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Manufacturing matters…but it's the jobs that count

Jesus Felipe,[⋆] Aashish Mehta[†] and Changyong Rhee[‡]

We assemble a large database of countries' manufacturing employment and output shares for 1970–2010. We ask whether increased global competition and labor-displacing technological change have made it more difficult for countries to industrialize in employment, and whether there are alternative routes to prosperity. We find that: (1) All of today's rich non-oil economies enjoyed at least 18% manufacturing employment shares in the past; (2) They often did so before becoming rich; (3) Manufacturing peaks at lower employment shares today (typically below 18%), than in the past (often over 30%); (4) Compared with employment, output shares are weak predictors of prosperity, and are under less pressure; and (5) Late developers' manufacturing employment shares peak at much lower per capita incomes than previous studies have shown. We demonstrate that final result through analysis and simulation of the dynamics implied by our regression model. Becoming rich through industrialization has therefore become much more difficult. We argue that this is in large part because of rapid growth in the manufacturing capabilities of some very populous countries.

Key words: Deindustrialization, Manufacturing, Structural transformation, Globalization
JEL classifications: O10, O14, O25

1. Introduction

A long tradition in development economics holds that manufacturing is the engine of growth.[1] Indeed, this conviction has been so strong that the terms 'industrialized' and 'high-income' were used interchangeably through much of the twentieth century. Unsurprisingly, governments around the world have targeted manufacturing in their

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⋆Asian Development Bank, jfelipe@adb.org

†University of California, Santa Barbara, mehta@global.ucsb.edu

‡International Monetary Fund, CRhee@imf.org

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[1] For some classic and more recent contributions, see Kaldor (1966), Chenery *et al.* (1986), Amable (2000), Fagerberg (2000), Peneder (2003), Rodrik (2009), Szirmai (2012), Szirmai and Verspagen (2015) and UNIDO (2013).

development plans. For example, India's 2011 National Manufacturing Policy aims at raising the share of manufacturing in GDP to 25% and creating 100 million manufacturing jobs, priorities reinforced by the current government's 'Make in India' campaign. The Philippines, seeking to reverse almost half a century of slow deindustrialization, is developing a comprehensive manufacturing road map. Indonesia, seeking to avoid the resource curse, passed a new Industry Law in 2014. Even China, the 'factory of the world', is pushing high-technology industries and the use of technology in manufacturing through its 'Made in China 2025' program. Developed countries like the US, Australia and the members of the European Union are also interested in industrializing, or rather, re-industrializing after decades of deindustrializing. These plans, particularly in late-industrializing societies, often involve big changes to policies and institutions, with land rights, labor laws, educational practices, trade and investment rules and financial and fiscal arrangements all on the table (Helper *et al.*, 2012; Felipe, 2015).

Given the far-reaching implications of these industrialization efforts, it is important to ask what the odds of their success in late-industrializing economies are, and whether there are alternative routes to prosperity. A related question is how success in industrialization should be measured—is it more important to produce large amounts of manufacturing value added, or to create manufacturing jobs?

Studies seeking answers to these questions have, until recently, been stymied by a dearth of good data on manufacturing employment shares, especially from developing economies (Dabla-Norris *et al.*, 2013; Herrendorf *et al.*, 2013).[2] To make progress on this agenda, we have, through meticulous cleaning, merging and verification efforts, assembled measures of manufacturing employment shares for 63 countries from 1970 to 2010. We also have manufacturing shares in real value added (henceforth 'output shares') for all these countries, plus for another 72.[3] The employment sample represents 82% of the world's population in 2010, and to our knowledge, is the largest such dataset collected. The Appendix describes our dataset and cleaning procedures, and shows that the countries with adequate employment data, which include many of today's late industrializing economies, tend to be richer and more populous than those for which we do not have these data. We use these data to study the historical role of manufacturing employment in development, and the constraints that may prevent today's late-industrializing economies from following in the footsteps of their predecessors.

There are at least three theoretical reasons for nations seeking economic growth to target manufacturing, and specifically, manufacturing employment.[4] First, shifting labor from traditional, low-productivity sectors of the economy into higher-productivity manufacturing lifts labor productivity—an effect that grows with the rate of manufacturing job creation (Lewis, 1954; Kaldor, 1966; Chenery *et al.*, 1986). Second, manufacturing has a potential for productivity catch-up that is unmatched by most services. Rodrik (2013) shows that manufacturing exhibits unconditional convergence in labor productivity—national manufacturing industries that start farther away from the labor productivity frontier experience significantly faster productivity growth even without conditioning

[2] One exception to this statement is Rodrik (2016), who has been working on similar problems in parallel to us. We elaborate below on the ways in which our work and his extend each other.

[3] We acknowledge that service activities that were once performed by manufacturing firms have increasingly been outsourced to dedicated service firms. This does raise the possibility that we have overestimated the rate at which manufacturing activity has declined within countries. Resolving this issue requires disaggregated data that are not generally available (UNIDO, 2013). Our main results are unlikely to be vitiated by this caveat (see Section 5).

[4] See the *Symposium on Kaldor's Growth Laws*, published in the Thirwall (1983).

on variables such as domestic policies, human capital, geography or institutional quality. Arithmetically, this effect will be larger the more manufacturing jobs there are. Third, to the extent that manufactured goods have high income elasticities of demand, and are produced under increasing returns to scale, industrialization sets in motion a virtuous cycle (Rosenstein-Rodan, 1943; Murphy *et al.*, 1988). As costs in manufacturing industries drop, the demand for manufactured goods increases, in turn causing more investment in manufacturing activity and higher incomes, which spur further demand increases and cost reductions. As noted, the first two mechanisms are activated by manufacturing employment rather than output. And, while the third ('big push') mechanism relies on output, rather than employment growth, it should diminish in importance as globalization makes countries less reliant on local demand to propel industrialization. It follows that in a world of export-led industrialization, manufacturing employment is likely to be a stronger predictor of prosperity than manufacturing output.[5]

There is a growing perception that countries are finding it more difficult in recent times to sustain high levels of manufacturing employment, while simultaneously increasing wages and living standards (Rodrik, 2009). This difficulty has been attributed to two forces. First, the internationalization of supply chains and strong unconditional convergence between nations in manufacturing labor productivity have dramatically increased competition from lower-income economies to host manufacturing activities. This makes it harder to sustain manufacturing activity in higher-wage economies. Second, there is growing concern that technological change and the efficiencies that derive from globalized mass production are labor displacing (Cowen, 2013; Brynjolfsson and McAfee, 2014). These forces are potentially inter-related—growing international competition creates incentives to adopt labor-displacing technologies, especially in higher-wage economies.

To examine these concerns, we start with the widely recognized stylized fact that national manufacturing employment and output shares first grow with per capita GDP and then fall with it (Chenery, 1960; Kuznets, 1965; Herrendorf *et al.*, 2013). The two forces just reviewed have three testable implications for changes over time in the inverted-U relationships between manufacturing shares (on the vertical axis) and income levels (on the horizontal).

(1) Globalization and unconditional convergence in manufacturing labor productivity make it harder for rich, high-wage countries to compete in manufacturing. As a result, national manufacturing shares should now peak at lower income levels.
(2) To the extent that the effects of wage increases can be ameliorated by substituting capital for labor, the resulting leftwards movement of the inverted-U should be more pronounced for employment than for output shares.
(3) More rapid labor-displacing productivity growth in manufacturing than in non-manufacturing should reduce the manufacturing sector's share in national employment relative to its share in output.

[5] There is another reason to care about manufacturing, related to the balance of payments: as income per capita increases, so does per capita demand for manufactured products (many of these have high-income elasticities of demand). If a developing country does not have a strong manufacturing sector, it will end up running a trade deficit in manufactured goods. To cover this deficit, the country will either have to borrow, or to secure an equally large surplus of non-manufactured goods (e.g. services, minerals, food, etc.). Either route is very difficult for the typical developing country. We thank a referee for pointing this out.

In addition to confirming all three implications of increasing international competition and labor-displacing productivity growth within countries,[6] this paper makes four entirely new contributions to the literature on industrialization and development. First, consistent with the above theoretical arguments about the importance of manufacturing employment, we show that every country in our employment sample that is rich today (i.e. had a per capita GDP of over $12,000 in 2010) experienced a manufacturing employment share of over 18% sometime since 1970. In other words, high levels of manufacturing employment have been necessary for becoming rich. Second, we show that output shares have little such predictive power. Third, we present a survival analysis that shows that high manufacturing employment shares precede the achievement of rich-country status, suggesting a causal connection from factory jobs to riches. And fourth, we explore the dynamic implications of a shifting inverted-U, use it to explain the extremely diverse industrialization trajectories of several countries and show how today's developing economies' low early incomes and growth rates have seriously impaired their industrialization prospects. A key lesson of this dynamic analysis is that late industrializers generally begin to deindustrialize at much lower income levels and manufacturing employment shares than previous studies have shown.

The remainder of this paper is structured as follows. Section 2 motivates our study using a simple cross-sectional analysis. In Section 3, we show that all (non-oil) rich countries had high manufacturing employment shares, and that high manufacturing employment often preceded becoming rich. We also show that output shares don't play this role. In Section 4, we present panel data regressions and draw out their dynamic implications to show just how difficult it has become to achieve high manufacturing employment shares and sustain them in the face of income growth. Section 5 discusses possible interpretations of our results and caveats.

