms) in the vector of covariates within a linear regression framework. Since we are interested in the trend of manufacturing relative to income, we follow Rodrik (2016) by including the logarithm of population (POP) and per capita GDP ($GDPPC$) as well as their respective quadratic terms in our vector of control variables. Thus, the basic econometric framework can be described by

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 log(GDPPC)_{it} + \beta_2 log(GDPPC)^2_{it} + \\ &\quad \beta_3 log(POP)_{it} + \beta_4 log(POP)^2_{it} + \boldsymbol{X_{it}\gamma} + \alpha_i + \varepsilon_{it}, \end{aligned} \tag{1}$$

where Y_{it} denotes any of our dependent variables of interest for country i at time t, $\boldsymbol{X_{it}}$ is a set of country-specific, time-varying explanatory variables (which may include time trends), α_i are country fixed effects, and ε_{it} is the idiosyncratic error term.

There are a number of econometric challenges to investigating whether manufacturing follows an inverted U-shape or not in equation (1). The first challenge concerns the appropriate approach for testing for the presence of an inverted U-shaped relationship. The most common approach in the literature is to specify a regression equation such as equation (1) and conclude based on the sign and statistical significance of the coefficients estimates of β_1 and β_2. For instance, if both coefficients are statistically significant and $\hat{\beta}_1 > 0$ while $\hat{\beta}_2 < 0$, then one concludes an inverted U-shape exists (provided the estimated extremum is within the data range). However, Lind & Mehlum (2010) argues painstakingly that the aforementioned procedure is a weak and deeply flawed test for U-shaped or inverted U-shaped relationships. They suggest a new test based on prior work by Sasabuchi (1980), which we employ in this study as further described below. The second challenge in estimating the parameters of equation (1) is that the dependent variable of interest is bounded (i.e., it is a fractional response variable), thus, requiring an appropriate functional form specification. In fact, using linear models for fractional outcome a is subject to the same drawbacks and pitfalls as those related to linear probability models (LPM) for binary outcome. Finally, the fact that we have repeated measures on each country over time (longitudinal data) poses a peculiar difficulty for estimating fractional response models. While the panel structure of the data can be exploited to address unobserved heterogeneity in explaining the evolution of manufacturing shares in output and employment, the unbalanced nature of the panel poses special (often ignored) difficulties when the dependent variable is fractional as in this study. Panel data methods suitable for explaining fractional responses in the context of panel data is an active area of ongoing research. Papke & Wooldridge (1996)'s seminal work proposed direct methods for explaining the conditional mean of a fractional response using quasi-maximum likelihood estimation methods in cross section data. Such methods have come to be known as "fractional logit" models and have been applied widely. Papke & Wooldridge (2008) extends these methods to balanced panel data contexts by employing the Chamberlain-Mundlak device (Mundlak 1978, Chamberlain 1980) to handle the unobserved effects. Although an important advancement in the literature, Papke & Wooldridge (2008)'s work is limited to balanced panel data scenarios as they remark that, "[t]he nonlinear models we apply are difficult to extend to unbalanced panel data-a topic for future research."

In this paper, we employ the "fixed effects fractional logit" model (Wagner 2003, Hardin et al. 2007, Hausman & Leonard 1997). In particular, if we denote the logistic CDF with $\Lambda[.]$, then the conditional expectation of the manufacturing shares takes the form

$$\begin{aligned}\mathbb{E}[Y_{it}|X_{it},\alpha_i] &= \Lambda\big[\beta_0+\beta_1 log(GDPPC)_{it}+\beta_2 log(GDPPC)^2_{it}+\\ &\quad \beta_3 log(POP)_{it}+\beta_4 log(POP)^2_{it}+\boldsymbol{X_{it}\gamma}+\alpha_i\big]. \qquad (2)\end{aligned}$$

As noted by Hausman & Leonard (1997), this specification is not subject to the incidental parameters problem if we assume that the cross sectional units (i.e., countries) are fixed while the number of years per country goes to infinity, which seems natural in our case.[6] Because the logistic CDF is strictly monotonic, the regression coefficients give the direction of the marginal effects. Also, notice that the predicted manufacturing shares based on equation (2) are constrained to the unit interval.

