Manufacturing matters…but it's the jobs that count

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Abstract: 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, and often did so *before* becoming rich; (2) Manufacturing employment peaks at lower incomes and shares today (typically below 18%), than in the past (often over 30%); (3) Although manufacturing labor productivity grew faster than non-manufacturing labor productivity within countries, they grew at similar rates globally, because factory jobs moved to less productive countries; and (4) Manufacturing's global employment share has not declined during the last 40 years. Industrialization has become more difficult, not because the sector has eliminated labor globally, but because of heightened international competition.

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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 20th century. Unsurprisingly, governments around the world have targeted manufacturing in their development plans. For example, India's 2011 National Manufacturing Policy aims at raising the share of manufacturing in GDP to 25% and calls for setting up manufacturing zones to create 100 million manufacturing jobs. 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 early 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 de-industrializing (Felipe, 2015; Helper et al., 2012).

Given the resources being allocated to 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 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). To make progress on this agenda, we have, through meticulous cleaning, merging and verification efforts, assembled international 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.[2] The employment sample represents 82% of the world's population in 2010,

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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 (2011) and UNIDO (2013).

[2] 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

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 to target manufacturing, and specifically, manufacturing employment.[3] 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 (Baumol, 1967; Lewis, 1954). 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 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 (Murphy et al., 1988; Rosenstein-Rodan, 1943). As manufacturing costs drop, the demand for manufactured goods increases, in turn causing more 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.

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

issue requires disaggregated data that are not generally available (UNIDO, 2013). Our core results are unlikely to be vitiated by this caveat (see Section 5).

[3] See the *Symposium on Kaldor's Growth Laws*, published in the Journal of Post Keynesian Economics (1983).

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 income economies. Second, it has long been accepted that technological change has placed downward pressure on the sector's demand for less skilled workers (e.g., Berman et al., 1998; Goldin and Katz, 2009; Kijima, 2006), and there is now growing concern that technological change and the efficiencies that derive from globalized mass production are generally labor displacing (Brynjolfsson and McAfee, 2014; Cowen, 2013). At the national level, rapid labor-saving technology change would result in fewer manufacturing jobs *relative to manufacturing output*, but, it would likely lead to more manufacturing jobs overall by increasing net exports and output. However, technological change at a global scale could reduce the sector's global labor requirements, in turn reducing the manufacturing employment levels countries can sustain.

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; Herrendorf et al., 2013; Kuznets, 1965). 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.

In addition to confirming all three implications of increasing international competition and labor displacing productivity growth within countries,[4] this paper makes four contributions to the literature on industrialization and development. First, consistent with the above theoretical arguments about the importance of manufacturing employment, we show that a country's peak historical manufacturing employment share is an extremely robust predictor of subsequent prosperity. Moreover, every single country in our employment sample with a per capita GDP of $12,000 in 2010 achieved a manufacturing employment share of 18% sometime since 1970: no country (save some oil-producing nations) got rich without a lot of manufacturing jobs. We show that output shares have little such predictive power. Second, we present a survival analysis that shows that high manufacturing employment shares precede the achievement of rich-country status, suggesting that causality runs from factory jobs to riches, not the other way around. Third, 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.

Finally, we aggregate up to take a global view of the manufacturing sector. We show that, notwithstanding the fact that labor productivity growth within countries was much faster in manufacturing than in non-manufacturing, global manufacturing labor productivity did not grow much faster than aggregate labor productivity. Moreover, the sector's share in global employment has not changed since the 1970s. This is because while labor productivity rose within countries, manufacturing jobs moved to other countries with even lower labor productivity levels. Thus, the sector has not shed labor globally. Increased competition from developing economies simply confines manufacturing employment to ever poorer economies.

The remainder of this paper is structured as follows. Section 2 motivates our study using a simple cross-sectional analysis. Section 3 analyzes the (changing) role of manufacturing in three stages. In Section 3.1, 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 3.2 we show that high

[4] We first confirmed these implications in a 2014 working paper. Rodrik (2015) reconfirms them using our original dataset and a longer panel of fewer countries from the Groningen Growth and Development Center (GGDC). Amirapu and Subramaniam (2015) show that implications 1 and 3 hold in a cross-section of industrial employment shares from the World Development Indicators.

manufacturing employment shares are becoming more difficult to achieve. Section 3.3 draws out the dynamic implications of our analysis. Section 4 takes a global view. Section 5 concludes.

2. Motivation

To motivate the detailed analysis that follows, Figures 1-3 and Table 1 present a cross-sectional description of the historical experience. Manufacturing employment and output shares in this cross-sectional view are calculated as 7-year moving averages between 1970 and 2010. A country's peak historical share is the maximum of its moving average series.[5]

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 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 peaks 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 respects. Indeed, when both regressors are included (Regression 3), only

[5] 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.

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 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 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 industrialization (Figure 2a). Achieving both a high and early peak matters, but only in employment terms. Section 3.1 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, and also that historical peak output shares display no such trend in either sample of countries. 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 3.2.

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. Analysis

3.1 Are industrialized countries rich economies?

We now examine the relationship between recent income per capita and countries' peak historical manufacturing employment shares in two distinct ways. First, we ask 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 7-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 no predictive power.[6] 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

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[6] 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.

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 all cutoffs below $8,000; 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.[7]

To make this exercise concrete, Table 4 categorizes our 63 countries according to whether they achieved 18% employment and output shares. We selected this cutoff to ensure that the fractions of countries that had industrialized in output and employment were equal to each other, and that both fractions were in the vicinity of one half.[8] Countries with

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

[8] For output shares, 18% 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 5 countries in the non-

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 are 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 suggest a stronger 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.[9] The model estimates the determinants of graduation in each year, conditional on not having graduated in previous years (i.e., of being "at risk" of graduation). We present results using $12,000 and $21,000 cutoffs for being rich. Thus, for example, looking at regressions (1)-(4), 44 countries had the requisite data and had incomes below $12,000 in 1970 and 7 of these "at risk" countries became rich between 1970 and 2010.[10] 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.[11,12] The results clearly indicate that having

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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.

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

[10] The remaining 19 of our 63 countries cannot be included in the survival analysis; 18 of them because they had graduated by 1970, and 1 because it lacked the agricultural share data.

[11] 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.

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), (6) and (7) 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 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 high 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.

3.2 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. It shows 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. It also provides some evidence on the causes of premature deindustrialization.

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[12] 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.

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: [13]

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

We estimate various versions of this regression with and without country fixed effects (a_c), with various sets of controls $(\mathbf{x}_{c,t})$, and taking employment or output shares as the dependent variable. Amongst other things, the fixed effects capture time-invariant inter-country differences in policy. The $\mathbf{x}_{c,t}$ capture time-varying country characteristics.

This specification permits us to ask four questions about the relationship between per-capita incomes and manufacturing shares. First, we examine whether, correcting for time and country characteristics, the shares follow an inverted-U shape with respect to per capita income. We do so by testing whether $e < 0$, and whether the per-capita income at which the shares are likely to be largest in a given year is within the observed income range. This counterfactual income at peak is given by:

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

Given evidence in support of the inverted-U shape, we ask, second, whether $\tilde{y}_t$ has fallen over time. This happens whenever $f < 0$. Third, we ask whether the manufacturing shares expected at these counterfactual peaks, $\bar{a} + b*t + d*\tilde{y}_t + e*\tilde{y}_t^2 + f*t*\tilde{y}_t$, have declined over time. Finally, we ask whether country fixed effects are statistically and economically significant.