2. Motivation

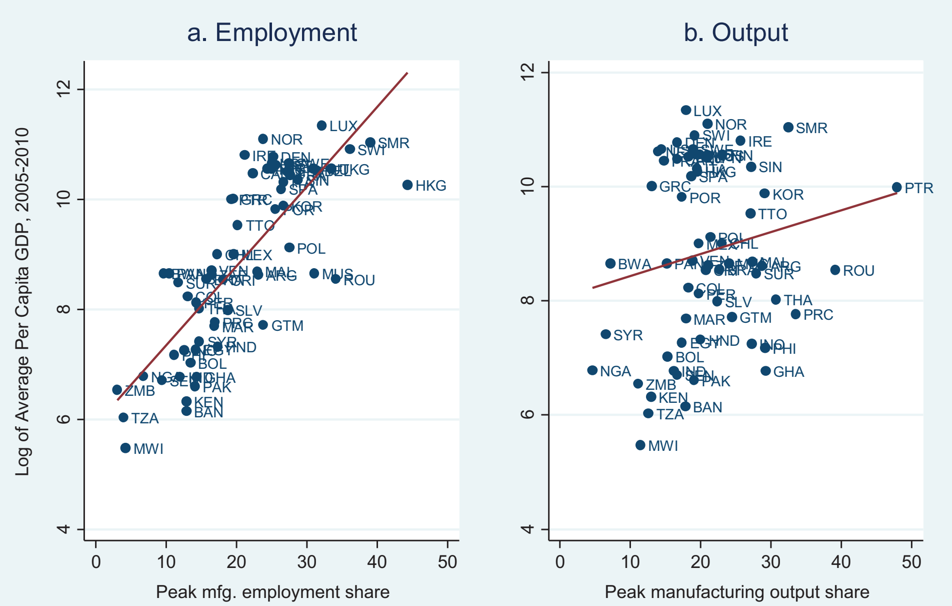
To motivate the detailed analysis that follows, Figures 1–3 and Table 1 present a cross-sectional description of the historical data. Manufacturing employment and output shares in this cross-sectional view are calculated as seven-year moving averages between 1970 and 2010. A country's peak historical share is the maximum of its moving average series.[7]

Figure 1a shows a clear positive correlation between countries' average income per capita in 2005–2010 and their peak historical manufacturing employment shares. Figure 1b shows a much noisier relationship with peak historical output shares. This is our first indication that manufacturing employment is extremely important, and is a better predictor of eventual prosperity than is manufacturing output.

Figures 2 and 3 suggest that the path to prosperity through manufacturing employment is becoming more difficult. Figure 2 shows that peak employment shares have fallen over

[6] We provided initial evidence on these three implications in a 2014 working paper (Felipe *et al.*, 2014). Rodrik (2016) reconfirms them using our original dataset and a longer panel of fewer countries from the Groningen Growth and Development Center (GGDC). Amirapu and Subramanian (2015) show that Implications 1 and 3 hold in a cross-section of industrial employment shares from the World Development Indicators.

[7] Figures 1–3 use data from only the 63 employment-share countries, for comparability, but the output share graphs for 135 countries are very similar, and are available on request.

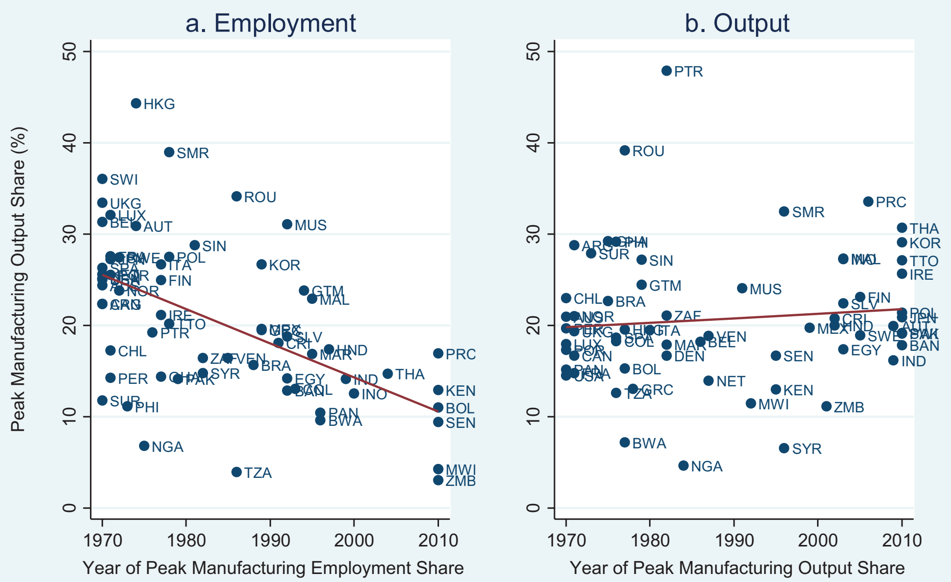


Note: X-axis shows the level at which the 7-year moving average of the manufacturing employment and output shares peaked between 1970 and 2010. The dates of these peaks vary across countries. Only the 63 countries with adequate employment data are included.

Fig. 1. *Industrialization in employment is a better predictor of future prosperity than industrialization in output.*

time, with peaks averaging around 25% and often exceeding 30% until the mid-1980s, averaging 20% and rarely crossing 30% until the mid-1990s, and peaking below 20% during the last 15 years. It also shows that peak output shares have not fallen. Several countries whose maximum output share is observed in 2010 may not have peaked yet. Figure 3 shows that the per capita income at the time that employment peaked has declined quickly over time, while GDP per capita at the time that output peaked did not decline.

Table 1, Panels A–C, respectively check whether the trends discernable in Figures 1–3 are robust to the inclusion of control variables. Regression 1 in Panel A of Table 1 shows that a one percentage point difference in the peak manufacturing employment share is associated with a 14.4 percent difference in per capita GDP in 2005–10. Peak historical manufacturing employment shares account for 63% of the variation in subsequent incomes. Regression 2 confirms that peak historical output shares are *much* worse predictors of subsequent incomes than employment shares in both these respects. Indeed, when both regressors are included (Regression 3), only employment shares are significant, suggesting that industrialization predicts future prosperity only insofar as it generates manufacturing jobs. Next, we introduce the value of EXPY in the year the employment share peaked. EXPY is a proxy measure for the sophistication of a country's export mix, calculated as a weighted average of the sophistication of the products (the calculation does not include services) that a country exports with revealed comparative advantage, and is known to be a solid predictor of a country's subsequent economic performance (Hausmann *et al.*, 2007). Regression 4 confirms that what a country exports matters; but even with this correction, manufacturing



Note: X-axis shows the year that the 7-year moving average of the manufacturing sector's employment and output shares peaked between 1970 and 2010. Y-axis shows the per capita income that year. Only the 63 countries with adequate employment data are included.

Fig. 2. *Recent industrializers have peaked at lower employment shares; but not at lower output shares.*

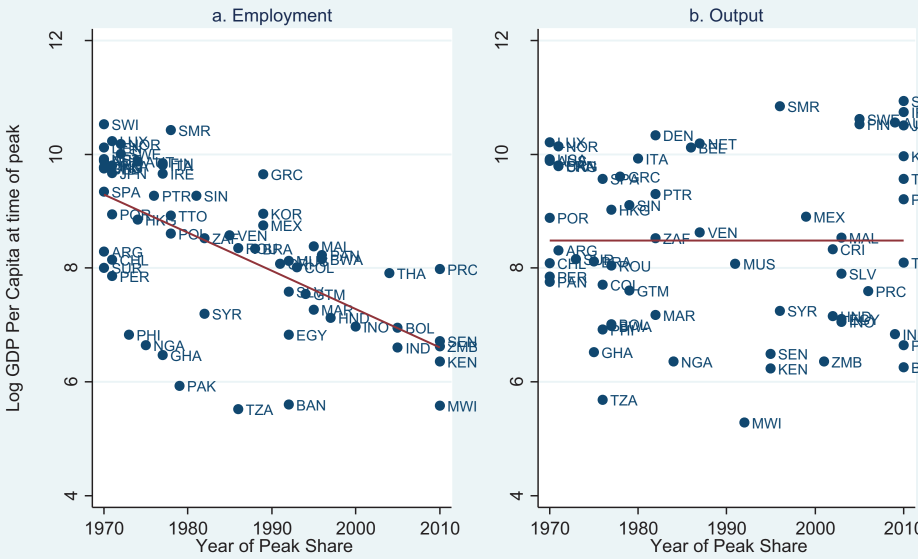
employment is still strongly related to future prosperity. Regression 5 checks whether peak manufacturing shares predict prosperity once one controls for how long ago a country industrialized. This is important to check, given the strong inverse correlation between the date and extent of peak manufacturing employment (Figure 2a). Achieving both a high and early peak matters, but only in employment terms. Section 3 checks whether high manufacturing employment precedes prosperity, as would be required to interpret this relationship causally.

Panel B confirms a statistically significant decline in peak historical manufacturing employment shares (Regression 1), and also that historical peak output shares display no such trend in either sample of countries (Regressions 2 and 3). Panel C likewise confirms a steep, statistically significant decline in the per capita GDP at which employment shares peaked, and the absence of such a trend for output shares in both samples. We return to these points in Section 4.

International comparisons therefore suggest that manufacturing jobs are critical for prosperity, but that they are becoming harder to sustain, especially in the face of higher incomes.

3. Are industrialized countries rich countries, and is output or employment the relevant measure of industrialization?

We now examine the relationship between recent income per capita and countries' peak historical manufacturing employment shares in two distinct ways. First, we ask



Note: X-axis shows the year that the 7-year moving average of the manufacturing sector's employment and output shares peaked between 1970 and 2010. Y-axis shows the per capita income that year. Only the 63 countries with adequate employment data are included.

Fig. 3. *Deindustrialization in employment begins at lower incomes than it once did. Not as obvious for output.*

whether there are thresholds for historical peak manufacturing output and employment shares that separate rich countries from the rest. Second, we examine the dynamic relationship between industrialization and achieving rich-country status using a survival analysis.