4 Deindustrialization in Sub-Saharan Africa?

This section presents the regression results based on equation (2) for our measures of deindustrialization. Tables 2 and 3 show the coefficients estimates as well as the estimated average marginal effects for real manufacturing output shares and manufacturing employment shares, respectively. Panels A and B of Table 2 further break down these results by the full sample and low-exporting SSA countries, respectively. We classify countries as low-exporting countries if across their respective years of available data, their average shares of manufacturing in total volume of exports exceeds 50 percent. For this subgroup analysis, the excluded high-exporting countries in our sample are Botswana, Lesotho, Swaziland, Cape Verde, and Mauritius. It is important to examine results by this dichotomy because the premature deindustrialization results for sub-Saharan Africa in Rodrik (2016) depend crucially on whether Mauritius, a high-exporting country is included in the sample or not. Rodrik (2016) remarks that "[f]inally, the estimates for sub-Saharan Africa depend heavily on whether Mauritius – a strong manufactures exporter – is included in the sample or not. Without Mauritius in the sample, sub-Saharan African countries emerge as large losers on all three measures of industrialization." We argue that SSA's manufacturing experience is more nuanced than whether a single country is included or not and varies meaningfully across countries and geographic subregions.

For both Panels A and B in Table 2, the coefficient estimates for β_1 and β_2 are statistically significant and suggest that RMVA is inversely U-shaped based on their signs following the conventional test. The turning points occur at around \$7,500 (constant 2011 US dollars) and the Lind & Mehlum (2010) test confirms an inverted U-shaped relationship. For comparison, the turning point at which manufacturing output shares falls for Rodrik (2016)'s full sample is above \$70,000 (1990 US dollars), which is admittedly implausible as it falls outside the data range in his paper. The corresponding turning point for Indian and African countries is reported to be around \$700 Rodrik (2016). Also, using data on 135 economies, Felipe, Mehta & Rhee (2014) finds evidence of deindustrialization, with manufacturing output shares declining after about \$2000 (constant 2000 US dollars). Thus,

[6] Also, see Wooldridge (2018) for a more recent discussion of Chamberlain-Mundlak style strategies for dealing with unobserved heterogeneity in unbalanced panel data.

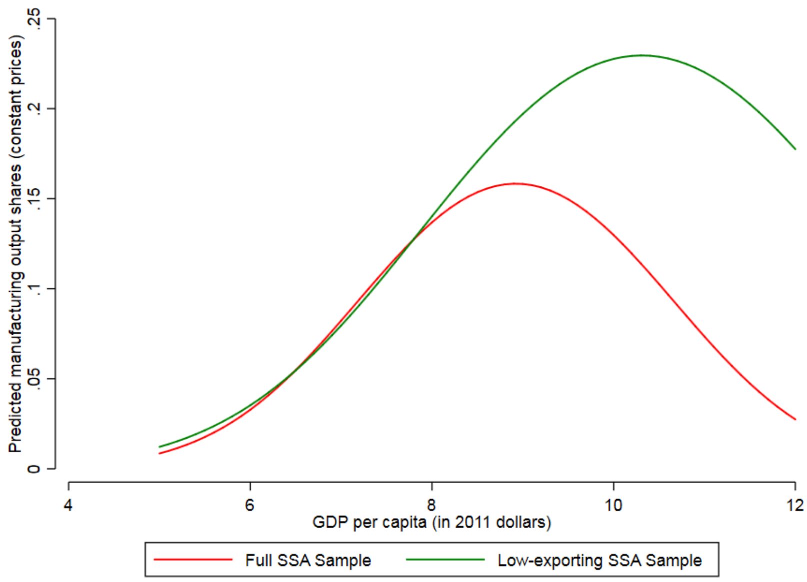


Figure 6: Predicted manufacturing shares (constant prices) as a function of GDP per capita (in 2011 dollars)

while there are discrepancies regarding the turning point at which manufacturing output shares falls, the results suggest SSA has deindustrialized.

However, the results in Panel B when we exclude the high-exporting countries depicts a weaker U-shaped relationship. Although the conventional test still suggests an inverted U-shape, the Lind & Mehlum (2010) test indicates a much weaker relationship; the slope at the maximum GDP per capita is positive and statistically not significant; the overall Lind & Mehlum (2010) U test is also not statistically significant. Also, RMVA now peaks at about $30,000 (which is much closer to the maximum value in the sample). As depicted in Figure 6, which plots the predicted RMVA using the estimates from Table 2, the predicted RMVA shows an inverted U-shape for the full sample while that of the low-exporting countries shows a much weaker relationship. Put together, although we find evidence that SSA has deindustrialized on the basis of manufacturing output shares, this finding may be driven by a smaller subset of countries (we return to this point in the next section).