Concluding in the affirmative on the second and third questions implies that more recent industrializers find it more difficult to achieve high manufacturing shares, and to sustain them as incomes (and wages) rise. To the extent that the second, third and fourth questions are answered in the affirmative, it is misleading for countries to forge expectations of achievable manufacturing shares based on the experiences of other countries that industrialized earlier.

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

The regression results also allow us to examine implications of two key theories regarding the causes of premature deindustrialization: labor-saving technological change and increasing global competition to host manufacturing activity.[14]

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.

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.

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, the relatively simple model allows countries to follow a very diverse array of dynamic paths. We will characterize them in section 3.3. The static peaks characterized in this section are useful for characterizing a "typical" country's industrialization prospects.

The first six regressions in Table 6 provide results for employment shares. Several trends in employment are visible, more or less throughout. Regression (1) is the most basic specification. Regression (2) adds country fixed effects. Regression (3) corrects for population, and is our preferred specification, whose implications we explore later on. Regressions (4) and (5) split the sample into two halves by time and omit the interaction between time and log-income. Regression (6) adds a correction for countries' average years of schooling. Regressions

[14] 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).

(7) and (8) are the analogs to the Regression (3), but run for output shares, using 63 and 134[15] countries respectively.

The following answers to our four questions are immediately apparent. First, the inverted-U shape appears (e<0) throughout, although it appears more strongly in the latter half of our sample (Regressions 4 and 5). The fact that e is not always statistically significant when country fixed effects are included suggests that one of the key national characteristics captured by a country's fixed effect is the per capita income at which its industrial employment peaked (and by extension, when it industrialized).

Second, the per capita income at which the employment share is expected to be largest $(\tilde{y}_t)$ falls quite dramatically over time in regressions in which it is permitted to move (1, 2, 3 and 6). Similarly, comparing 1970-1990 with 1990-2010 (Regressions 4 and 5), we find that the expected manufacturing employment share in the earlier period increases over the entire range of observed incomes, but peaks at only $4,817 in the latter period. In regression (3), the expected income at maximum employment share drops from $30,486 in 1970 to $7,500 in 2010. Thus, the data are consistent with Implication 1: manufacturing jobs have become more footloose. The output share regression for the same countries (7) reveals a much slower decline in income at peak to that found in regression (3). Thus, at least for the 63 larger economies with good employment series, the data are consistent with Implication 2. Mechanization may have permitted countries to retain manufacturing output even as manufacturing jobs become footloose in the face of rising incomes.[16]

Third, employment shares decline over time. This is true of the shares at maximum employment share (shown at the bottom of the table) and of the shares at any other relevant income level (the derivative of the expected share with respect to time, $b + fy$, is always negative and usually significant[17]). Conversely, peak expected output shares do not change over time. This is consistent with the existence of much more rapid labor-saving changes within manufacturing than within non-manufacturing (Implication 3).

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[15] Zimbabwe is dropped because its constant price series are unreliable.

[16] 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.

[17] Results are available on request.

Fourth, 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 employment share Regression (3), once they are normalized to have a population-weighted mean of zero. Table 7 shows that Asian economies 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.

These differences might reflect policy differences, though this is of course difficult to study in the absence of, for example, comparable measures of industrial policy across countries. Regression (6) 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 county fixed effects by roughly two thirds (compare Regressions 6 and 7).

Summing up, the results in this section are consistent with high manufacturing employment shares becoming harder to sustain due to growing international competition, and more rapid labor saving changes in manufacturing than in non-manufacturing. Indeed, it appears unlikely that today's industrializing nations will be able to achieve the high shares that have typified all those economies that graduated into rich-country status in the past. There is also support for the view that policies matter for sustaining manufacturing employment shares.

3.3 Dynamic analysis

This section characterizes the dynamic path of manufacturing shares and incomes for specific countries. The dynamic path traces a country's position along the static inverted-U curve as that curve moves down and to the left over time. Unlike the static analysis in the previous section, which characterizes the prospects of a "typical" country, the dynamic analysis helps to make sense of the prospects of specific countries, which are influenced by their initial conditions. The analysis yields two important findings. First, the dynamic paths peak at lower income levels and manufacturing employment shares than do the static paths. 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 static analysis in section 3.2, which is typical of this literature (e.g., Rodrik, 2015), understates the difficulties that today's late industrializing economies face.

To make matters concrete, we consider a country that grows at a constant growth rate $g_c > 0$. That is $y_{c,t} = y_{c,0} + g_c * t$, 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:

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

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

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

Given that $b, d > 0$ and $e, f < 0$ in Regressions (1)-(7) in Table 6, the following propositions are derived readily from equations (1), (3) and (4). Each is stated relative to a condition, which turns out to hold for every employment regression in Table 6. Our "baseline" coefficients are those in Regression 3 in that table.

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* $\left(y_c^*\right)$ *whenever* $-df + e\left(b - fy_{c,0}\right) > 0$.

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

<u>Discussion:</u> Given baseline coefficients, this condition holds whenever $y_{c,0}$ < 15.14, or for per capita GDP s below \$3.76 million. Thus, every single country in our sample is expected to deindustrialize sooner than the discussion in section 3.2 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 $dy_c^* / dy_{c,0} > 0$ because $e, f < 0$; and (ii) that $dy_c^* / dg_c > 0$ so long as $-df + e(b - fy_{c,0}) > 0$.

Discussion: As just noted, the condition $-df + e(b - fy_{c,0}) > 0$ 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* $s_c(y_{c,t})$*, will be higher, the larger its (i) initial per capita GDP and (ii) growth rate.*

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

Discussion: Using the baseline coefficient values, the result holds whenever current income $(y_{c,t})$ 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 $(\mathbf{x}_{c,t})$ conducive to manufacturing, increase the manufacturing shares expected at peak.

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 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 for several countries with the actual peaks observed, as well as with the static peaks in the year that manufacturing employment actually peaked. Simulations are based on the coefficients and country fixed effects estimated by Regression 3 in Table 6. We use observed incomes and populations until 2010. For 2010-2030 we used population growth projections from United Nations (2012), and per capita GDP projections from Felipe et al. (2012).

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 incomes at the static peaks $(\tilde{y}_t)$ are 50%-3,100% higher than the peaks each country was predicted to achieve, and 50%-3,400% higher than those actually achieved. The static shares 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, 2015) 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 will actually 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 model fits these countries well), their divergent experiences cleanly illustrate the propositions.

Specifically, Malaysia's per capita income in the early 1970s was 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 explains why Nigeria, which looked nothing like the US and UK, went 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 5 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 2 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 $1,100, 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 twelve years earlier at half the income level it should have.

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 (The 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 and environmental pressures of concentrated industrial growth (Fan, 2006). While the data needed to check these predictions are not yet available, it seems possible that China's manufacturing employment share has peaked. This could open up new space for other countries to industrialize.