We classify a country as 'rich' (R) if its average per capita GDP during 2005–10 exceeds a given cutoff. A cutoff of $12,000 in 2005 prices (not PPP corrected) is a convenient benchmark, corresponding roughly to the World Bank's definition of a high-income economy. Using this cutoff, 41% of the 63 countries for which we have employment data, and 27% of the full sample of 135 countries, are rich. We will also see what happens if we use different income cutoffs. We will similarly propose that countries have 'industrialized in employment' (I) if their seven-year moving average manufacturing employment shares crossed a particular threshold at any point between 1970 and 2010. Industrialization in output is defined analogously.

We experiment with multiple thresholds for manufacturing shares. For a given income cutoff and threshold manufacturing share, we will conclude that industrialization has been *necessary* for becoming rich if all rich countries industrialized (i.e. Pr(R|~I)=0); and we will say that it is a *sufficient* condition if all industrialized countries are rich (i.e. Pr(R|I)=1). We will also select, for each income cutoff, the threshold manufacturing share that gives us the most separation between rich and non-rich countries (i.e. the manufacturing share threshold that maximizes Δ ≡ Pr(R|I) - Pr(R|~I)). The higher this difference is, the more powerful the manufacturing share becomes as a predictor of eventual prosperity. A difference of zero indicates that industrialization has

Table 1. *Cross-country relationships between recent income, income when manufacturing peaked, and manufacturing shares.*

A. Determinants of log per-capita GDP in 2005–2010.

	(1)	(2)	(3)	(4)	(5)
Peak Mfg. Emp. Share	0.144*** (0.016)		0.148*** (0.017)	0.112*** (0.019)	0.110*** (0.007)
Peak Mfg. VA Share		0.038 (0.024)	-0.014 (0.022)		-0.007 (0.020)
EXPY at year of peak mfg. emp. share				0.173*** (0.037)	
Year of Peak Mfg. Emp. Share					-0.043*** (0.013)
Year of Peak Mfg. VA Share					-0.002 (0.010)
Constant	5.904*** (0.321)	8.052*** (0.575)	6.121*** (0.481)	4.389*** (0.342)	96.688*** (19.732)
N	63	63	63	52	63
R-Squared	0.632	0.032	0.635	0.764	0.726

B. Peak Manufacturing Employment Shares Fell Over Time; Peak Output Shares Did Not

	Employment	Value Added	
	(1)	(2)	(3)
Year of Peak Mfg. Emp. Share	-0.374*** (0.06)		
Year of Peak Mfg. VA Share		0.050 (0.050)	-0.019 (0.046)
Constant	762.756*** (117.08)	-78.581 (98.816)	55.645 (90.660)
N	63	63	135
R-Squared	0.309	0.01	0.001

C. Log Per Capita GDP at the time the country achieved its peak share of:

	Employment	Value Added	
	(1)	(2)	(3)
Year of Peak Mfg. Emp. Share	-0.067*** (0.01)		
Year of Peak Mfg. VA Share		-0.000 (0.013)	0.002 (0.010)
Constant	141.748*** (16.49)	8.699 (25.536)	4.16 (19.688)
N	63	63	135
R-Squared	0.408	0.000	0.000

Note: All results from cross-country OLS regressions. Standard errors are robust. * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

no predictive power.[8] If crossing some manufacturing share threshold is both necessary and sufficient for being rich (i.e. Pr(R|I) - Pr(R|~I)=1), the set of industrialized countries and rich countries would coincide, a situation that would correspond to the traditional usage of the term 'industrialized nation' to connote a high-income economy. We will examine these relationships separately for employment- and output-based definitions of industrialization. We emphasize that we use the terms 'probability', 'necessary' and 'sufficient' strictly to describe historical data, and not as statements of what is theoretically possible.

Table 2 shows P(R|I) in the top panel and P(R|~I) in the bottom panel, calculated using employment share data for 63 countries. The first column in each panel gives the percentage of countries that have reached the income per capita shown in each row (e.g. 41.3% of the countries achieved incomes over $12,000). The last row in the top and bottom panels, respectively, provide the percentage of countries that did and did not cross the threshold manufacturing share indicated in each column (e.g. 55.6% of our 63 countries reached a peak manufacturing employment share of 18%, and the other 44.4% did not). We have also marked in boldface the cells within each row corresponding to the employment threshold that maximizes Pr(R|I) - Pr(R|~I) for the income level in that row.

These figures indicate that having crossed an 18% employment threshold between 1970 and 2010 is necessary for achieving $12,000 per capita income today (i.e. Pr(R|~I)=0), and that while it was not sufficient for achieving rich-country status, a large majority of those that achieved this share are rich today (Pr(R|I)=0.743). The lower panel indicates that a 10% employment share was necessary for crossing even $6000; that an employment share of 18% was necessary for crossing $10,000; and that a share of 20% was necessary for crossing $24,000.

Table 3 provides the same information for manufacturing output shares for the same 63 countries. Results indicate that a 12% manufacturing output share achieves maximal separation for all income cutoffs.

Two comparisons between Tables 2 and 3 emphasize the importance of employment over output. First, the maximum degree of separation, Pr(R|I) - Pr(R|~I), is much larger when a country's industrialization status is determined based upon employment than when it is based upon output. For example, it is 0.743–0.000 = 0.743 at an 18% employment threshold and $12,000 income cutoff; while the maximal separation for the $12,000 cutoff using output shares (achieved at a 12% threshold) is only 0.448. Second, while all rich countries have passed a 14% output share threshold, this is not particularly informative, because only 8% of countries failed to reach that threshold. In contrast, 18% is the highest peak employment share below which no country crossed $12,000, and 44.4% of countries did not reach that cutoff.[9]

To make this exercise concrete, Table 4 categorizes our 63 countries according to whether they achieved 18% employment shares and 20% output shares. We selected these cutoffs to ensure that the fractions of countries that had industrialized in output and employment were roughly equal to each other, and that both fractions were in

[8] We use a separation analysis instead of a probit or logit regression because moderate levels of industrialization in employment are often perfect predictors of rich-country status. Perfect prediction precludes regression analysis.

[9] Results for the output share separation analysis using 135 countries are not qualitatively different, and are available on request.

Table 2. *Probabilities of being rich, conditional on achieving manufacturing employment thresholds.*

A. Probability that a country has crossed per capita GDP threshold, given that it has crossed the manufacturing employment share threshold.

Per Capita GDP Threshold	*Probability that GDPPC > threshold*	Manufacturing employment share threshold: 10	12	14	16	18	20	22	24	26
6K	*0.476*	0.526	0.566	0.612	**0.732**	0.800	0.833	0.821	0.913	0.882
10K	*0.413*	0.456	0.491	0.531	0.634	**0.743**	0.800	0.786	0.870	0.824
12K	*0.413*	0.456	0.491	0.531	0.634	**0.743**	0.800	0.786	0.870	0.824
16K	*0.397*	0.439	0.472	0.510	0.610	0.714	0.767	0.786	**0.870**	0.824
20K	*0.365*	0.404	0.434	0.469	0.561	0.657	0.700	0.714	**0.783**	0.765
24K	*0.333*	0.368	0.396	0.429	0.512	0.600	0.700	0.714	**0.783**	0.765
28K	*0.317*	0.351	0.377	0.408	0.488	0.571	**0.667**	0.679	0.739	0.706
Probability that manufacturing share > threshold		*0.905*	*0.841*	*0.778*	*0.651*	*0.556*	*0.476*	*0.444*	*0.365*	*0.270*

B. Probability that a country has crossed per capita GDP threshold, given that it has not crossed the manufacturing employment share threshold.

Per Capita GDP Threshold	*Probability that GDPPC > threshold*	Manufacturing employment share threshold: 10	12	14	16	18	20	22	24	26
6K	*0.476*	0.000	0.000	0.000	**0.000**	0.071	0.152	0.200	0.225	0.326
10K	*0.413*	0.000	0.000	0.000	0.000	**0.000**	0.061	0.114	0.150	0.261
12K	*0.413*	0.000	0.000	0.000	0.000	**0.000**	0.061	0.114	0.150	0.261
16K	*0.397*	0.000	0.000	0.000	0.000	0.000	0.061	0.086	**0.125**	0.239
20K	*0.365*	0.000	0.000	0.000	0.000	0.000	0.061	0.086	**0.125**	0.217
24K	*0.333*	0.000	0.000	0.000	0.000	0.000	0.000	0.029	**0.075**	0.174
28K	*0.317*	0.000	0.000	0.000	0.000	0.000	**0.000**	0.029	0.075	0.174
Probability that manufacturing share < threshold		*0.095*	*0.159*	*0.222*	*0.349*	*0.444*	*0.524*	*0.556*	*0.635*	*0.730*

Note: Cells highlighted in **bold** correspond to the manufacturing employment share threshold at which P(R|I)-P(R|~I) is maximized for each per capita GDP cutoff.

Table 3. *Probabilities of being rich, conditional on achieving manufacturing output share thresholds (63 countries).*

A. Probability that a country has crossed per capita GDP threshold, given that it crossed the manufacturing output share threshold.

	Probability that GDPPC > threshold	Manufacturing output share threshold								
		10	12	14	16	18	20	22	24	26
Per Capita GDP Threshold 6K	0.476	0.500	**0.517**	0.519	0.520	0.537	0.429	0.381	0.353	0.357
10K	0.413	0.433	**0.448**	0.444	0.440	0.439	0.357	0.333	0.353	0.357
12K	0.413	0.433	**0.448**	0.444	0.440	0.439	0.357	0.333	0.353	0.357
16K	0.397	0.417	**0.431**	0.426	0.420	0.415	0.321	0.286	0.294	0.286
20K	0.365	0.383	**0.397**	0.389	0.380	0.390	0.286	0.238	0.235	0.214
24K	0.333	0.350	**0.362**	0.370	0.360	0.366	0.250	0.190	0.176	0.143
28K	0.317	0.333	**0.345**	0.352	0.340	0.341	0.250	0.190	0.176	0.143
Probability that manufacturing share > threshold		*0.952*	*0.921*	*0.857*	*0.794*	*0.651*	*0.444*	*0.333*	*0.270*	*0.222*

B. Probability that a country has crossed per capita GDP threshold, given that it has not crossed the manufacturing output share threshold.