Finally, the manufacturing employment shares results in Table 3 are not consistent with an inverted U-shape. The coefficient estimate on the quadratic term in GDP per capita in Table 3 is positive and statistically significant at the 10% significance level. Again, the Lind & Mehlum (2010) test trivially rejects an inverted U-shape and we do not report the results. Thus, we find conflicting evidence re-

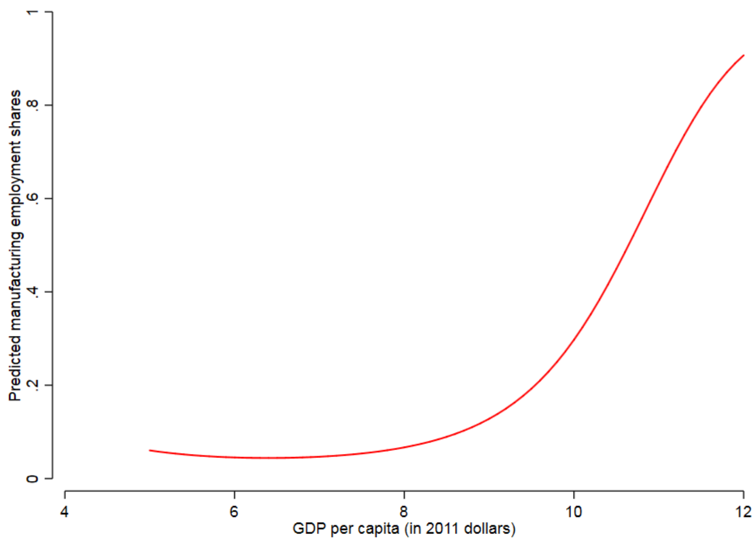


Figure 7: Predicted employment shares as a function of GDP per capita (in 2011 dollars)

garding output and employment shares, with the former showing weak evidence for deindustrialization while the latter showing none. Felipe et al. (2014) also notes the differential results for output and employment shares in their sample. Our results highlight one important point, that is, the evidence regarding premature deindustrialization (in output and employment shares) in the literature may not be as robust as previously understood.

Overall, the results so far demonstrate that unlike previous studies, we do not find an overwhelming evidence that manufacturing in sub-Saharan Africa follows an inverted U-shape, except for the full sample using RMVA. Even in the case of the RMVA finding, our results contrast with Rodrik (2016) who documents an inverted U-shape relationship for sub-Saharan Africa only after excluding Mauritius. We find that excluding high-exporting countries works in the opposite way as the U-shape relationship weakens (or vanishes per Lind & Mehlum (2010)'s test). Our interpretation is that these findings are indicative of important geographic variation in deindustrialization and we explore this further in the next section at the SSA subregional level.

Table 2: Manufacturing value added as percent of GDP (constant prices) regressions

	Panel A: All SSA		Panel B: Low-exporting countries	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Panel A: Regression Estimates				
Population (logarithm)	2.827**	-0.039	3.122**	-0.011
	(1.148)	(0.031)	(1.437)	(0.035)
Population squared (logarithm)	-0.104***		-0.102**	
	(0.040)		(0.049)	
GDP per capita (logarithm)	3.576***	0.042***	2.328***	0.055***
	(0.899)	(0.007)	(0.859)	(0.011)
GDP per capita squared (logarithm)	-0.200***		-0.113**	
	(0.057)		(0.053)	
Intercept	-36.523***		-36.887***	
	(9.767)		(12.278)	
Panel B: Lind & Mehlum (2010) U Test				
Slope at minimum GDP per capita (logarithm)	1.229***		0.958***	
	(0.244)		(0.238)	
Slope at maximum GDP per capita (logarithm)	-0.732**		0.043	
	(0.366)		(0.257)	
Lind & Mehlum (2010) Test statistic	2.180		0.31	
	[0.015]		[0.377]	
Observations	1540	1540	1293	1293
Number of countries	41	41	36	36
Country Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses and p-values in square brackets. Results based on fixed effects fractional logistic regressions in equation (2).
$*p < 0.10, **p < 0.05, ***p < 0.010$

Table 3: Manufacturing share of total employment regressions

	Coefficients	Marginal Effects
Population squared (logarithm)	2.390	0.130***
	(2.855)	(0.040)
Population (logarithm)	-0.011	
	(0.096)	
GDP per capita (logarithm)	-2.177	0.041***
	(1.553)	(0.013)
GDP per capita squared (logarithm)	0.170*	
	(0.095)	
Intercept	-27.114	
	(22.918)	
Observations	523	523
Number of countries	11	11
Country Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes

Standard errors in parentheses. Results based on fixed effects fractional logistic regressions in equation (2). $*p < 0.10, **p < 0.05, ***p < 0.010$

5 Deindustrialization at the SSA subregional levels

This section explores deindustrialization by subregional groups. This is important for two reasons. First, there is no reason to expect that countries in different regions share the same deindustrialization experience and geographic differences across SSA may mask any evidence of (premature) deindustrialization. Second, examining the evolution of manufacturing for different regions may shed light on why SSA countries may have undergone deindustrialization. We perform subregional analysis for only the manufacturing output shares since we only have a small number of countries with data on manufacturing employment shares. Nonetheless, this is fitting for our purposes as it is also for manufacturing output shares that we find some evidence of deindustrialization in the previous section.