4. A global perspective

Our dataset permits us to assess trends in manufacturing employment and output levels at the "global" level. We estimate total national employment by combining WDI data on the population, the share of the population aged 15-64, and the employment rate within that group. In order to be able to compare employment and output trends over time, we restrict attention to the 63 countries for which we have fairly consistent data over time, and also replace our

Chinese employment estimates from the national Census with annual estimates from GGDC. "Global" in this context therefore corresponds to 82% of the world's population. Unlike the panel regressions in the previous section, here we are compelled to apply log-linear interpolation (and extrapolation for some smaller countries) to fill in missing values.[18]

Figure 4 depicts the manufacturing sector's share of global employment over time, and the contributions of eight regions of the world to it. A region's contribution is simply the estimated number of manufacturing jobs in that region divided by global employment. One striking feature of this chart is the near constancy of the global manufacturing employment share over time, at roughly 14% of global employment. This implies that the decline in national manufacturing employment is not caused by declines in labor requirements of the global manufacturing sector. Another feature, which suggests competition from lower-income countries is more likely to be the culprit, is the large continual shift in the location of manufacturing jobs. In particular, Europe and North America have lost roughly as many manufacturing jobs as China and South Asia have gained.

Figure 5 provides analogous charts for value added shares. Here a country's contribution is that country's estimated manufacturing value added divided by global value added, all measured in constant 2005 US$. Both features observed in Figure 4 reappear. The manufacturing sector's share in global value added remains roughly constant over time, though at 16-17%, rather than 14%. And, Europe and North America have lost about as much manufacturing value added as South Asia, East Asia and China have gained.[19]

The constancy of both the global manufacturing employment and value added shares could appear counter-intuitive. After all, they together imply that global labor productivity (value added per worker) in manufacturing has grown no faster than global labor productivity in aggregate. Yet, we have already shown, in section 3.2, that, within countries, manufacturing labor productivity typically grew faster than aggregate labor productivity. And, indeed, the regional contributions in Figures 4 and 5 tell the same story: China's value added contribution, for example, grew by 1650%, while its employment contribution grew by 250%, implying that

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[18] Results to the analysis using only those countries that not require extrapolation are not qualitatively different.

[19] These results are consistent with Haraguchi's (2014) finding that, aggregating across developing economies: (i) manufacturing's share in total output has not changed since the 1970s, hovering at around 20-23%; and (ii) the aggregate manufacturing employment share increased since 1970.

Chinese manufacturing labor productivity grew 6.6 times faster than global manufacturing labor productivity. Similarly, South Asia's value added contribution grew by 350%, while its employment contribution grew by 60%; the European and North American value added contributions shrank much more slowly than their employment contributions; and East Asia's output contribution grew slightly, while its employment contribution fell.[20] The obvious explanation is that even as manufacturing labor productivity steamed ahead of aggregate productivity within countries, this was counteracted by a continual movement of manufacturing jobs from higher to lower labor productivity economies.

To study the contributions of these two opposing forces, we adapt a standard labor productivity decomposition, used to obtain the contributions to labor productivity growth of labor reallocations across sectors and labor productivity growth within sectors (e.g., Maroto-Sánchez and Cuadrado-Roura, 2009). Here we utilize it to break out the contributions of reallocations between countries and growth within countries. This exercise has not, to our knowledge, been conducted in the literature before. Let λ_m^0, λ_m^1 and $\overline{\lambda}_m$ be global manufacturing value added per worker in an initial year, in a subsequent year, and the average of the two. Let $\lambda_{m,c}^0$, $\lambda_{m,c}^1$ and $\overline{\lambda}_{m,c}$ be the analogous country-level measures. Finally, let $\alpha_{m,c}^0$, $\alpha_{m,c}^1$ and $\overline{\alpha}_{m,c}$ indicate country c's share of global manufacturing employment initially, subsequently, and on average. Then, the growth rates of aggregate and manufacturing labor productivity can be decomposed as follows:

(3) $$\hat{\lambda}_m \equiv \frac{\lambda_m^1 - \lambda_m^0}{\lambda_m^0} \equiv \frac{1}{\lambda_m^0}\sum_{c=1}^{C}\overline{\lambda}_{m,c}\left(\alpha_{m,c}^1 - \alpha_{m,c}^0\right) + \frac{1}{\lambda_m^0}\sum_{c=1}^{C}\overline{\alpha}_{m,c}\left(\lambda_{m,c}^1 - \lambda_{m,c}^0\right)$$

The first summation captures the effects of labor reallocations across countries, and will be negative if manufacturing employment moves towards countries with lower levels of manufacturing labor productivity. The second summation captures the effects of labor

[20] The contribution of the manufacturing sector (M) to global employment is simply L_M/L, and its contribution to global value added is VA_M/VA. Constant manufacturing contributions in both dimensions therefore imply that $\%\Delta(VA_M/L_M) \approx \%\Delta(VA/L)$. Next, consider the contributions of country c's manufacturing sector to global employment and output, $L_{M,c}/L$ and $VA_{M,c}/VA$. More rapid growth in the former than the latter is equivalent to $\%\Delta(VA_{M,c}/L_{M,c}) \approx \%\Delta(VA/L)$, which indicates that labor productivity grew faster in manufacturing than non-manufacturing.

productivity growth within countries, weighted by their shares of global manufacturing employment. The sum of the terms for a given country is the country's contribution to global manufacturing labor productivity growth. The same decomposition works for aggregate productivity.

Table 9 provides the detailed decompositions of global aggregate and manufacturing labor productivity growth using identity (3), across the eight regions represented in Figures 4 and 5. It also provides the analogous bottom line results when the decomposition is conducted across 63 countries. As indicated by the constancy of the global value added and employment shares in Figures 4 and 5, aggregate and manufacturing labor productivity grew at a fairly similar pace between 1970 and 2010. This might at first seem to be at odds with the literature on the role of manufacturing discussed previously: how could a sector that grows at 1.3% per annum (or 68.3% over 40 years), with no expansion in its employment share, serve as an engine of growth? Table 9 shows that the tension is the result of large differences in the sector's performance at the global and national levels.

Specifically, it shows that dramatic productivity growth within countries was offset by a constant reallocation of manufacturing jobs to lower productivity countries and regions. Counterfactually, if manufacturing jobs had not moved, within-region manufacturing productivity growth would have lifted output per worker 207% during this 40 year period. However, the reallocation of jobs from higher productivity manufacturing sectors in Europe and North America to lower productivity sectors in China and South Asia dragged productivity down 139%. The decomposition at the country level shows starker results, with within-country productivity growth pulling manufacturing productivity up 232% and relocation pulling it down 164%. Thus, the dynamics of rising productivity within countries and greater competition between countries, captured at the country level in section 3.2, lead to global manufacturing productivity growth that operates at par with the rest of the world economy.

Table 9 also shows some important shifts in productivity trends and regional roles over time. Globally manufacturing productivity grew more slowly than aggregate productivity between 1970 and 1990. During 1990-2010, manufacturing labor productivity grew 50% faster than aggregate productivity and nearly three times faster than it grew during 1970-1990. The latter period also saw a dramatic increase in China's contribution to manufacturing productivity growth. Between 1970 and 1990, two thirds of global manufacturing labor productivity growth came from East Asia and the Pacific (11.2%/15.9%). North America's contributions were negligible in the earlier period, as productivity growth and job losses within this high productivity region offset each other (- 20.5% + 20.3%= - 0.2%). However, the region's contributions picked up in the latter period, despite continuing job losses, as productivity boomed. Europe was a non-issue throughout, as productivity growth was offset almost exactly by job losses.