	Probability that GDPPC > threshold	Manufacturing output share threshold								
		10	12	14	16	18	20	22	24	26
Per Capita GDP Threshold 6K	*0.476*	0.000	**0.000**	0.222	0.308	0.364	0.514	0.524	0.522	0.510
10K	*0.413*	0.000	**0.000**	0.222	0.308	0.364	0.457	0.452	0.435	0.429
12K	*0.413*	0.000	**0.000**	0.222	0.308	0.364	0.457	0.452	0.435	0.429
16K	*0.397*	0.000	**0.000**	0.222	0.308	0.364	0.457	0.452	0.435	0.429
20K	*0.365*	0.000	**0.000**	0.222	0.308	0.318	0.429	0.429	0.413	0.408
24K	*0.333*	0.000	**0.000**	0.111	0.231	0.273	0.400	0.405	0.391	0.388
28K	*0.317*	0.000	**0.000**	0.111	0.231	0.273	0.371	0.381	0.370	0.367
Probability that manufacturing share < threshold		*0.048*	*0.079*	*0.143*	*0.206*	*0.349*	*0.556*	*0.667*	*0.730*	*0.778*

Note: Cells highlighted in **bold** correspond to the manufacturing output share threshold at which P(R|I)-P(R|~I) is maximized for each per capita GDP cutoff.

Table 4. *Countries categorized by industrialization in output and employment, and by high-income status.*

		Employment Share relative to 18%	
		Not Industrialized	Industrialized
		(0/28 Countries is rich)	(26/35 Countries are rich)
Output Share Relative to 20%	Not Industrialized (16/35 countries are rich)	Bangladesh, Bolivia, Botswana, Colombia, Egypt, India, Kenya, Malawi, Morocco, Nigeria, Pakistan, Panama, Peru, Senegal, Syria, Tanzania, Venezuela, Zambia (0/18 countries are rich)	**Austria, Belgium, Canada, Denmark, France, Greece, Hong Kong, Italy, Luxembourg**, Mexico, **Netherlands, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States** (16/17 countries are rich)
	Industrialized (10/28 countries are rich)	Brazil, Chile, China, Ghana, Honduras, Indonesia, Philippines, South Africa, Suriname, Thailand (0/10 countries are rich)	Argentina, **Australia**, Costa Rica, El Salvador, **Finland**, Guatemala, **Ireland**, **Japan, Korea**, Malaysia, Mauritius, **Norway**, Poland, **Puerto Rico**, Romania, **San Marino, Singapore, Trinidad & Tobago** (10/18 countries are rich)

Note: Countries appearing in **bold** had per capita GDPs in 2005–10 in excess of $12,000.

the vicinity of one-half.[10] Countries with GDPPC>$12,000 appear in boldface. It is immediately obvious that the employment threshold does a much better job at distinguishing rich from non-rich countries than the output threshold; 100% of rich countries industrialized in employment and 74% of those that industrialized in employment are rich. Conversely, only 38% of rich countries industrialized in output, and only 36% of those that industrialized in output are rich. Indeed, those that did not industrialize in output are *more* likely to be rich than those that did (16/35 > 10/28).

Finally, Table 5 presents the results of a survival analysis, using a Cox Proportional Hazards model, in order to examine the dynamics of achieving rich-country status. Looking at dynamics permits us to ask whether countries are more likely to become rich subsequent to industrializing—a sequence that would more strongly suggest a causal connection from industrialization to becoming rich than would the static analyses just presented. The dependent variable, measured each year, is an indicator that a country graduated into rich-country status that year. All the regressions correct for agricultural employment shares, which proxy for how far along a country is in its structural transformation. This should help to ensure comparable baseline probabilities of graduation.[11] The model estimates the determinants of graduation in each year, conditional on not having graduated in previous years (i.e. on being 'at risk' of graduation). We present results using $12,000 and $21,000 cutoffs for being rich. In Regressions (1)–(4), 44 countries had the requisite data and had incomes below $12,000 in 1970; and seven of these 'at risk' countries became rich between 1970 and 2010.[12] Similarly, 13 out of 52 at risk countries crossed the $21,000 income cutoff during the same period.

Regressions (1) and (5) ask whether the probability of graduating into rich-country status increases with the fraction of the previous decade a country has spent above 18% manufacturing employment and output shares.[13,14] The results clearly indicate that having spent time above the 18% employment threshold is associated with graduation, while time spent above an 18% output threshold is not. Regressions (2) and (6) ask how important the maximum (to date) manufacturing shares are for predicting prosperity. Once again, it is employment, not output shares, that matter. Regressions (3), (4), (7) and (8) also correct for the number of past years in our dataset during which the manufacturing output or employment share was within two percentage points of the highest value to date; as well as for the interactions of this variable and the maximum manufacturing shares to date. We do this in order to ask whether countries that have

[10] For output shares, 20% is not the cutoff that maximizes separation between rich and non-rich countries. However, as noted, the cutoff that does maximize separation (12%) leaves only five countries in the non-industrialized row. The purpose of the table is not to run a 'fair' horserace between employment and output shares, but to allow the reader to see where countries fall in this scheme.

[11] Eliminating this variable adds significantly to our sample size (the agricultural share series are incomplete), but does not change our qualitative results at all.

[12] The remaining 19 of our 63 countries cannot be included in the survival analysis; 18 of them because they had graduated by 1970, and one because it lacked the agricultural share data.

[13] For observations in the 1970s for which employment shares in the previous decade are not available, the independent variable is the fraction of years since 1970 for which the manufacturing employment share exceeded 18%. We have also run these regressions excluding observations from the 1970s, and the results do not change.

[14] Once again, we use a common threshold for the employment and output shares. Since very few countries had failed to achieve the separation-maximizing 12% output share, using a 12% threshold in the survival analysis created numerical problems.

Table 5. *Survival analysis—manufacturing shares and graduation to rich-country status*

	Cutoff for rich-country status							
	$12,000 (2005 constant $)				$21,000 (2005 constant $)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of last 10 years with mfg. emp. share over 18%	3.732***				2.944***			
	[1.151]				[0.773]			
Share of last 10 years with mfg. VA share over 18%	–0.541				–0.314			
	[0.896]				[0.712]			
Max mfg. employment share to date		0.169***	0.227***			0.119***	0.108***	
		[0.028]	[0.055]			[0.021]	[0.038]	
Max mfg. VA share to date		0.065		0.088***		0.001		–0.001
		[0.061]		[0.030]		[0.064]		[0.048]
Number of years to date spent within 2 p.p. of max emp. share			0.139				0.080	
			[0.092]				[0.086]	
(Max emp sh.) x (number of years to date spent within 2 p.p. of max emp. sh. to date)			–0.004*				0.002	
			[0.002]				[0.002]	
Number of years to date spent within 2 p.p. of max VA share to date				–0.035				–0.068
				[0.097]				[0.095]
(Max VA sh.) x (number of years to date spent within 2 p.p. of max VA sh. to date)				–0.003				0.002
				[0.003]				[0.004]
Log agricultural employment share	–0.034	–0.069	–0.055*	–0.000	–0.048	–0.049	–0.079	–0.029
	[0.030]	[0.050]	[0.032]	[0.027]	[0.033]	[0.034]	[0.057]	[0.031]
Number of 'at risk' observations	1379	1379	1379	1379	1557	1557	1557	1557
Number of countries not rich in 1970	44	44	44	44	52	52	52	52
Number of countries graduating since 1970	7	7	7	7	13	13	13	13

Note: Cox proportional hazards models, with time varying independent variables. Robust standard errors clustered on country appear in brackets. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

achieved lower manufacturing shares were able to make up for this by sustaining them for a longer time. The results indicate that the maximum output share to date is helpful for predicting graduation to above \$12,000 (Regression 4), but not to above \$21,000 (Regression 8). In contrast, high manufacturing employment is associated with crossing both income cutoffs (Regressions 3 and 7). The regressions provide no indication that maintaining near-peak manufacturing shares for longer periods of time is helpful.

The survival analysis therefore confirms our conclusions from the separation analysis. Industrialization in employment is far more important for becoming rich than is industrialization in output; and industrialization, especially in employment, has often preceded a country becoming rich.

4. Has it become more difficult to achieve high manufacturing shares?

This section turns to panel data regressions to deepen the analysis in Figures 2 and 3 and Panels B and C of Table 1. We use a standard descriptive framework in this literature (Chenery *et al.*, 1975; Chenery *et al.*, 1986) to characterize the changing relationship over time between the manufacturing shares and income per capita. We begin by showing that it has become more difficult to achieve high manufacturing shares over time, and specifically, that today's late industrializing economies are unlikely to be able to achieve the 18% manufacturing employment share threshold that all the rich countries in our sample enjoyed. The first stage in this analysis is a simple panel data analysis which traces how the inverse-U-shaped relationships between per capita GDP and manufacturing's shares in employment and output have shifted over time. It shows that this hump has shifted down and to the left, so that both the highest manufacturing share on the curve and the per capita income at which it occurs have declined over time. It also shows that these trends are more pronounced for employment than for output. The second stage is to trace out the dynamic implications of these shifts for manufacturing employment. Specifically, we show that countries' actual trajectories peak at *much* lower manufacturing employment levels and incomes than the humps do. Analysis and simulation of the dynamics implied by the first-stage regression results shows that this is because countries do not move along a single static hump, but rather trace out a path along a sequence of shifting humps. Thus, developing late carries a very large penalty insofar as industrialization is concerned. We also show that these dynamic paths provide a much better fit to countries' actual experiences. The first-stage analysis has appeared in the literature before (Felipe *et al.*, 2014; Rodrik, 2016), so we present only those details that are essential to the second stage.