The subregional group results are presented in Table 4, with the predicted manufacturing output shares plotted in Figure 8. These results highlight significant regional differences. From Table 4, the coefficient estimate on the quadratic term in GDP per capita is only statistically significant for Southern SSA. Figure 8 graphically sums up this finding: only Southern SSA appears to have deindustrialization in Sub-Saharan Africa and maybe the group of countries driving our findings in the previous section. The inverted U-shape of manufacturing output shares is also confirmed by the Lind & Mehlum (2010) test for Southern SSA. After peaking at around 20 percent, the estimated turning point for manufacturing output shares occurs at GDP per capita level of $5,800. Thus, it turns out that only the exploratory observations for Southern SSA in Figure 5 hold up in formal statistical analysis. For West Africa, the predicted RMVA values are flat in Figure 8. Both East and Central Africa have increasing predicted RMVA values. This confirms our conjecture in the previous section that deindustrialization in output shares is not the experience of the vast majority of sub-Saharan African countries.

Given that we find robust deindustrialization in Southern SSA, we ask whether this deindustrialization can be considered to be *premature*. We do this by examining how the turning point in manufacturing shares changes over time by temporally dividing our sample at the 1990 year mark. Mechanically, this amounts to including interactions of a post-1990 dummy variable with the logarithm of GDP per capita (and its quadratic term) in equation (1).[7] Table 5 presents the results of this analysis for Southern SSA, and shows that the observed deindustrialization does not appear to be occurring prematurely. In other words, while Southern SSA has deindustrialized, this phenomenon is not occurring at lower levels of per capita income. The estimated coefficients on both interaction terms in Table 5 are not statistically significant, suggesting that the turning points for manufacturing output shares in Southern SSA have not changed over time. This is graphically illustrated in Figure 9, where the turning points for the pre- and post-1990 period are essentially the same.

[7]The results are not sensitive to other breakpoints such as 1995.

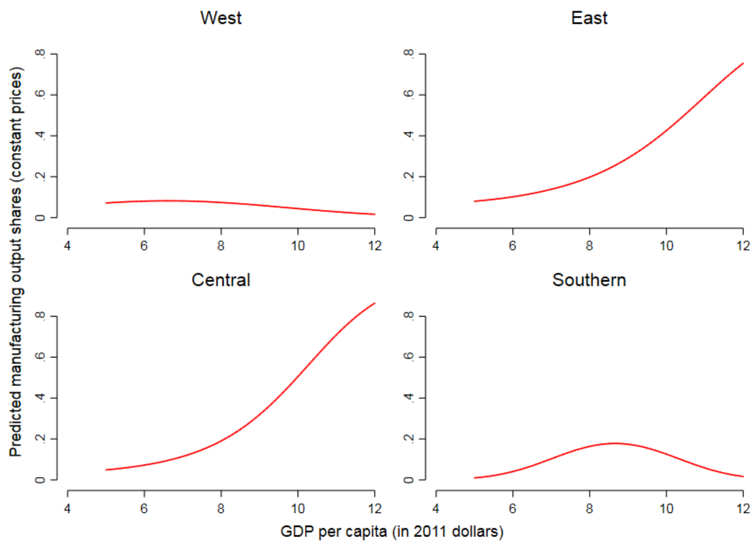


Figure 8: Predicted manufacturing shares (constant prices) as a function of GDP per capita by subregional blocks (in 2011 dollars)