Indeed, the contribution of relocation across countries to productivity is the same in both periods (60-61%). The difference in manufacturing productivity growth between the latter and earlier period is driven entirely by the increased contributions from within-region productivity growth $\left(45.2\% - 15.9\% \approx 105.5\% - 76.6\%\right)$, which is explained almost exclusively by the contributions of faster productivity growth in China (19.3% vs. 1.2%) and North America (33.5% vs. 20.3%, offset by slower productivity growth in Europe.

Finally, it is worth noting the connection with previous results. Section 3.2 documents a reduction in the incomes at which countries typically begin to deindustrialize. We suggested that this reflects growing competition from lower productivity economies, and have now documented that such a movement occurred, and that, arithmetically, it preserved manufacturing jobs globally. The absence of a decline in the global manufacturing employment share suggests that global productivity growth is at best of second order importance in explaining declining manufacturing employment within countries.

5. Interpretation and Conclusions

We have collected and analyzed manufacturing employment and output shares for a large number of countries to study, first, what the odds of successful industrialization are today, and whether there are alternative routes to prosperity; and second, how success in industrialization should be measured – is it more important to produce large amounts of manufacturing value added, or to create manufacturing jobs?

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.

We have also provided evidence that this inability is primarily a function of unconditional convergence in manufacturing labor productivity. The increased competition from poorer countries that this brings results in deindustrialization 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 in order to withstand competition in markets for manufactured products. Further, while peak output shares have not fallen, higher rates of labor productivity growth in national manufacturing than non-manufacturing sectors have reduced manufacturing employment shares relative to output shares.

Finally, we have studied the global implications of growing global competition and rapid manufacturing labor productivity growth within countries, and shown that they more or less cancel each other out. Between 1970 and 2010, manufacturing labor productivity growth exceeded aggregate labor productivity growth within countries. However, because growing global competition pushed manufacturing jobs increasingly to lower-income, lower-productivity countries, manufacturing labor productivity growth did not exceed aggregate labor productivity growth at the global level. Thus, with the sector's share of global value added remaining unchanged, its contribution to global employment has not changed either.

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 declines 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). Finally, it is worth noting that 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).

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 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.

[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.

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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.[22] 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). For our regression analyses (sections 2 and 3.1-3.3) we calculated Chinese shares directly from the Census, but we use GGDC for China in section 4, where breaks in the employment share series are most problematic.[23] 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 (6 countries). For another 8 countries, we use GGDC data and fill in the gaps 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

[22] 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.
[23] We opted for Chinese census over data from the Statistical yearbooks, because the yearbook data are considered less reliable (Li and Gibson, 2013), and do not cover the rural sector post-2003.

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 its economic history.

We consider a country's employment data usable if we have at least 5 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

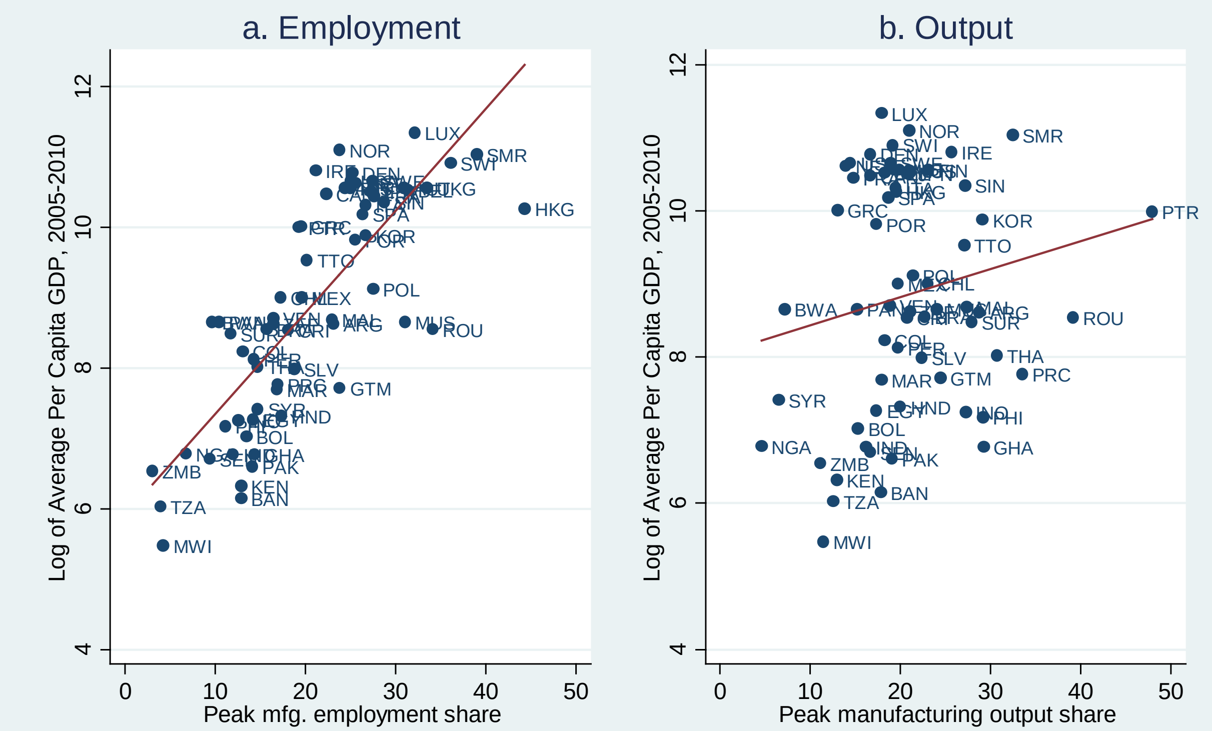
Manufacturing output shares are from the United Nations Statistics Division. They capture the sector's share in value added, measured in constant dollars. These data were sufficiently complete for an additional 72 countries. The UN does not provide output share data for China separately from Taiwan, 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 1 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 1 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.

Figure 1: Industrialization in employment is a better predictor of future prosperity than industrialization in output.



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.

Figure 2: Recent industrializers have peaked at lower employment shares; but not at lower output shares.