Denote employment or output shares by s, log per capita income by y, country c, the year t and a set of control variables $\mathbf{x}$. All right-hand-side variables are normalized to have a mean of zero. Our basic specification is then of the form: [15]

$$s_{c,t} = a_c + b \star t + d \star y_{c,t} + e \star y_{c,t}{}^2 + f \star t \star y_{c,t} + \mathbf{g}'\mathbf{x}_{c,t} + e_{c,t} \tag{1}$$

Table 6 presents six versions of this regression. The dependent variables are manufacturing employment shares for the first four regressions, and output shares for the

[15] See Rowthorn and Ramaswamy (1997, 1999), Nickell *et al.* (2008), Bah (2011), Dabla-Norris *et al.* (2013) and Rodrik (2016), who use frameworks similar to ours to study related questions on structural transformation.

Table 6. *Regressions of (log) Manufacturing Employment and Value Added Shares Over Time and Across Countries*

Dependent Variable	Manufacturing Employment Share				Mfg. value added share	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample Period	1970–2010	1970–1990	1990–2010	1970–2010	1970–2010	1970–2010
Year [*b*]	0.022 (0.017)	-0.023*** (0.005)	-0.018*** (0.004)	0.027 (0.019)	0.014 (0.023)	-0.028** (0.120)
Log GDP Per Capita (LGDPPC) [*d*]	1.197* (0.599)	1.377** (0.628)	1.453*** (0.506)	0.806 (0.633)	0.776 (0.851)	1.526*** (0.398)
LGDPPC Squared [*e*]	-0.058 (0.038)	-0.061 (0.039)	-0.088*** (0.028)	-0.036 (0.040)	-0.042 (0.060)	-0.100*** (0.032)
Log GDP Per Capita x Year [*f*]	-0.004** (0.002)			-0.005** (0.002)	-0.002 (0.002)	0.003** (0.001)
Log-Population	0.242 (0.236)	0.724*** (0.205)	0.744** (0.345)	0.134 (0.233)	-0.244 (0.351)	0.366 (0.249)
Log-Population Squared	-0.055* (0.028)	-0.052 (0.037)	0.000 (0.049)	-0.034 (0.029)	0.035 (0.026)	0.018 (0.018)
Years of Schooling (Pop. age 15+)				0.063** (0.030)		
Constant	-2.797 (2.308)	-3.959 (2.488)	-2.756 (2.240)	-1.093 (2.433)	-0.863 (2.844)	-2.977** (1.213)
Sample Size	2,217	1,138	1,079	2,083	2,239	4,537
Number of countries	63	63	63	63	63	134
R-squared	0.931	0.959	0.956	0.932	0.846	0.868
Country Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Std. Dev. Of Fixed Effects	0.768	1.390	1.516	0.417	0.662	0.844
Per Capita GDP at Peak during:						
1970	$30,486			$62,596	$11,135	$2,062
1980	$21,471	$84,933		$31,685	$9,232	$2,370
1990	$15,121			$16,038	$7,654	$2,723
2000	$10,649		$4,817	$8,118	$6,346	$3,129
2010	$7,500			$4,109	$5,262	$3,595
Peak manufacturing share expected by a "typical" country in:						
1970	29.5%	47.30%		28.7%	15.7%	17.3%
1980	24.4%	37.80%		22.1%	15.6%	16.1%
1990	20.5%	30.20%	18.30%	17.5%	15.7%	15.1%
2000	17.5%		15.30%	14.4%	15.8%	14.1%
2010	15.1%		12.80%	12.3%	15.9%	13.3%

Note: *, **, and *** capture signicance at the 10%, 5% and 1% levels, respectively. Standard errors are robust and clustered on countries.

last two. The regressions are distinguished by the numbers of countries and years they include; the choice of controls; and whether they include an interaction between time and per capita GDP, or instead allow that the curve move left over time by splitting the sample into two 20-year periods. *Inter alia*, the country fixed effects capture time-invariant inter-country differences in policy. The $\mathbf{x}_{c,t}$ are time-varying country characteristics—population and years of schooling.

In this framework, manufacturing shares follow an inverted-U shape with respect to per capita income so long as e is negative and the per capita income at which the shares are likely to be largest in any given year is within the range of per capita incomes actually observed. That counterfactual per capita GDP at peak is calculated as

$$\tilde{y}_t \equiv -(d + ft)/2e \tag{2}$$

and the manufacturing shares expected at these counterfactual peaks are calculated as $\bar{a} + b\star t + d\star \tilde{y}_t + e\star \tilde{y}_t^2 + f\star t\star \tilde{y}_t$. Table 6 shows that e is indeed negative (and usually significant) in all regressions. Therefore, in addition to regression coefficients, Table 6 presents the per capita incomes at which the inverted-U shape peaks at the end of each decade, as well as the peak manufacturing shares expected (for a hypothetical country with a fixed effect of zero). The results indicate that $\tilde{y}_t$ is small enough that some countries are on the downward-sloping portion of the hump, at least in later decades.

The regression results can be used to test the implications of two key theories regarding the causes of premature deindustrialization: labor-saving technological change and increasing global competition to host manufacturing activity.[16]

> ***Implication 1:*** If increasing global competition from low-income economies makes manufacturing employment harder to sustain in high-income economies, then $\tilde{y}_t$ should have fallen over time, at least for the employment share regression. This happens if and only if f is negative.
> ***Implication 2:*** If countries experiencing wage increases can continue to compete in manufactured goods markets by replacing labor with capital, then the decline in $\tilde{y}_t$ should be less pronounced for output shares than for employment shares.
> ***Implication 3:*** If technological change within countries' manufacturing sectors and/or shifts into less labor-intensive activities increased labor productivity faster in manufacturing than in non-manufacturing, then (holding income constant) countries' employment shares should have fallen faster over time than their output shares.

Table 6 clearly confirms each of these implications. In the 63 countries with good employment data, the per capita GDPs at which employment and output shares peak have declined over time.[17] This suggests growing global competition (Implication 1). We also note that these declines are less pronounced for output shares, which suggests that labor-saving technological change permits countries to sustain manufacturing

[16] It appears that, historically, technical progress has been a combination of labor-saving and capital using in Harrod's sense (Foley and Marquetti, 1999; Foley and Michl, 1999).

[17] The income at peak output share increases slightly over time when we expand the sample to 134 countries. These results are included for completeness, but we suspect that they reflect problems that arise from combining countries with very different demographic and geographic capacities for industrialization.

activity even while losing jobs to other countries (Implication 2). And the expected employment shares have fallen rapidly (the derivative of the expected share with respect to time, $b + fy$, is always negative and usually significant, and the predicted shares appearing in Table 6 decline fast) while the output shares in the sample of 63 countries with employment shares did not change (column 5). This is consistent with the existence of much more rapid labor-saving changes within manufacturing than within non-manufacturing (Implication 3).

Finally, we note that there are large unexplained differences between countries' manufacturing shares. This is apparent from the large standard deviation of the fixed effects in Table 6, and from Table 7, which provides the country fixed effects from the main employment share regression (Table 6, column 1), once they are normalized to have a population-weighted mean of zero. Table 7 shows that the Asian economies

Table 7. *Country fixed effects (employment share regression, Table 6, column 1) and year of peak mfg employment*

Economy/region	Fixed effect	Peak date	Economy/ region	Fixed effect	Peak date	Economy/ region	Fixed effect	Peak date
High-income economies	**–0.057**	**1971**	**LAC**	**–0.248**	**1989**	**Asia**	**0.109**	**1992**
Australia	–0.140	1970	Argentina	–0.130	1970	Bangladesh	0.031	1992
Austria	0.548	1974	Bolivia	0.146	2010	China	0.209	2010
Belgium	0.314	1970	Brazil	–0.423	1988	Hong Kong	0.560	1974
Canada	–0.200	1970	Chile	–0.024	1971	India	0.135	1999
Denmark	0.462	1970	Colombia	–0.405	1993	Indonesia	–0.247	2000
Finland	0.530	1977	Costa Rica	0.523	1991	Korea, Rep.	0.036	1989
France	–0.058	1971	El Salvador	0.473	1992	Malaysia	0.150	1995
Greece	0.059	1989	Guatemala	0.292	1994	Pakistan	0.075	1979
Ireland	0.525	1977	Honduras	0.474	1997	Philippines	–0.385	1973
Italy	0.066	1977	Mexico	–0.177	1989	Singapore	0.859	1981
Japan	–0.002	1971	Panama	0.167	1996	Thailand	–0.395	2004
Luxembourg	1.762	1971	Peru	–0.318	1971			
Netherlands	0.020	1970	Suriname	0.912	1970	**Africa**	**–0.538**	**1994**
Norway	0.372	1972	Trinidad and Tobago	0.615	1978	Botswana	0.159	1996
Portugal	0.385	1971	Venezuela, RB	–0.225	1985	Egypt, Arab Rep.	–0.028	1992
Puerto Rico	0.369	1976				Ghana	0.173	1977
San Marino	4.613	1978	**Other**	**0.261**	**1982**	Kenya	–0.493	2010
Spain	–0.006	1970	Poland	0.169	1978	Malawi	–0.542	2010
Sweden	0.322	1972	Romania	0.448	1986	Mauritius	1.484	1992
Switzerland	0.537	1970	Syrian Arab Republic	0.191	1982	Morocco	0.045	1995
United Kingdom	–0.032	1970				Nigeria	–1.066	1975
United States	–0.239	1970				Senegal	–0.231	2010
						South Africa	–0.328	1982
						Tanzania	–0.859	1986
						Zambia	–1.633	2010

Note: Renormalized country fixed effects are deviations from the population-weighted average fixed effect across countries. We provide median dates of peak manufacturing employment share (unweighted) in each region, average fixed effects for each region calculated by weighting each country's renormalized fixed effect by its share in the region's population in 1990.

have generally enjoyed a higher manufacturing employment share than their Latin American or African counterparts. While the typical Asian employment share was 11% above its predicted value, the typical Latin American country was 25% below, and the typical African nation was 54% below. The comparison with Latin America is particularly telling, given that the median Latin American nation industrialized earlier than its Asian counterpart, which suggests that Asia's shares are not higher because countries in this region industrialized early.[18]

The above differences between countries might reflect policy differences, though this is of course difficult to study in the absence of internationally comparable measures of industrial policies. Regression (4) in Table 6 does confirm a relationship with changes in one policy outcome. A one-year increase in average years of schooling is associated with a 6.3% increase in the manufacturing employment share. Moreover, adding in this variable cuts the standard deviation of the country fixed effects by roughly two-fifths (compare Regressions 4 and 1).

