Essays on Technological Change, Skill Premia and Development

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4 Premature Deindustrialization through the Lens of Occupations: Which Jobs, Why, and Where?[1]

4.1 Introduction

Manufacturing has long been considered a quintessential stepping stone on the development ladder due to its ability to employ unskilled workers productively (Lewis, 1954). Reallocating workers from agriculture to manufacturing promises large gains in economy-wide productivity, and structural transformation-fuelled growth can take place even if "fundamentals" such as educational attainments lag behind (Rodrik, 2013a). Moreover, Rodrik (2013b) finds that unlike other industries, manufacturing exhibits unconditional convergence in labor productivity, which makes it a potential driver of convergence in living standards across countries. However, a growing literature documents that developing countries have been running out of manufacturing employment opportunities earlier and at much lower levels of income in recent decades, compared to the experience of early industrializers (Rowthorn and Coutts, 2004; Dasgupta and Singh, 2006; Amirapu and Subramanian, 2015; Rodrik, 2016; Felipe et al., 2018). This raises the question to what degree manufacturing is still able to play its traditional role in economic development.

Existing studies of premature deindustrialization focus on aggregate manufacturing employment, which leaves open the question *what kind* of jobs have disappeared "prematurely". In particular, is it jobs that unskilled workers from the countryside may previously have been able to take up? Moroever, many of the benefits ascribed to manufacturing pertain in particular to *formal* manufacturing, whereas La Porta and Shleifer (2008) paint a rather bleak picture of wages and productivity in informal manufacturing firms. Hence, the consequences of premature deindustrialization for development prospects hinge on whether it is mostly formal or informal manufacturing jobs that have disappeared. A better characterization of the disappearing jobs also helps to clarify in what sense the normative flavor of the term "premature deindustrialization" is warranted.

Second, there is some debate about the main drivers of the phenomenon: while Rodrik (2016) and Felipe et al. (2018) assign a prominent role to labor-saving technological

[1] This chapter is based on Kunst (2019b).

progress, Haraguchi et al. (2017) argue that developing countries´ difficulties are entirely due to globalization- and more specifically, due to the entry of China into the world market, with its strong comparative advantage in manufacturing.[2] Moreover, the recent increases in manufacturing employment in some lower income countries such as Vietnam or Cambodia raise questions about the generality of the phenomenon of premature job losses.

From the perspective of the task literature initiated by Autor et al. (2003), a testable implication of the technological change-based explanations is a reduction in labor demand in particular for the production tasks that have only recently become automatable (as opposed to manufacturing employment across the board). Finding such a 'task-biased' labor demand trend would not necessarily imply that premature deindustrialization is driven exclusively by technological change. However, it would provide evidence against the view that the phenomenon just reflects China's size and comparative advantage in manufacturing, and does not also reflect the adoption of labor-saving technologies within developing countries. Such an assessment requires moving beyond aggregate manufacturing employment.

To address these questions, I analyze trends in manufacturing employment by occupation in 125 countries for multiple years between 1960 and 2014, obtained from harmonized household surveys. While the sample is imbalanced, country coverage goes significantly beyond the 42 countries in Rodrik (2016) and the 62 countries in Felipe et al. (2018), and the sample includes a greater number of poorer developing countries in particular. A subset of the surveys also includes data on education, wages, and the formality of employment. Analyzing employment trends in manufacturing from the perspective of occupations is insightful because occupations differ along three dimensions that are relevant to the open questions: they require different levels of *skill,* differ in their typical level of *formality* of employment, and also differ in their intensity in *tasks* that are suitable to automation by ICT.

Drawing on the survey data, I document four stylized facts about premature deindustrialization: first, it is mostly unskilled jobs that have disappeared, and also the wage premium of workers with little formal education in manufacturing, relative to other industries, has declined. Second, disappearing jobs tend to be formal–both relative to the overall labor market, and to the manufacturing average. Third, it is driven by occupations which are intensive in tasks that are that are suitable to automation by ICT. And finally, it has to date been a high and middle income country-phenomenon, as low income countries have been spared from premature job losses.

In the next Section, I present my data and look for evidence of premature deindustrialization separately by occupation: essentially, I compare the results from regressing manu-

[2]This makes Haraguchi et al. (2017) considerably more optimistic about the future prospects for manufacturing-led growth in developing countries: *"After its success in labor intensive industries, China is likely to upgrade its industrial structure following the path of high-income countries. Once this happens, there may be greater opportunities for current low-income countries to pursue manufacturing activities; manufacturing would then perhaps become more, not less, important for them. Thus, the recommendation for developing countries is to not turn away from manufacturing and abandon the path of economic development through industrialization, but to emulate the experience of rapid industrialization that occurred even in recent years"* (p. 307).

facturing employment shares by occupation on country fixed effects and ln GDP per capita–including an interaction of ln GDP per capita with a time-dummy for the later part of my sample period, in order to identify which occupations account for the "premature" losses in aggregate manufacturing employment. Section 4.3 presents the four stylized facts about premature deindustrialization, drawing on the trends in the occupational employment structure and additional survey evidence. Section 4.4 offers an interpretation of my findings.