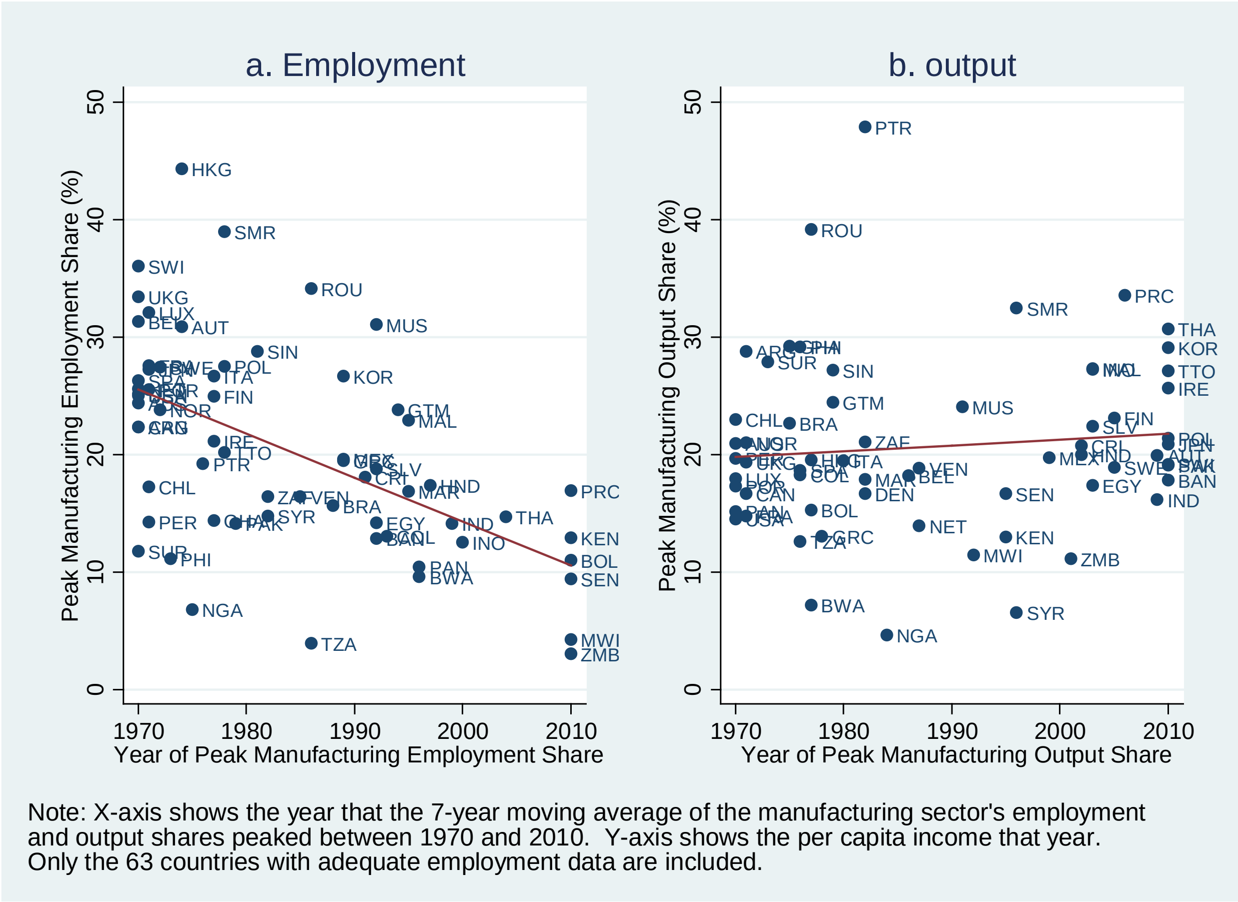
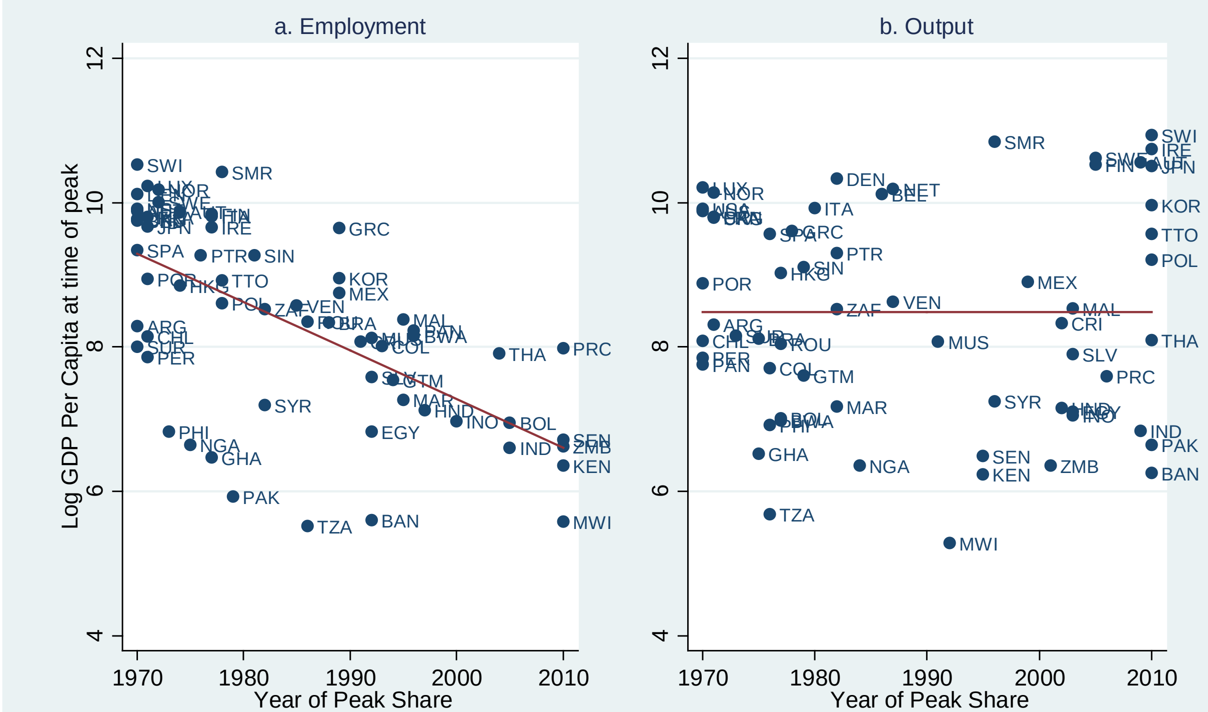


Figure 3: Deindustrialization in employment begins at lower incomes than it once did. Not as obvious for output.



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.

Figure 4: Share of Manufacturing in Global Employment, with Regional Contributions