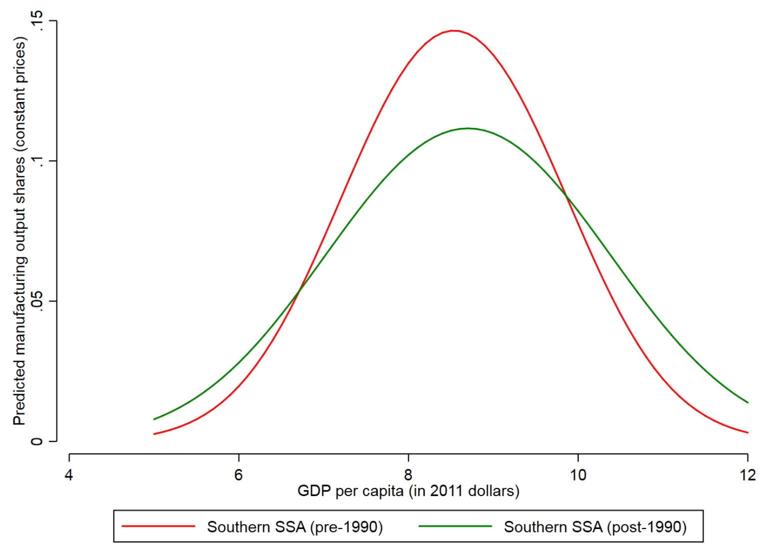


Figure 9: Predicted manufacturing shares (constant prices) as a function of GDP per capita (in 2011 dollars)

Table 4: SSA Region Regressions: Manufacturing value added as percent of GDP (constant prices)

	West		East		Central		Southern	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Population (logarithm)	0.777	0.100*	1.749	0.083	9.353***	-0.146	4.178***	-0.148***
	(1.491)	(0.057)	(3.170)	(0.058)	(2.458)	(0.108)	(0.779)	(0.053)
Population squared (logarithm)	0.013		-0.022		-0.340***		-0.177***	
	(0.061)		(0.089)		(0.054)		(0.034)	
GDP per capita (logarithm)	0.762	-0.009	-0.177	0.036***	-0.084	0.055***	3.960***	0.029*
	(1.914)	(0.016)	(1.823)	(0.012)	(1.395)	(0.009)	(1.088)	(0.017)
GDP per capita squared (logarithm)	-0.058		0.040		0.045		-0.229***	
	(0.122)		(0.118)		(0.092)		(0.071)	
Intercept	-17.989		-22.421		-68.173**		-45.201***	
	(15.324)		(28.636)		(26.858)		(6.886)	
Observations	464	464	398	398	284	284	394	394

Standard errors in parentheses. Results based on fixed effects fractional logistic regressions in equation (2). Sub-regions based on the African Union geographic classification of SSA countries. See Table A.3 for additional details. $*p < 0.10, **p < 0.05, ***p < 0.010$

Table 5: Manufacturing output shares (% GDP) regressions with post-1990 indicator - Southern SSA

	Coefficients
Population (logarithm)	4.384***
	(1.409)
Population squared (logarithm)	-0.184***
	(0.044)
GDP per capita (logarithm)	5.689*
	(3.011)
GDP per capita squared (logarithm)	-0.333*
	(0.196)
GDP per capita (logarithm) $\times$ post1990=1	-2.185
	(2.399)
GDP per capita squared (logarithm) $\times$ post1990=1	0.132
	(0.152)
Constant	-53.967**
	(21.526)
Observations	394

Standard errors in parentheses. Results based on fixed effects fractional logistic regressions in equation (2) with a post-1990 dummy variable for Southern SSA. See Table A.3 for additional details on subregional grouping. $*p < 0.10, **p < 0.05, ***p < 0.010$

6 Robustness and other considerations

Our main finding so far is that we do not find robust evidence for deindustrialization in SSA. While manufacturing employment shares do not appear to follow an inverted U-shaped relationship, manufacturing output shares tends to be inversely U-shaped. Our results suggest that the RMVA result is driven by Southern SSA countries who appear to have deindustrilized when examining manufacturing output shares. This section investigates two specification issues in an attempt to understand the nature of SSA's manufacturing experience. First, we augment the set of covariates beyond the population size and per capita income in equation (2). In particular, we include other potential correlates of deindustrialization such as the levels of remittances and foreign direct investments (FDI) (Lartey, Mandelman & Acosta 2012). Second, we also conduct our analysis by limiting the sample to countries for which we have non-oil GDP data. Recall that we have a subsample of SSA countries for which we have non-oil GDP data spanning 2004-2016 (see Section 2 for details). Our objective is to examine whether there other channels that might have led to the observed (de)industrialization patterns. Spefically, we look at whether resource booms such as oil have induced sustained real exchange rate appreciation that could be linked to slower or less industrialization in resource rich countries. Finally, we also test implications of the Dutch disease and resource-curse hypotheses to the outcome of SSA's deindustrialization, although this analysis is limited to only four countries with significant oil-exporting sectors.

Table 6 presents the regression results based on equation (2) with and without the additional covariates specified above in Columns (1) and (2), respectively. The results in Table 6 suggest that personal remittances may be an important correlate of deindustrialization in sub-Saharan Africa. In particular, higher personal remittances are associated with lower manufacturing output shares in SSA.