These results have direct implications for policy. Declines in the manufacturing shares and per capita incomes 'at peak' imply that more recent industrializers find it more difficult to achieve high manufacturing shares, and to sustain them as incomes rise. Along with the significance of the country fixed effects, they imply that it is misleading for countries to forge expectations of achievable manufacturing shares based on the experiences of other countries that industrialized earlier.

We emphasize that the inverted-U relationship discussed here is cross-sectional at a moment in time, and that $\tilde{y}_t$ is therefore a static peak. It is the log-income level at which the manufacturing share is expected to be highest under conditions prevailing at time t. In fact, because these conditions are changing, and countries are at very different levels of development in a given year, each country will follow a different path over time. Indeed, this relatively simple model allows countries to follow a very diverse array of such dynamic paths.

We now characterize the dynamic path of manufacturing shares and incomes for specific countries. The dynamic path traces a country's position along the sequence of static inverted-U curves as its income rises and those curves move down and to the left over time. The dynamic analysis helps make sense of the prospects of specific countries, which are influenced by their initial conditions and growth rates. The analysis yields two important findings. First, the dynamic paths peak at much lower income levels and manufacturing employment shares than do the static curves. Second, low per capita incomes and growth rates early on in a country's history dramatically reduce the incomes and manufacturing employment shares that it is likely to attain. Thus, the analysis of static peaks which is typical of this literature (Felipe *et al.*, 2014; Subramanian and Amirapu, 2014; Rodrik, 2016) understates the difficulties that today's late-industrializing economies face.

[18] As a referee correctly noted, our analysis does not consider the influence of external trade on the employment structure. The negative African fixed effects may be, for example, a consequence of the Dutch disease resulting from these countries' dependence on mineral exports. Rowthorn and Ramaswamy (1997) documented that the manufacturing trade balance (a proxy for trade specialization) is an important determinant of the manufacturing employment share: a fall of one percentage point in the ratio of net manufactured exports to GDP causes the manufacturing employment share to fall by 0.44 percentage points. More recently, McMillan *et al.* (2014) find that the share of a country's exports that is accounted for by raw materials is negatively related to the rate at which structural change contributes to growth.

To make matters concrete, we consider a country that grows at a constant growth rate $g_c > 0$. That is, $y_{c,t} = y_{c,0} + g_c \star t$, where $y_{c,0}$ is initial income per capita. Using this to substitute for t in (1) yields the dynamic path for s as a function of y:

$$s_c\left(y_{c,t}\right) = a_c - \frac{by_{c,0}}{g_c} + \left(\frac{b}{g_c} + d - \frac{fy_{c,0}}{g_c}\right)y_{c,t} + \left(e + \frac{f}{g_c}\right)y_{c,t}^2 + \text{g'}\mathbf{x}_{c,t} \tag{3}$$

The log-income at which this function peaks is then given by:

$$y_c^\star \equiv \frac{dg_c + b - fy_{c,0}}{-2\left(eg_c + f\right)}. \tag{4}$$

Given that $b, d > 0$ and $e, f < 0$ in Regressions (1) and (4) in Table 6, the following propositions are derived readily from Equations (1)–(4). Each is stated relative to a condition, which turns out to hold for the parameter estimates in employment Regressions (1) and (4) in Table 6 (the other regressions do not include all relevant parameters or concern output shares). Our 'baseline' coefficients are those in Regression (1).

Proposition 1: *At any initial moment in time (denoted t=0), the static income at peak* $\left(\tilde{y}_t\big|_{t=0}\right)$ *overstates the income at which the manufacturing share will actually peak* $\left(y_c^\star\right)$ *whenever* $-df + e\left(b - fy_{c,0}\right) > 0$.

Proof: Using (4) for $y_c^\star$ and $\tilde{y}_t\big|_{t=0} = -d/2e$, rearrange the inequality $y_c^\star \le \tilde{y}_t\big|_{t=0}$.

Discussion: Given baseline coefficients, this condition holds whenever $y_{c,0} < 15.14$, or for per capita GDPs below \$3.76 million. Thus, every single country in our sample is expected to deindustrialize sooner than Table 6 indicates.

Proposition 2: *Whenever* $-df + e\left(b - fy_{c,0}\right) > 0$, *the per capita GDP at the dynamic peak will be higher, the larger its (i) initial per capita GDP and (ii) growth rate.*

Proof: Differentiating (4) shows: (i) that $dy_c^\star / dy_{c,0} > 0$ because $e, f < 0$; and (ii) that $dy_c^\star / dg_c > 0$ so long as $-df + e\left(b - fy_{c,0}\right) > 0$.

Discussion: As just noted, the condition $-df + e\left(b - fy_{c,0}\right) > 0$ implies that the dynamic peak occurs at a lower income than the static peak, and holds under the baseline coefficients. Thus, throughout our sample, being poor early on and/or failing to grow quickly predisposes a country to deindustrialize at lower incomes.

Proposition 3: *So long as* $b + fy_{c,t} < 0$, *a country's manufacturing employment share, conditional on its current income* $s_c\left(y_{c,t}\right)$, *will be higher, the larger its (i) initial per capita GDP and (ii) growth rate.*

Proof: Differentiating (3) shows that: (i) $ds\left(y_{c,t}\right)/dy_{c,0} > 0$, and (ii) $ds\left(y_{c,t}\right)/dg_c > 0$ whenever $b + fy_{c,t} < 0$.

Discussion: Using the baseline coefficient values, the result holds whenever current income $\left(y_{c,t}\right)$ exceeds \$244. Thus, for all countries in our sample, being initially poor and/or growing slowly are doubly damaging, reducing both the income level at which deindustrialization sets in, and the employment share achievable at that income level.

It is also obvious from (3) that larger country fixed effects, or observed country characteristics $\left(\mathbf{x}_{c,t}\right)$ conducive to manufacturing, increase the manufacturing shares expected at peak. Moreover, it is straightforward to show that the year of the dynamic peak should arrive sooner in countries that were richer in 1970.[19]

Our econometric specification can therefore capture a wide variety of dynamics. Countries that start out poor, grow slowly and have low fixed effects are expected to deindustrialize later, but at much lower income levels and manufacturing shares than are rich, early industrializers with characteristics conducive to high manufacturing employment shares.

Table 8 compares the simulated dynamic employment peaks (columns 1–3) for several countries with the peaks actually observed in the data to date (columns 4–6). For

Table 8. *Manufacturing employment share forecasts*

	Simulated dynamic employment peak			Highest share in data so far			GDPPC in 1970	GDPPC Growth Rate, 1970–1982
	Year	GDPPC	Share	Year	GDPPC	Share		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
United States	1970	$20,115	26.1	1970	$20,115	26.4	$20,115	1.8%
United Kingdom	1970	$17,541	30.7	1970	$17,541	34.7	$17,541	1.6%
South Africa	1970	$4694	16.6	1981	$5197	16.8	$4693	0.6%
Mexico	1970	$1660	21.9	1990	$6498	20.0	$4660	3.3%
Brazil	1976	$3596	15.9	1986	$4215	16.4	$2328	4.2%
Korea, Rep.	1979	$3936	22.6	1989	$7747	27.8	$1921	6.7%
Malaysia	1996	$4665	19.4	1993	$3813	23.4	$1201	6.2%
Philippines	1980	$1116	10.8	1971	$854	11.7	$834	2.5%
Nigeria	1974	$831	5.2	1973	$767	7.3	$664	–0.1%
Thailand	1996	$2447	11.9	2007	$3079	15.1	$614	3.9%
Egypt, Arab Rep.	2012	$1706	14.4	1995	$985	15.0	$360	4.0%
Pakistan	2020	$1231	14.4	1981	$410	14.5	$337	1.9%
Indonesia	2011	$1672	11.6	2002	$1122	13.0	$318	4.8%
India	2014	$1237	12.2	2002	$600	12.5	$267	1.0%
Bangladesh	2025	$1103	13.2	1989	$255	13.9	$210	1.1%
China (Census)	2009	$2682	15.4	2010	$2943	16.9	$150	4.4%
China (GGDC)*	2007	$2263	18.3	2010	$2943	19.2	$150	4.4%

Note: All forecasts are from Regression (1) in Table 6, except for the row marked China (GGDC), which displays results from the same specification but estimated on a dataset which uses Chinese manufacturing employment share data from GGDC rather than the census. Bangladesh's per capita GDP and income growth rate in columns (7) and (8) use 1972, not 1970 figures. Countries are arranged according to their per capita GDP in 1970.