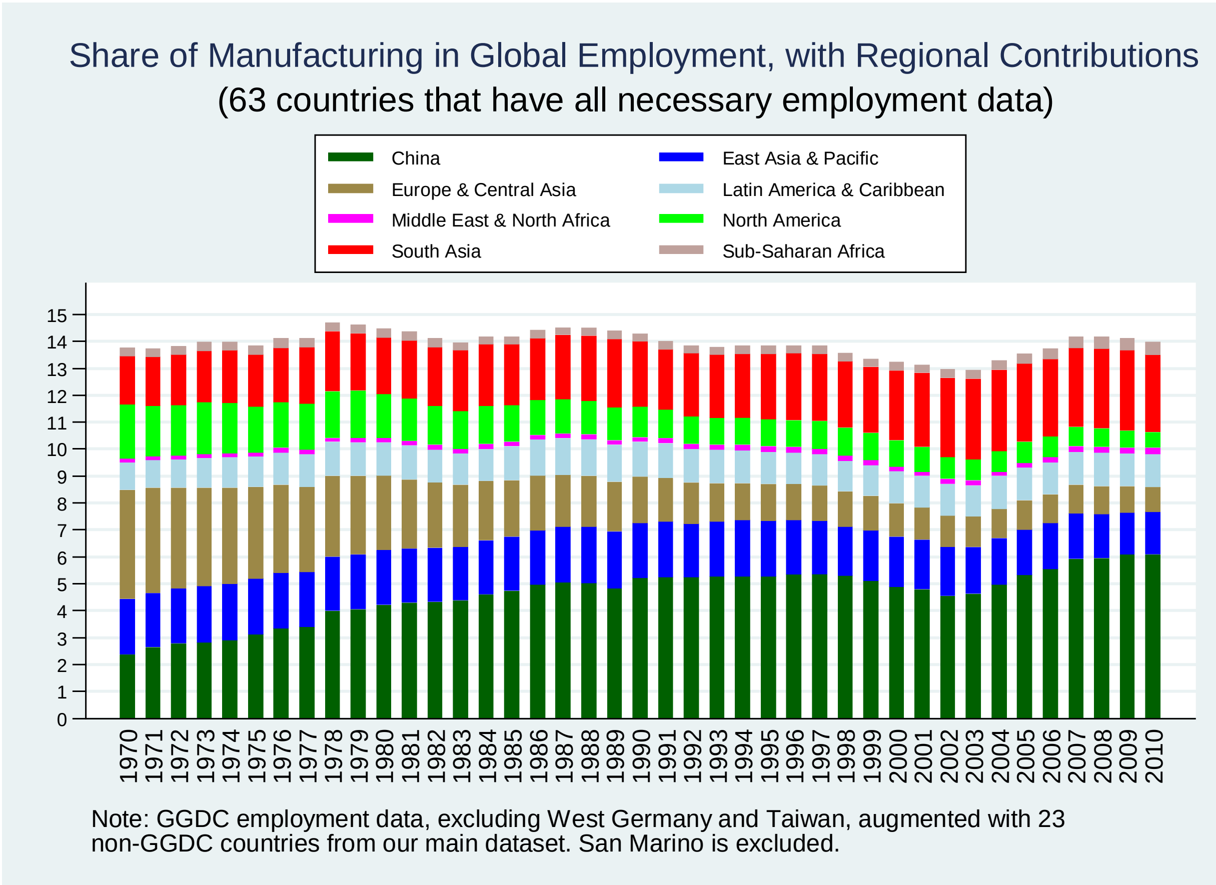


Figure 5: Share of Manufacturing in Global Output, with Regional Contributions

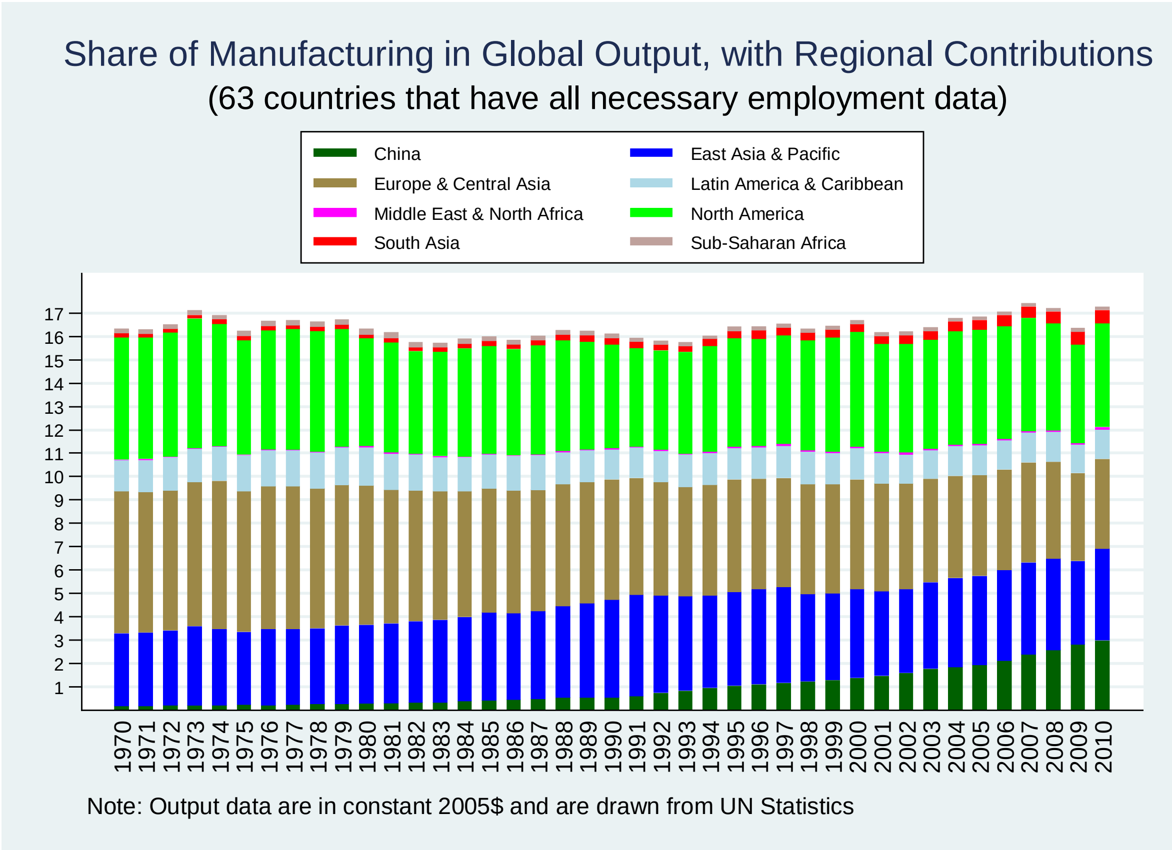


Table 1: Cross-country relationships between recent income, income when manufacturing peaked, and manufacturing shares.

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 Share	Value Added Share	
	(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.

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 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	28	30
6K	*0.476*	0.526	0.566	0.612	**0.732**	0.800	0.833	0.821	0.913	0.882	0.800	0.778
8K	*0.46*	0.509	0.547	0.592	0.707	**0.800**	0.833	0.821	0.913	0.882	0.800	0.778
10K	*0.413*	0.456	0.491	0.531	0.634	**0.743**	0.800	0.786	0.870	0.824	0.800	0.778
12K	*0.413*	0.456	0.491	0.531	0.634	**0.743**	0.800	0.786	0.870	0.824	0.800	0.778
14K	*0.397*	0.439	0.472	0.510	0.610	0.714	0.767	0.786	**0.870**	0.824	0.800	0.778
16K	*0.397*	0.439	0.472	0.510	0.610	0.714	0.767	0.786	**0.870**	0.824	0.800	0.778
18K	*0.397*	0.439	0.472	0.510	0.610	0.714	0.767	0.786	**0.870**	0.824	0.800	0.778
20K	*0.365*	0.404	0.434	0.469	0.561	0.657	0.700	0.714	**0.783**	0.765	0.800	0.778
22K	*0.349*	0.386	0.415	0.449	0.537	0.629	0.700	0.714	**0.783**	0.765	0.800	0.778
24K	*0.333*	0.368	0.396	0.429	0.512	0.600	0.700	0.714	**0.783**	0.765	0.800	0.778
26K	*0.333*	0.368	0.396	0.429	0.512	0.600	0.700	0.714	**0.783**	0.765	0.800	0.778
28K	*0.317*	0.351	0.377	0.408	0.488	0.571	**0.667**	0.679	0.739	0.706	0.800	0.778
30K	*0.302*	0.333	0.358	0.388	0.463	0.543	**0.633**	0.643	0.696	0.647	0.700	0.667
Probability that manufacturing share > threshold		*0.905*	*0.841*	*0.778*	*0.651*	*0.556*	*0.476*	*0.444*	*0.365*	*0.270*	*0.159*	*0.143*