Table 6: Manufacturing output shares regressions (additional covariates)

	(1)	(2)
Population (logarithm)	2.803***	2.848***
	(0.965)	(0.965)
Population squared (logarithm)	-0.099***	-0.092***
	(0.035)	(0.034)
GDP per capita (logarithm)	2.528**	2.047**
	(1.169)	(1.001)
GDP per capita squared (logarithm)	-0.145**	-0.117*
	(0.074)	(0.064)
Foreign direct investment, net inflows (% of GDP)		-0.002
		(0.002)
Personal remittances, received (% of GDP)		-0.003***
		(0.001)
Observations	1031	1031

Standard errors in parentheses. Results based on fixed effects fractional logistic regressions in equation (2). $*p < 0.10, **p < 0.05, ***p < 0.010$

Table 7 presents results for the non-oil GDP sample. For an apples-to-apples comparison, we estimate the same regression specification on the non-oil GDP sample but using first, the usual manufacturing output shares in GDP (RMVA) and second, the share of manufacturing value added in non-oil GDP (RMVA-NOIL). As shown in Table 7, the results are qualitatively the same regardless of the deindustrialization measure used in terms of statistical significance. Although the coefficient estimates on the quadratic terms in both columns are statistically insignificant, the signs on the GDP per capita and its quadratic terms are flipped. Given the caveats of our reduced sample size for the non-oil GDP case, the opposite signs are suggestive of different trajectories for the manufacturing output shares in GDP versus non-oil GDP. This also suggests that studies on SSA's deindustrialization should take into account the potential role for the natural resource endowment.

Table 7: Manufacturing output shares regressions for non-oil GDP sample

	Dependent variable	
	RMVA	RMVA-NOIL
Population (logarithm)	3.774*	-5.298***
	(2.031)	(2.038)
Population squared (logarithm)	-0.098*	0.148**
	(0.059)	(0.061)
GDP per capita (logarithm)	-1.160	0.638
	(0.983)	(0.840)
GDP per capita squared (logarithm)	0.071	-0.044
	(0.058)	(0.052)
Observations	368	368

Standard errors in parentheses. Results based on fixed effects fractional logistic regressions in equation (2) for the non-oil GDP sample. Column *RMVA* presents results using the manufacturing output shares in GDP as dependent variable while Column *RMVA-NOIL* is based on the share of manufacturing value added in non-oil GDP. $*p < 0.10, **p < 0.05, ***p < 0.010$

Finally, we focus on four countries in sub-Saharan Africa with significant oil-exporting sectors for which we have data to test the Dutch disease - Cameroon, Ghana, Nigeria and South Africa. To do so, we specify an equation similar to (2) but use as our dependent variable, the share of manufacturing value added in non-oil GDP. We use the same set of explanatory variables, but add oil revenues (% GDP), the real effective exchange rate and the monthly minimum wage. The monthly minimum wage variable serves as a proxy for the wage in domestic oil industries. In this specification, the presence of the Dutch disease can be inferred from the coefficient on the monthly minimum wage variable. From Table 8, the sign of marginal effect of the monthly minimum wage variable is negative (although not statistically significant), providing supporting evidence for the Dutch disease. Given the caveats of a limited size for this analysis, the results in Table 8 suggest that future studies should account for the role of the Dutch disease in studying

Table 8: The Dutch disease hypothesis: manufacturing output shares (% non-oil GDP) regressions

	Marginal Effects
Population (logarithm)	-0.0851***
	(0.0314)
GDP per capita	0.0872***
	(0.0253)
Real effective exchange rate	0.0004
	(0.0003)
Oil rents (% of GDP)	0.0017**
	(0.0007)
Monthly minimum wage (2011 US dollars)	-0.0000735
	(0.0002)
Observations	27

Marginal Effects are reported. Standard errors in parentheses. Results based on fixed effects fractional logistic regressions in equation (2) for Cameroon, Ghana, Nigeria, and South Africa. $*p < 0.10, **p < 0.05, ***p < 0.010$

sub-Saharan Africa's manufacturing experience.