4.2 Premature Deindustrialization through the Lens of Occupations

Existing studies of premature deindustrialization rely on data sources that do not distinguish between different groups of manufacturing workers.[3] To address this gap, I combine census and survey data from the "Integrated Public Use Microdata Series" (IPUMS), provided by the Minnesota Population Center (2018), with survey data from the "International Income Distribution Database" (I2D2). I2D2 is a collection of harmonized and nationally representative household surveys introduced by Montenegro and Hirn (2009) and maintained by the World Bank.[4] Census and other survey data have the additional advantage that they tend to have more complete coverage of informal employment than national accounts data (McMillan et al., 2014).

The resulting dataset contains the distribution of manufacturing employment across the nine major occupation groups of the "International Standard Classification of Occupations" (ISCO) for 980 country-year observations from 148 countries between 1960 and 2016. I add data on GDP in 2011 international dollar and population from the Penn World Table (Feenstra et al., 2015) to obtain my main analysis sample: it contains data on employment and income from 125 countries, accounting for 91 percent of the world population in 2014, for at least two years between 1960 and 2014 (with an average of 7.4 years per country, and an average spread of 19 years between the first and the last survey). Appendix 4.B describes the sample construction and coverage in more detail.

To examine how the manufacturing employment share of a country typically varies with income, Column (1) of Table 4.1 regresses it on ln GDP per capita and its square, ln popu-

[3] They use data from either the UN National Accounts Main Aggregates Database, the Groningen Growth or Development Center (Timmer et al., 2015a), or the database on manufacturing employment for 63 countries assembled by Felipe et al. (2018) from various sources. The UN data and the dataset by Felipe et al. (2018) go back to 1970, whereas the Timmer et al. (2015a) dataset includes only 42 countries, but goes back to the late 1940s/ early 1950s for many of them. Rodrik (2016) does present evidence of a recent reduction in the demand for unskilled workers in the manufacturing industries of the countries represented in the "World Input Output Database" by Timmer et al. (2015b) (see Section 4.3 for a more detailed discussion). However, the countries in this sample are mostly high income countries, and the data start only in 1995. Hence, this result cannot easily be compared to his finding of premature deindustrialization in developing countries when comparing the pre-1990 to the post-1990 period.

[4] I2D2 is currently not openly available to researchers outside the World Bank. I am grateful to Kathleen G. Beegle, Claudio E. Montenegro, David Newhouse and Aditi Mishra for making these data available to me.

lation and its square, decade dummies and country fixed effects (corresponding to the specification in Rodrik (2016)). The population terms control for the size of the home market (although results are not sensitive to omitting them), and the country fixed effects control for differences in time invariant differences between countries, for instance related to geography. The results confirm Rodrik´s finding that aggregate manufacturing employment exhibits a significant inverse U-shape in income, using a different data source.

In Table 4.2, I test for a tendency of total manufacturing employment to decline "prematurely" in recent decades by replacing the decade dummies with a dummy variable taking a value of one for surveys from the period after 1990 and its interactions with the ln GDP per capita-terms.[5] Column (1) shows that the hump-shaped relationship between manufacturing employment and income is driven by the post-1990 observations, as the GDP per capita-terms without post 1990-interactions are jointly insignificant (p-value=0.21). For a visual representation, Figure 4.1 plots the corresponding fitted employment share for a "typical" country with median population and average country fixed effects against income, both with and without taking into account the post 1990-interactions: while the predicted peak employment share is close to 16 percent in both periods, the estimated GDP per capita level at the peak of manufacturing employment declines substantially, from \$18,700 to \$5,000.[6]

Next, I move beyond the previous literature by distinguishing between five sub-groups of manufacturing workers, which allow for a refined perspective on the phenomenon of premature deindustrialization: "elementary occupations", "machine operators", "craftsmen" and "clerks" correspond directly to ISCO major groups, whereas "professionals" subsume ISCO major groups 1-3.[7]These occupations will be characterized in increasing detail throughout the rest of the paper.[8] To start with, columns (2)-(6) of Table 4.1 show how manufacturing

[5]As Rodrik writes, using the 1990 year as a break-point is somewhat arbitrary–but it ensures a sufficient number of observations on either side, and is also useful as a demarcation of the period in which globalization and the adoption of ICT gathered speed.