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	28	30
6K	*0.476*	0.000	0.000	0.000	**0.000**	0.071	0.152	0.200	0.225	0.326	0.415	0.426
8K	*0.46*	0.000	0.000	0.000	0.000	**0.036**	0.121	0.171	0.200	0.304	0.396	0.407
10K	*0.413*	0.000	0.000	0.000	0.000	**0.000**	0.061	0.114	0.150	0.261	0.340	0.352
12K	*0.413*	0.000	0.000	0.000	0.000	**0.000**	0.061	0.114	0.150	0.261	0.340	0.352
14K	*0.397*	0.000	0.000	0.000	0.000	0.000	0.061	0.086	**0.125**	0.239	0.321	0.333
16K	*0.397*	0.000	0.000	0.000	0.000	0.000	0.061	0.086	**0.125**	0.239	0.321	0.333
18K	*0.397*	0.000	0.000	0.000	0.000	0.000	0.061	0.086	**0.125**	0.239	0.321	0.333
20K	*0.365*	0.000	0.000	0.000	0.000	0.000	0.061	0.086	**0.125**	0.217	0.283	0.296
22K	*0.349*	0.000	0.000	0.000	0.000	0.000	0.030	0.057	**0.100**	0.196	0.264	0.278
24K	*0.333*	0.000	0.000	0.000	0.000	0.000	0.000	0.029	**0.075**	0.174	0.245	0.259
26K	*0.333*	0.000	0.000	0.000	0.000	0.000	0.000	0.029	**0.075**	0.174	0.245	0.259
28K	*0.317*	0.000	0.000	0.000	0.000	0.000	**0.000**	0.029	0.075	0.174	0.226	0.241
30K	*0.302*	0.000	0.000	0.000	0.000	0.000	**0.000**	0.029	0.075	0.174	0.226	0.241
Probability that manufacturing share < threshold		*0.095*	*0.159*	*0.222*	*0.349*	*0.444*	*0.524*	*0.556*	*0.635*	*0.730*	*0.841*	*0.857*

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

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.

Per Capita GDP Threshold	*Probability that GDPPC > threshold*	Manufacturing output share threshold										
		10	12	14	16	18	20	22	24	26	28	30
6K	0.476	0.500	**0.517**	0.519	0.520	0.537	0.429	0.381	0.353	0.357	0.333	0.400
8K	0.46	0.483	**0.500**	0.500	0.500	0.512	0.429	0.381	0.353	0.357	0.333	0.400
10K	0.413	0.433	**0.448**	0.444	0.440	0.439	0.357	0.333	0.353	0.357	0.333	0.400
12K	0.413	0.433	**0.448**	0.444	0.440	0.439	0.357	0.333	0.353	0.357	0.333	0.400
14K	0.397	0.417	**0.431**	0.426	0.420	0.415	0.321	0.286	0.294	0.286	0.333	0.400
16K	0.397	0.417	**0.431**	0.426	0.420	0.415	0.321	0.286	0.294	0.286	0.333	0.400
18K	0.397	0.417	**0.431**	0.426	0.420	0.415	0.321	0.286	0.294	0.286	0.333	0.400
20K	0.365	0.383	**0.397**	0.389	0.380	0.390	0.286	0.238	0.235	0.214	0.222	0.400
22K	0.349	0.367	**0.379**	0.370	0.360	0.366	0.250	0.190	0.176	0.143	0.111	0.200
24K	0.333	0.350	**0.362**	0.370	0.360	0.366	0.250	0.190	0.176	0.143	0.111	0.200
26K	0.333	0.350	**0.362**	0.370	0.360	0.366	0.250	0.190	0.176	0.143	0.111	0.200
28K	0.317	0.333	**0.345**	0.352	0.340	0.341	0.250	0.190	0.176	0.143	0.111	0.200
30K	0.302	0.317	**0.328**	0.333	0.320	0.317	0.250	0.190	0.176	0.143	0.111	0.200
Probability that manufacturing share > threshold		*0.952*	*0.921*	*0.857*	*0.794*	*0.651*	*0.444*	*0.333*	*0.270*	*0.222*	*0.143*	*0.079*

b. Probability that a country has crossed per capita GDP threshold, given that it <u>has not</u> crossed the manufacturing output share threshold.

Per Capita GDP Threshold	*Probability that GDPPC > threshold*	Manufacturing output share threshold										
		10	12	14	16	18	20	22	24	26	28	30
6K	*0.476*	0.000	**0.000**	0.222	0.308	0.364	0.514	0.524	0.522	0.510	0.500	0.483
8K	*0.46*	0.000	**0.000**	0.222	0.308	0.364	0.486	0.500	0.500	0.490	0.481	0.466
10K	*0.413*	0.000	**0.000**	0.222	0.308	0.364	0.457	0.452	0.435	0.429	0.426	0.414
12K	*0.413*	0.000	**0.000**	0.222	0.308	0.364	0.457	0.452	0.435	0.429	0.426	0.414
14K	*0.397*	0.000	**0.000**	0.222	0.308	0.364	0.457	0.452	0.435	0.429	0.407	0.397
16K	*0.397*	0.000	**0.000**	0.222	0.308	0.364	0.457	0.452	0.435	0.429	0.407	0.397
18K	*0.397*	0.000	**0.000**	0.222	0.308	0.364	0.457	0.452	0.435	0.429	0.407	0.397
20K	*0.365*	0.000	**0.000**	0.222	0.308	0.318	0.429	0.429	0.413	0.408	0.389	0.362
22K	*0.349*	0.000	**0.000**	0.222	0.308	0.318	0.429	0.429	0.413	0.408	0.389	0.362
24K	*0.333*	0.000	**0.000**	0.111	0.231	0.273	0.400	0.405	0.391	0.388	0.370	0.345
26K	*0.333*	0.000	**0.000**	0.111	0.231	0.273	0.400	0.405	0.391	0.388	0.370	0.345
28K	*0.317*	0.000	**0.000**	0.111	0.231	0.273	0.371	0.381	0.370	0.367	0.352	0.328
30K	*0.302*	0.000	**0.000**	0.111	0.231	0.273	0.343	0.357	0.348	0.347	0.333	0.310
Probability that manufacturing share < threshold		*0.048*	*0.079*	*0.143*	*0.206*	*0.349*	*0.556*	*0.667*	*0.730*	*0.778*	*0.857*	*0.921*

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

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

		Employment Share relative to 18%	
		Not Industrialized (0/28 Countries is rich)	Industrialized (26/35 Countries are rich)
Output Share Relative to 18%	Not Industrialized (16/35 countries are rich)	Bangladesh, Bolivia, Botswana, Colombia, Egypt, Honduras, 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.