7 Concluding Remarks

This paper investigates the cross-country patterns and trends in the share of manufacturing in national output and employment among sub-Saharan Africa. Rodrik (2016) claims that several developing countries including those from sub-Saharan Africa are prematurely deindustrializing because manufacturing has begun to shrink at levels of income that are much lower than those at which the advanced economies started to deindustrialize. We study the extent to which African countries differ regarding the scale, timing and causes of "deindustrialization" using recent panel data methods for fractional responses. We use two main measures of industrialization, namely the share of manufacturing valued added in GDP at constant prices and the share of manufacturing employment in economy-wide employment. Our data come from a variety of sources and comprises of an unbalanced panel of 41 African countries. We also explore potential explanations or correlates of deindustrialization such as natural resource endowment. Our key finding is that deindustrialization does not appear to be the common experience of the majority of Sub-Saharan African countries. Only the Southern SSA subregion appears to have deindustrialized over the period under study. We do not, however, find evidence that this deindustrialization of the southern subregion has occured prematurely. We also uncover meaningful geographic variation in manufacturing experience across sub-Saharan Africa, and a potential role of the Dutch disease in understanding SSA's manufacturing experience. Although alaysis of the latter hinges on the sample size of oil-exporting countries and the availability of key variables such as non-oil GDP, which are limited in this study, it suggests that future research should account for the role of the Dutch disease in studying Sub-Saharan Africa's manufacturing experience.

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Table A.1: Manufacturing Value Added (constant prices, % of GDP)

Country	1960s	1970s	1980s	1990s	2000s	2010s
Burundi				0.17	0.12	0.09
Number of years				3	10	7
Benin		0.22	0.18	0.22	0.19	0.13
Number of years		9	10	10	10	7
Burkina Faso		0.14	0.13	0.12	0.1	0.07
Number of years		10	10	10	10	7
Botswana	0.01	0.08	0.07	0.07	0.07	0.08
Number of years	6	10	10	10	10	1
Central African Republic	0.02	0.04	0.08	0.07	0.06	0.07
Number of years	5	10	10	10	10	6
Cote d'Ivoire					0.13	0.12
Number of years					2	7
Cameroon	0.1	0.11	0.15	0.15	0.14	0.14
Number of years	5	10	10	10	10	7
Congo, Dem. Rep.	0.68	0.64	0.57	0.37	0.24	0.16
Number of years	2	10	10	10	10	7
Congo, Rep.		0.03	0.03	0.03	0.03	0.04
Number of years		2	10	10	10	7
Comoros			0.04	0.05	0.04	0.05
Number of years			10	10	10	5
Cabo Verde				0.11	0.06	0.06
Number of years				9	10	7
Ethiopia	0.03	0.03	0.05	0.05	0.05	0.05
Number of years	9	10	10	10	10	3
Gabon			0.01	0.01	0.02	0.04
Number of years			10	10	10	6
Ghana	0.15	0.17	0.12	0.12	0.1	0.09
Number of years	10	10	10	10	10	2
The Gambia	0.05	0.05	0.06	0.06	0.06	0.05
Number of years	4	10	10	10	10	7
Guinea-Bissau					0.12	0.11
Number of years					5	7
Equatorial Giunea					0.15	0.21
Number of years					4	7
Kenya	0.07	0.09	0.13	0.13	0.12	0.12
Number of years	6	10	10	10	10	2
Liberia					0.04	0.04
Number of years					10	7
Lesotho		0.03	0.05	0.08	0.14	0.11
Number of years		10	10	10	10	7
Mozambique				0.09	0.13	0.09
Number of years				9	10	7
Mauritania			0.15	0.14	0.11	0.08
Number of years			5	10	10	7

Table A1 cont.: Manufacturing Value Added (constant prices, % of GDP)

Country	1960s	1970s	1980s	1990s	2000s	2010s
Mauritius		0.18	0.22	0.25	0.21	0.18
Number of years		10	10	10	10	3
Malawi	0.1	0.11	0.11	0.11	0.1	0.1
Number of years	4	10	10	10	10	1
Namibia			0.12	0.13	0.13	0.11
Number of years			10	10	10	7
Niger					0.05	0.06
Number of years					4	7
Nigeria	0.02	0.02	0.04	0.04	0.03	0.04
Number of years	10	10	10	10	10	2
Rwanda	0.1	0.09	0.09	0.07	0.07	0.06
Number of years	5	10	10	10	10	7
Sudan		0.04	0.06	0.06	0.05	0.06
Number of years		10	10	10	10	2
Senegal		0.15	0.16	0.17	0.16	0.15
Number of years		10	10	10	10	1
Sierra Leone				0.04	0.03	0.02
Number of years				10	10	7
Sao Tome and Principe					0.08	0.08
Number of years					9	7
Swaziland		0.2	0.23	0.33	0.32	0.31
Number of years		9	10	10	10	7
Seychelles		0.05	0.06	0.09	0.11	0.08
Number of years		2	10	10	10	7
Chad					0.01	0.01
Number of years					3	7
Togo		0.07	0.06	0.07	0.08	0.08
Number of years		4	10	10	10	7
Tanzania	0.1	0.12	0.09	0.08	0.09	0.1
Number of years	10	10	10	10	10	2
Uganda			0.05	0.07	0.09	0.08
Number of years			8	10	10	7
South Africa	0.17	0.22	0.23	0.21	0.2	0.18
Number of years	10	10	10	10	10	2
Zambia	0.1	0.13	0.14	0.12	0.11	0.09
Number of years	5	10	10	10	10	1
Zimbabwe	0.18	0.17	0.17	0.16	0.12	0.09
Number of years	1	10	10	10	10	7