[6]In Rodrik (2016), peak manufacturing employment declines from 21.5 to 18.9 percent between both periods, and the income level at which it is reached falls from \$11,000 to \$4,300 (in 1990 dollars). Part of the difference to his numbers is explained by the fact that Rodrik does not include the post 1990-dummy also independently in his empirical specification (cf. his Table 9), thereby not allowing for a trend in the share of manufacturing employment between both periods that is unrelated to differences in ln GDP per capita. If I follow him and exclude the independent post-1990 dummy, my estimates of the income level at peak manufacturing employment for both periods are closer to his estimates (namely, they change to \$11,000 and \$5,100 respectively, in 2011 dollars), whereas my estimates of the peak manufacturing employment shares remain lower than his (namely, they change to 16.3 and 16.2 percent respectively). This is likely because the 42 countries in his sample include a larger share of relatively industrialized countries (compared to my sample of 125 countries), and because his sample reaches back to the late 1940s/early 1950s (compared to at most 1960 in my sample). With respect to the heterogeneity of premature deindustrialization across occupations documented below, results are similar regardless of whether I omit the independent post 1990-dummy or include it.

[7]And hence, "managers", "professionals" and "technicians and associate professionals". Occupations in these major groups tend to be intensive in skilled and non-routine tasks, and distinguishing between them reveals no large differences that would be relevant to the arguments made in this paper. See Appendix 3.C of chapter 3 for a description of the ISCO major groups by the ILO, which I will introduce in more detail in Section 4.3 of this chapter.

[8]These characterizations will stay at the level of major groups and total manufacturing, since the surveys contain occupation and industry-coding only at the 1-digit level of ISCO and ISIC. However, the "Occupa-

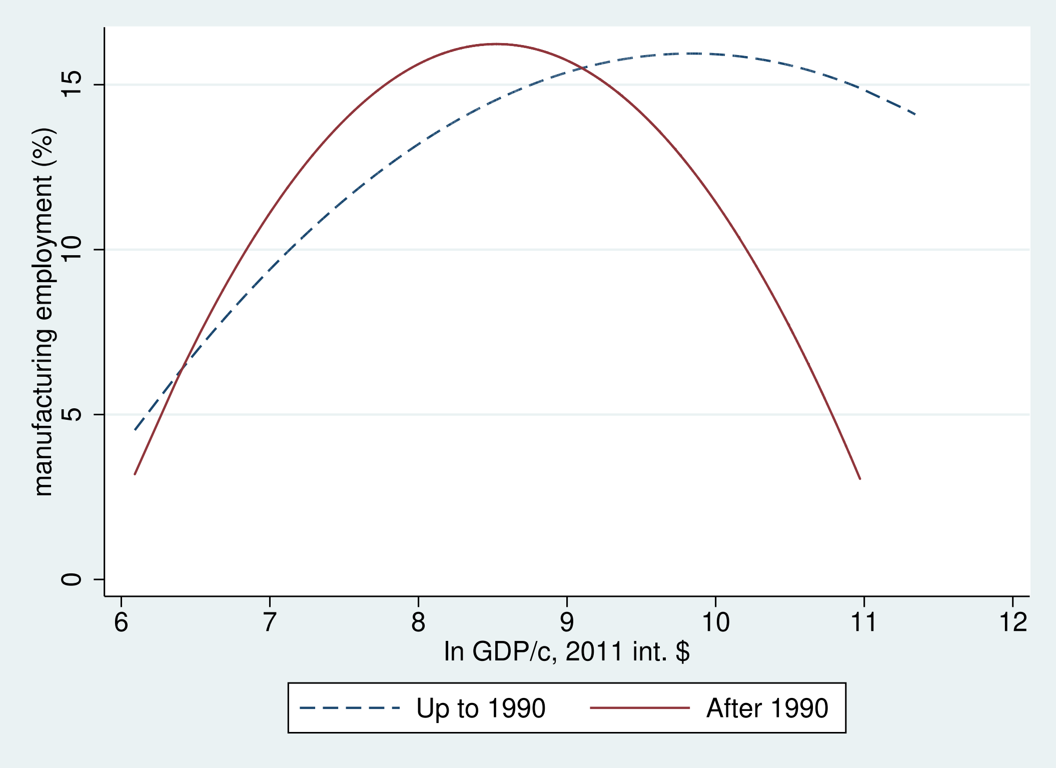

Figure 4.1: Simulated Employment Shares for Total Manufacturing: period up to versus post-1990

The Figure shows the predicted manufacturing employment shares in the periods up to and after 1990 from a regression on ln GDP per capita and its square, a post-1990 dummy and its interactions with the ln GDP per capita-terms, ln population and its square, and country fixed effects. Period and country effects are all averaged and the population size is set to the sample median to obtain the relationship for a "typical" country in the sample. Column (1) of Table 4.2 presents the specification.

employment in these five occupation groups varies with income. Point estimates suggest that employment shares for all of them, except professionals, follow an inverse U-shape.