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

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

Dependent Variable	Manufacturing Employment Share						Manufacturing value added share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample Period	1970-2010	1970-2010	1970-2010	1970-1990	1990-2010	1970-2010	1970-2010	1970-2010
Year [*b*]	0.019*** (0.005)	0.041** (0.016)	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*]	1.511*** (0.066)	0.661 (0.552)	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*]	-0.071*** (0.004)	-0.024 (0.035)	-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*]	-0.003*** (0.001)	-0.006*** (0.002)	-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	-4.708*** (0.281)	-0.976 (2.136)	-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	2,217	2,217	1,138	1,079	2,083	2,239	4,537
Number of countries	63	63	63	63	63	63	63	134
R-squared.	0.580	0.930	0.931	0.959	0.956	0.932	0.846	0.868
Country Fixed Effects?	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Std. Dev. Of Fixed Effects		0.408	0.768	1.390	1.516	0.417	0.662	0.844
Per Capita GDP at Peak during:								
1970	$43,768	$855,783	$30,486			$62,596	$11,135	$2,062
1980	$33,986	$253,425	$21,471	$84,933		$31,685	$9,232	$2,370
1990	$26,643	$75,047	$15,121			$16,038	$7,654	$2,723
2000	$20,822	$22,224	$10,649		$4,817	$8,118	$6,346	$3,129
2010	$16,218	$6,581	$7,500			$4,109	$5,262	$3,595
In middle of period								
Peak manufacturing share expected by a "typical" country in:								
1970	28.8%	34.4%	29.5%	47.30%		28.7%	15.7%	17.3%
1980	24.2%	24.0%	24.4%	37.80%		22.1%	15.6%	16.1%
1990	20.6%	18.0%	20.5%	30.20%	18.30%	17.5%	15.7%	15.1%
2000	17.6%	14.5%	17.5%		15.30%	14.4%	15.8%	14.1%
2010	15.2%	12.6%	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.

Table 7: Country Fixed Effects (Employment Share Regression 3) 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.

Table 8: Manufacturing Employment Share Forecasts

	GDPPC in 2010	Peak, per Baseline Specification			Highest share in data so far			GDPPC at Static Peak in Year of Max Observed Share
		Year	GDPPC	Share	Year	GDPPC	Share	
United States	$41,871	1970	$20,115	26.1	1970	$20,115	26.4	$30,302
United Kingdom	$40,837	1970	$17,541	30.7	1970	$17,541	34.7	$30,302
Nigeria	$980	1974	$831	5.2	1973	$767	7.3	$26,398
Malaysia	$6,520	1996	$4,665	19.4	1993	$3,813	23.4	$12,362
Mexico	$8,971	1970	$1,660	21.9	1990	$6,498	20.0	$30,302
Brazil	$5,662	1976	$3,596	15.9	1986	$4,215	16.4	$24,639
Korea, Rep.	$20,892	1979	$3,936	22.6	1989	$7,747	27.8	$22,217
South Africa	$5,766	1970	$4,694	16.6	1981	$5,197	16.8	$30,302
Thailand	$3,381	1996	$2,447	11.9	2007	$3,079	15.1	$12,362
Egypt, Arab Rep.	$1,571	2012	$1,706	14.4	1995	$985	15.0	$7,120
Indonesia	$1,594	2011	$1,672	11.6	2002	$1,122	13.0	$7,370
Philippines	$1,466	1980	$1,116	10.8	1971	$854	11.7	$21,464
Bangladesh	$525	2025	$1,103	13.2	1989	$255	13.9	$4,548
Pakistan	$809	2020	$1,231	14.4	1981	$410	14.5	$5,404
India	$1,011	2014	$1,237	12.2	2002	$600	12.5	$6,646
China (Census)	$2,943	2009	$2,682	15.4	2010	$2,943	16.9	$7,896
China (GGDC)*	$2,943	2007	$2,263	18.3	2010	$2,943	19.2	$8,460

Note: All forecasts are from regression (3) in Table 6, except for the row marked China (GGDC), which displays results from the same specification with Chinese data from GGDC substituted for Census data. Countries appear in the order they are mentioned in the text.

Table 9: Decomposing shifts in "Global" Manufacturing and Aggregate Labor Productivity

	1970-2010			1970-1990			1990-2010		
	Relocation	Within Region	Total	Relocation	Within Region	Total	Relocation	Within Region	Total
Aggregate									
China	0.3%	13.4%	13.7%	0.2%	1.4%	1.6%	-0.7%	10.6%	9.9%
East Asia & Pacific	-0.9%	14.3%	13.4%	-0.1%	9.3%	9.1%	-0.8%	4.2%	3.5%
Europe & Central Asia	-35.5%	42.8%	7.3%	-24.8%	27.2%	2.4%	-5.7%	9.6%	4.0%
Latin America & Caribbean	3.3%	2.1%	5.4%	1.4%	0.5%	1.8%	1.5%	1.4%	3.0%
Middle East & North Africa	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
North America	-14.3%	31.2%	17.0%	-7.3%	13.3%	6.0%	-4.8%	13.8%	9.0%
South Asia	0.6%	3.4%	4.0%	0.1%	0.5%	0.7%	0.3%	2.4%	2.7%
Sub-Saharan Africa	0.5%	0.3%	0.8%	0.0%	0.0%	0.0%	0.4%	0.3%	0.6%
World (decomposed by region)	**-45.9%**	**107.5%**	**61.7%**	**-30.4%**	**52.1%**	**21.7%**	**-9.7%**	**42.5%**	**32.8%**
Manufacturing									
China	9.6%	18.3%	28.0%	1.7%	1.2%	2.9%	2.3%	19.3%	21.7%
East Asia & Pacific	-8.0%	27.4%	19.4%	-1.0%	12.1%	11.2%	-6.8%	13.9%	7.1%
Europe & Central Asia	-78.8%	78.9%	0.1%	-38.5%	37.9%	-0.6%	-19.7%	20.3%	0.6%
Latin America & Caribbean	1.6%	3.1%	4.6%	1.6%	-0.1%	1.5%	-0.3%	3.0%	2.7%
Middle East & North Africa	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
North America	-65.1%	76.5%	11.4%	-20.5%	20.3%	-0.2%	-23.5%	33.5%	10.0%
South Asia	1.3%	3.1%	4.4%	0.4%	0.6%	0.9%	0.6%	2.4%	3.0%
Sub-Saharan Africa	0.5%	-0.1%	0.4%	-0.2%	0.3%	0.1%	0.6%	-0.4%	0.2%
World (decomposed by region)	**-138.9%**	**207.2%**	**68.3%**	**-56.4%**	**72.3%**	**15.9%**	**-46.7%**	**91.9%**	**45.2%**
World (decomposed by country)	**-163.8%**	**232.1%**	**68.3%**	**-60.7%**	**76.6%**	**15.9%**	**-60.3%**	**105.5%**	**45.2%**

Note: Results of a between-within country/region decomposition of the percentage change in "global" aggregate and manufacturing labor productivity. "Global" refers to the aggregate of the 63 countries for which we have employment share data.

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	$8,337
Mean per capita GDP at time of peak manufacturing output share	$9,801	$5,889
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					