The table reports mean shares of manufacturing valued added in GDP (constant prices) for each south-Saharan African country by decade (e.g., 1960-1969, etc) based on our main sample of 41 SSA countries. Each column represents decade-specific mean shares followed (on the corresponding row) by the number of years for which data are available.

Table A.2: Manufacturing employment (% of total employment)

	1960s	1970s	1980s	1990s	2000s	2010s
Botswana	0.01	0.02	0.03	0.06	0.06	0.06
Observations	6	10	10	10	10	1
Ethiopia	0.02	0.02	0.02	0.02	0.04	0.07
Observations	9	10	10	10	10	2
Ghana	0.1	0.13	0.12	0.12	0.11	0.11
Observations	10	10	10	10	10	2
Kenya	0.04	0.04	0.04	0.07	0.12	0.13
Observations	1	10	10	10	10	2
Mauritius		0.17	0.26	0.3	0.24	0.19
Observations		10	10	10	10	2
Malawi	0.03	0.03	0.03	0.03	0.03	0.04
Observations	4	10	10	10	10	1
Nigeria	0.06	0.07	0.05	0.04	0.04	0.04
Observations	10	10	10	10	10	2
Senegal		0.06	0.06	0.07	0.09	0.1
Observations		10	10	10	10	1
Tanzania	0.01	0.02	0.01	0.01	0.02	0.03
Observations	10	10	10	10	10	2
South Africa	0.11	0.14	0.16	0.13	0.13	0.12
Observations	10	10	10	10	10	2
Zimbabwe	0.02	0.04	0.04	0.03	0.03	0.03
Observations	5	10	10	10	10	1

The table reports mean shares of manufacturing employment shares in total employment for each south-Saharan African country by decade (e.g., 1960-1969, etc) based on our employment sample 11 SSA countries. Each column represents decade-specific mean shares followed (on the corresponding row) by the number of years for which data are available.

Table A.3: Geographic subregions of Sub-Saharan Africa

	Dependent Variable	
Country	Manufacturing output shares (constant prices)	Manufacturing employment shares
West		
Benin	1971 - 2016	
Burkina Faso	1970 - 2016	
Cape Verde	1991 - 2016	
Cote d'Ivoire	2008 - 2016	
Gambia	1966 - 2016	
Ghana	1960 - 2011	1960 - 2010
Guinea-Bissau	2005 - 2016	
Liberia	2000 - 2016	
Mauritania	1985 - 2016	
Niger	2006 - 2016	
Nigeria	1960 - 2011	1960 - 2011
Senegal	1970 - 2010	1970 - 2010
Sierra Leone	1990 - 2016	
Togo	1976-2016	
East		
Comoros	1980 - 2014	
Ethiopia	1961 - 2012	1961 - 2010
Kenya	1964 - 2011	1969 - 2010
Mauritius	1970 - 2012	1970 - 2010
Rwanda	1965 - 2016	
Seychelles	1978 - 2016	
Sudan	1970 - 2011	
Tanzania	1960 - 2011	1960 - 2010
Uganda	1982 - 2016	
Central		
Burundi	1971 - 2016	
Cameroon	1965 - 2016	
Central African Republic	1965 - 2015	
Chad	2007 - 2016	
Congo Republic	1978 - 2016	
Democratic Republic of Congo (DR Congo)	1968 - 2016	
Equitorial Guinea	2006 - 2016	
Gabon	1908 - 2015	
Sao Tome and Principe	2001 - 2016	

Table A.3 cont.: Geographic subregions of Sub-Saharan Africa

	Dependent Variable	
Country	Manufacturing output shares (constant prices)	Manufacturing output shares (current prices)
Southern		
Botswana	1964 - 2010	1964 - 2010
Lesotho	1970 - 2016	
Malawi	1966 - 2010	1966 - 2010
Mozambique	1991 - 2016	
Namibia	1980 - 2016	
South Africa	1960 - 2011	1960 - 2010
Swaziland	1971 - 2016	
Zambia	1965 - 2010	1965 - 2010
Zimbabwe	1969 - 2016	

The table presents the sub-Saharan African countries (by geographic grouping) in our sample and indicates the years of data availability for our measures of industrialization.