[19] An expression for the year of the dynamic peak is derived by using Equation (4) to substitute for $y_c^\star$ in $t_c^\star = \left(y_c^\star - y_{c,0}\right)/g_c$. Under our parameter estimates, $\partial t_c^\star / \partial y_{c,0} < 0$.

the simulations, we calculated each country's expected manufacturing employment shares over time using Equation (1), the coefficients and country fixed effects from Regression (3) in Table 6, and countries' actual per capita GDPs and populations between 1970 and 2010. For 2010–2030 we used population growth projections from United Nations (2013), and per capita GDP projections from Felipe *et al.* (2012). Per capita income in 1970 $\left(y_0\right)$ and the per capita growth rate $\left(g\right)$ prior to the onset of the Debt Crisis appear in columns (7) and (8).

The results are useful in two ways. They demonstrate the dynamic possibilities just enumerated, and they provide a sense of countries' relative success in defying the common structural forces that our model picks up.

The empirical relevance of Proposition 1 is obvious. The income at the static peak in 1970 $\left(\tilde{y}_t\big|_{t=0}\right)$ is \$30,486 (Table 6), which is 50%–2800% higher than the incomes at the dynamic peaks each country was predicted to achieve (Table 8, column 2), and 50%–11,900% higher than the incomes at which manufacturing employment shares actually peaked (Table 8, column 5). The static peaks therefore dramatically overstate the incomes at which deindustrialization is likely to set in. As such, the declines in incomes and employment shares at static peaks documented in this literature (Amirapu and Subramanian, 2015; Rodrik, 2016) are only indicative that deindustrialization now begins at lower income and employment levels—they are not useful measures of how much lower these levels will be.

Knowing where countries are likely to peak requires a dynamic analysis, and these dynamic outcomes are extremely sensitive to countries' initial conditions, as shown in Propositions 2 and 3. Because the predicted and actual dates and incomes of peak manufacturing employment coincide in the US, UK, Nigeria and Malaysia (i.e. the regression model fits these countries well), their divergent experiences cleanly illustrate the propositions.

Specifically, Malaysia's per capita income in the early 1970s was almost twice Nigeria's, and yet Nigerian manufacturing employment went into decline while Malaysia's grew for another 20 years, even as its per capita GDP tripled. The propositions account for this difference: Nigeria's lower initial income and near zero growth rate over those two decades predicted a very low dynamic peak income and associated manufacturing employment share; Malaysia's higher income and growth rates did the opposite. Similarly, the model also accounts for Nigeria, which looked nothing like the US and UK, going into manufacturing decline at roughly the same time as these much richer and more industrial economies did.

Several countries defy the model's predictions. Brazil, Korea, South Africa and Thailand continued industrializing for one decade longer than expected; while Mexico postponed deindustrialization by two decades. For Brazil, South Africa and Thailand, this additional decade bought only an extra 10%–23% in per capita income before deindustrialization kicked in. On the other hand, Korea and Mexico achieved, respectively, 68% and 136% higher incomes than expected before beginning to deindustrialize. Yet, the Korean and Mexican experiences are sharply divergent. At peak, Korea achieved a manufacturing share five percentage points higher than predicted by a model that already incorporated Korea's slightly positive fixed effect (Table 7). Mexico, on the other hand, despite holding on to its manufacturing jobs longer, peaked two points lower than expected, even taking into account its large negative fixed effect. The ability to postpone the date of deindustrialization therefore did not buy most countries growth miracles, or large numbers of factory jobs. Korea is exceptional.

Indeed, several countries have deindustrialized far sooner than expected. Egypt, Indonesia and the Philippines peaked 9–17 years sooner than expected, at income levels 28%–55% lower than expected. Bangladesh and Pakistan are not expected to peak until they achieve incomes of $1100, which they are projected to do by 2020–2025. However, they peaked in 1989 and 1981, respectively, at incomes of $255 and $410.

India, predicted to peak in 2014, in fact peaked 12 years earlier at half the income level it should have. Confirming India's positive fixed effect (Table 7), its observed peak manufacturing employment share is larger than its predicted peak share. Thus, India has not necessarily done badly given the late date of its growth acceleration, but it is paying a price for its low growth early on.

Finally, we turn to China, whose recorded employment shares continued to rise through 2010. Our model predicts Chinese manufacturing job losses to begin in 2009 using our baseline regression (which uses census estimates of China's manufacturing employment share), and by 2007 when that regression is run using GGDC data for Chinese manufacturing employment. This period coincides with growing reports in the business press of manufacturing firms relocating away from China in response to wage pressures (*Economist*, 2007). It also coincides with concern over the implications of rising wages (Cai, 2007) and official recognition of the need to relocate production to lagging regions of the country and promote services employment in response to the wage pressures of concentrated industrial growth (Fan, 2006). If China's manufacturing employment share has indeed peaked, this could open up new space for other countries to industrialize.[20]

5. Interpretation and conclusions

We have collected and analyzed manufacturing employment and output shares for a large number of countries to study two questions. First, how should successful industrialization be measured—is it more important to produce large amounts of manufacturing value added, or to create manufacturing jobs? Second, what are the odds of successful industrialization today?

The analysis permits us to make several contributions to the literature on 'premature deindustrialization'. We have shown that practically all rich countries had manufacturing employment shares over 18%, and that most countries above this threshold are rich. High manufacturing output shares are not as important. We have then shown that today's late-industrializing economies are unlikely to meet that 18% employment threshold. Moreover, this occurs not simply because the static relationship between manufacturing employment and income levels has changed, but because these changes impose substantial dynamic penalties for coming late to the party. In our view, it is this inability to meet a historically derived manufacturing-jobs threshold, rather than simply the decline in manufacturing employment shares, that gives early deindustrialization its 'premature' character.

[20] In the context of China, Rodrik (2008) has argued that exchange rate undervaluation (a high real exchange rate) is a form of industrial policy that boosts growth. This operates through the size of industry. In many developing countries, tradables suffer from government or market failures that keep poor countries from converging toward countries with higher incomes. Rodrik (2008) documents that Chinese per capita economic growth tracks movements in his undervaluation index closely starting in the second half of the 1970s.

The evidence in this paper and beyond provides some clues to the reasons why industrialization in employment has become more difficult. All of our results are consistent with unconditional convergence in manufacturing labor productivity across countries being a key driving force. The increased competition from poorer countries that this brings results in deindustrialization in employment setting in at lower income levels than it once did. Deindustrialization in output also sets in at lower incomes than it used to, but this trend is less pronounced than is the decline in the incomes at which employment peaks—a finding that is consistent with higher-wage countries replacing manufacturing labor with capital or moving up the value chain in order to withstand competition in markets for manufactured products.

Policy analysts frequently ask whether premature deindustrialization in employment is a result of technological change or globalization. We argue that this presents something of a false dichotomy. The unconditional convergence explanation involves *both* technological changes at the national level, and globalization. This explanation holds that the internationalization of supply chains has induced more rapid increases in national manufacturing labor productivity in developing economies than in advanced economies, and that the resulting increase in competition promotes further technological change, especially in advanced economies. Therefore, unconditional convergence provides a unifying framework that is consistent with all the stylized facts we present in this paper.

Of course, one might argue that technological change occurs at the national level for exogenous reasons—reasons other than globalization. Such an explanation is insufficiently rich to explain all the results in this paper. It does not explain why manufacturing labor productivity grew faster (relative to aggregate productivity) in lower-income economies. Moreover, a companion study to this one (Felipe and Mehta, 2016) provides three pieces of evidence that show that the spread of manufacturing capabilities to populous, lower-income countries seems to be an integral part of the story. First, manufacturing labor productivity *has* grown more rapidly in poorer countries (not just relative to aggregate labor productivity—as we show in this paper). Second, even if these productivity trends might be considered suspect due to the usual problems of tracking output across time and countries, the employment data seem to tell the same story: manufacturing jobs have shifted from countries with initially more productive manufacturing sectors to countries with initially less productive manufacturing sectors. This is hard to reconcile with similar rates of productivity growth worldwide, especially as wages have at the same time risen faster in the destination countries. Third, if the only trend of relevance was rapid labor productivity growth in manufacturing everywhere, manufacturing's share of global employment should have fallen relative to its share of global output. It did not. Rather, while productivity in manufacturing grew faster than aggregate labor productivity within nations, the ongoing relocation of manufacturing jobs from more to less productive but more populous countries—especially China—cancelled this out. This permitted the global economy to retain constant shares of both employment and output in manufacturing. Thus, labor-saving technological change on its own is insufficient as an explanation for national deindustrialization trends.

Finally, we turn to caveats. Might our results be driven by growing outsourcing of manufacturing-related services activity to dedicated service companies? It is certainly likely that this explains part of the decline in measured manufacturing employment shares. However, this classification problem should afflict national manufacturing output shares as well, and yet, these have not shifted downwards at all (in our main sample). Also, if we add UNIDO's (2013) estimate of outsourced or manufacturing-related jobs to our figures, manufacturing employment shares would increase by around 25%.[21] If we apply this increase to developing and developed countries alike, many lower-income countries will likely still fail to reach the 18%–20% manufacturing employment share threshold (e.g. Bangladesh, India, Indonesia, the Philippines), and several countries in the Middle East and North Africa, Central Asia and Central America already in the deindustrialization phase did not reach this threshold either (Felipe *et al.*, 2014, Table 1).[22]

We interpret these findings as an argument for broad-based development strategies. Governments clearly need to pay attention to manufacturing job creation. Yet, with the scope for national manufacturing employment creation limited by increased global competition, and perhaps, in the future, by climate change mitigation efforts (Gutowski, 2007), we need to consider whether countries can get rich by shifting to services without achieving high manufacturing employment shares. The growing array of new services and service-delivery modes—some of which appear to have rather high economies of scale (e.g. Maroto-Sánchez and Cuadrado-Roura, 2009)—makes it difficult to rule out this possibility. However, our data show that there are not yet any examples of countries that have done so successfully.

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[21] UNIDO (2013) estimates that in 2009 there were 470 million manufacturing jobs worldwide, of which 95 million have been outsourced to services firms and so do not appear in national manufacturing employment statistics. We have spoken with UNIDO staff about how these jobs were estimated and their reliability. UNIDO has advised that their estimates are a first approximation that can certainly be used, but with great caution.

[22] We have been asked several times whether our results corroborate what some people refer to as the middle-income trap. Felipe *et al.* (2017) document that the data does not seem to show that this alleged trap exists. Indeed, the data indicate that, historically, countries have moved up, with the consequence that today there are many more advanced economies than in 1950. Historically, it has taken countries a median of 70 years to transit the middle-income segment (i.e. to go from low to high income). Given that many developing countries reached the middle-income threshold only a couple of decades ago, it is perhaps too soon to claim that they are trapped. Our results here do not mean that if countries do not reach the employment threshold that we have estimated, they will not reach high income. It means that it will take them longer.

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Appendix: Data

We have output share data for 135 countries, out of which we have usable employment share data for 63.[23] On average, the 63 countries with sufficient employment data had higher incomes both during 2005–2010, and in the year the manufacturing output share peaked, than the 72 countries without sufficient employment data. They also have bigger populations, higher peak manufacturing output shares and experienced their peak manufacturing output share earlier (Table A1).

Employment Shares

Our data on manufacturing employment shares come from a variety of sources, some of them spliced together. Data for 4 of our main sample of 63 countries come solely from the OECD Stan database, and data for another 15 come solely from the Groningen Growth Development Center (GGDC). Chinese shares come directly from the Census. The remaining countries all utilize data from the ILO's LABORSTA database. LABORSTA often provides multiple estimates for the same country and time period, differentiated by source, sampling restrictions and sector classification systems. We have carefully selected the series to achieve maximum consistency, and cleaned these data meticulously, as explained below. Data for 17 countries come from LABORSTA alone. However, in some cases, the LABORSTA series begin late into our sample period or end early. Where this is the case, we impute earlier and later employment shares using growth rates derived from the OECD Stan database (12 countries) or the GGDC data (six countries). For another eight countries, we use GGDC data and fill in the gaps

[23] We exclude all island economies with a 1990 population of less than one million from our sample. Felipe *et al.* (2014) show that these small island economies are quite different structurally to larger, non-island nations. They have lower output shares, and structural endowments (land and demographics) are much more important for explaining the behavior of output shares in small island nations than in other nations. Data from small island nations are also often incomplete. We also exclude nations that have split up or unified over the course of our sample to ensure meaningful analysis.

using growth rates calculated from LABORSTA. Prior to splicing series together, we corroborated that, for the common periods (i.e. periods when two sources provided data), the correlation between the two series was above 0.9. The list of sources for employment shares used for each country is provided in Table A2.

The cleaning of the ILO's LABORSTA data proceeded as follows. We began with the full LABORSTA database. In any given country and year, these data can include estimates from more than one source, and the sources may use different sectoral classifications. From this, we kept observations collected according to the International Standard Industrial Classification, versions 2, 3 or 4, and dropped other series. We then dropped sources that exclude major sections of the workforce (e.g. rural residents, agricultural workers). In those instances where employment levels in some sectors were missing, but could be inferred from total employment and employment in other sectors, we filled in the blanks and checked to see whether this yielded discontinuities in the series. Where discontinuities were observed, the series corresponding to that country-source combination were dropped.

After these adjustments, some countries still had multiple sources in some years. For these country-year pairs with overlapping series, we opted to use the longest continuous series. When the series had the same length, we chose the one that used ISIC revision 2. We checked the final series for each country graphically for structural breaks that could not be explained with reference to its economic history.

We consider a country's employment data usable if we have at least five observed employment shares for the country, including one as far in the past as the early 1980s and one in the new millennium. On average, each country has 34 observed employment shares. Table A3 provides the number of observed employment shares, and earliest and latest dates of these observations for each country.

Output shares

Manufacturing output shares are from the United Nations Statistics Division. They capture the sector's share in value added, measured in constant dollars. These data were sufficiently complete for an additional 72 countries. The UN does not provide output share data for China separately from Taiwan, and so we obtained China's value-added shares from the World Bank's constant price series. While this series is slightly less comprehensive than the UN's, the correlation between the two series across time and countries is 0.94.

We subjected the panel dataset of output shares used in the Survival Analysis in Section 3.1 and in Sections 3.2 and 3.3 to yet further cleaning procedures. Specifically, we dropped observations of output shares if the UN and World Bank's estimates of current price output shares for that country and year differed by more than one percentage point and by a factor of at least 30%; and for those observations lacking estimates from the World Bank, if the UN constant and current price shares differ by more than one percentage point and a factor of at least 50%. This restricts the sample to observations in which we have greater confidence.

Other series

We also draw upon the following series: per capita GDP in 2005 constant dollars (WDI); population (UNSD); and years of schooling in the population aged 15 and above (Barro and Lee 2010). Missing observations on these variables (other than those at the start and end of time series) are filled in through log-linear interpolation.

Table A1. *Countries with employment share data are different*

	With employment data (63 countries)	Without employment data (72 countries)
Mean per capita GDP (2005–2010)	$17,806	$8337
Mean per capita GDP at time of peak manufacturing output share	$9801	$5889
Mean population over the sample period.	68.1 Million	9.6 Million
Mean manufacturing output share in year of peak	24.30%	15.80%
Median year of manufacturing output share peak	1980	1989

Table A2. *List of countries by source of employment share data*

LABORSTA only	Bangladesh, Botswana, El Salvador, Guatemala, Honduras, Pakistan, Panama, Poland, Portugal, Puerto Rico, Romania, San Marino, Suriname, Syria, Switzerland, Trinidad & Tobago, United Kingdom
OECD only	Belgium, Denmark, France, Ireland
GGDC only	Argentina, Bolivia, Egypt, Ghana, India, Kenya, Malawi, Mauritius, Morocco, Nigeria, Peru, Senegal, South Africa, Tanzania, Zambia
LABORSTA + OECD growth rate	Australia, Austria, Canada, Finland, Greece, Italy, Luxembourg, Netherlands, Norway, Spain, Sweden, US
LABORSTA + GGDC growth rate	Chile, Costa Rica, Hong Kong, Japan, Korea, Malaysia
GGDC + LABORSTA growth rate	Brazil, Colombia, Indonesia, Mexico, Philippines, Singapore, Thailand, Venezuela
National Census	China

Table A3. *Coverage of manufacturing employment shares*

Economy	Code	# of obs.	Earliest obs.	Latest obs.	Economy	Code	# of obs.	Earliest obs.	Latest obs.
Argentina	ARG	36	1970	2005	Malaysia	MYS	34	1975	2008
Australia	AUS	38	1971	2008	Mauritius	MUS	41	1970	2010
Austria	AUT	34	1976	2009	Mexico	MEX	39	1970	2008
Bangladesh	BGD	9	1984	2005	Morocco	MAR	41	1970	2010
Belgium	BEL	40	1970	2009	Netherlands	NLD	40	1970	2009
Bolivia	BOL	38	1970	2007	Nigeria	NGA	41	1970	2010
Botswana	BWA	7	1985	2006	Norway	NOR	40	1970	2009
Brazil	BRA	38	1970	2007	Pakistan	PAK	36	1973	2008
Canada	CAN	39	1970	2008	Panama	PAN	35	1970	2008
Chile	CHL	39	1970	2008	Peru	PER	36	1970	2005
China	PRC	6	1982	2010	Philippines	PHL	38	1971	2008
Colombia	COL	39	1970	2008	Poland	POL	28	1981	2008
Costa Rica	CRI	39	1970	2008	Portugal	PRT	35	1974	2008
Denmark	DNK	40	1970	2009	Puerto Rico	PTR	39	1970	2008
Egypt	EGY	41	1970	2010	Romania	ROU	37	1970	2008
El Salvador	SLV	20	1975	2007	San Marino	SMR	29	1978	2008
Finland	FIN	40	1970	2009	Senegal	SEN	41	1970	2010
France	FRA	39	1970	2008	Singapore	SGP	39	1970	2008
Ghana	GHA	41	1970	2010	South Africa	ZAF	41	1970	2010
Greece	GRC	29	1981	2009	Spain	ESP	40	1970	2009
Guatemala	GTM	7	1981	2006	Suriname	SUR	25	1973	2004
Honduras	HND	29	1970	2007	Sweden	SWE	40	1970	2009
Hong Kong	HKG	32	1974	2005	Switzerland	CHE	32	1970	2008
India	IND	35	1971	2005	Syrian Arab Republic	SYR	15	1970	2007
Indonesia	IDN	39	1970	2008	Tanzania	TZA	41	1970	2010
Ireland	IRL	40	1970	2009	Thailand	THA	39	1970	2008
Italy	ITA	40	1970	2009	Trinidad and Tobago	TTO	26	1970	2008
Japan	JAN	39	1970	2008	United Kingdom	GBR	39	1970	2008
Kenya	KEN	41	1970	2010	United States	USA	40	1970	2009
Korea, Rep.	KOR	39	1970	2008	Venezuela, RB	VEN	36	1970	2005
Luxembourg	LUX	40	1970	2009	Zambia	ZMB	41	1970	2010
Malawi	MWI	41	1970	2010					