However, Figure 4.2 (which again plots the fitted employment shares for a "typical" country in the sample) highlights that the occupational employment structure varies strongly with income: at low income levels, manufacturing employment consists almost entirely of craftsmen. Craftsman employment in turn peaks already at a GDP per capita around $3,300–which is when employment in the other occupations, and especially of machine operators, tends to grow rapidly. Employment in clerical and elementary occupations peaks at intermediate income levels ($8,900 and $9,100 respectively), whereas machine operator employment only declines after an income of $17,000 has been reached. Employment of manufacturing pro-

tional Wages Around the World" (OWW) database, described in Freeman and Oostendorp (2020), contains examples from each of these five aggregated occupation groups at the 4-digit level of ISCO, and the 2-digit level if ISIC. For instance, it includes the machine operator occupations *"thread and yarn spinner"* and *"cloth weaver (machine)"* from the textiles industry, as well as the craftsman occupation *"loom fixer, tuner"* and the elementary occupation *"labourer"*. The occupations from the printing & publishing industry include the clerical occupation *"office clerk"*, and occupations from the chemical industry include the *"chemical engineer"*. See Kunst (2019a) for more examples at the level of more disaggregated occupations and industries, including detailed task descriptions.

fessionals even increases over the entire observed income range.[9]

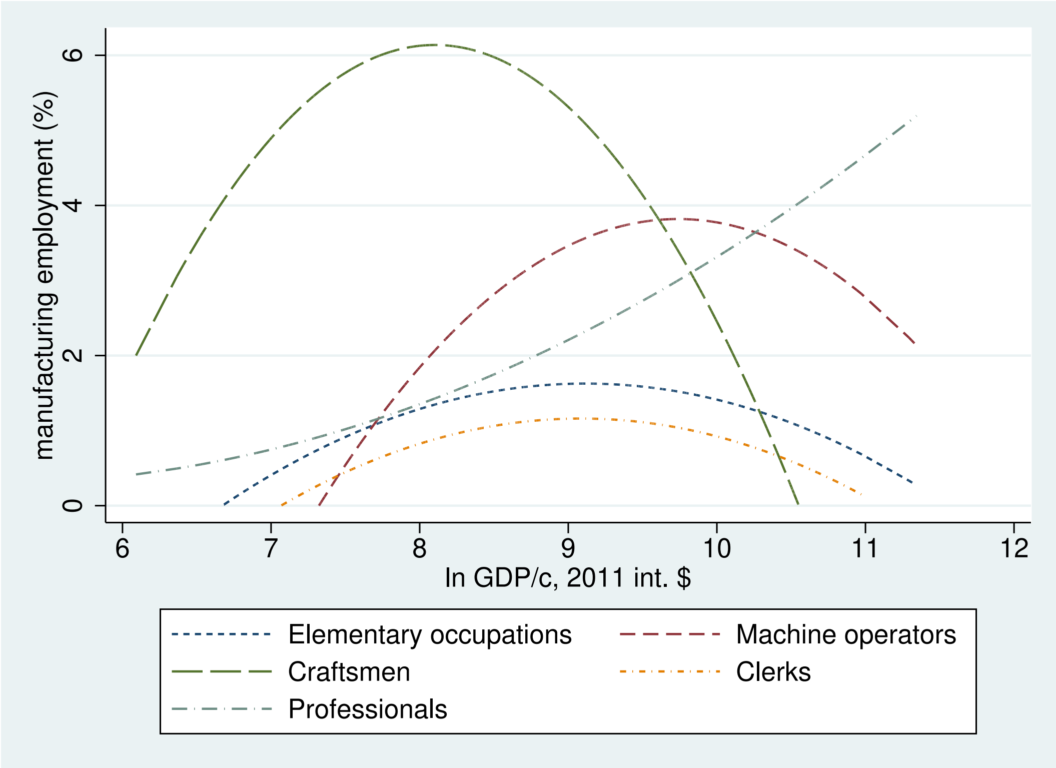

Figure 4.2: Simulated Manufacturing Employment in Total Employment (Percentage Points)

The Figure shows the predicted manufacturing employment shares from a regression on ln GDP per capita and its square, ln population and its square, decade fixed effects and country fixed effects. Period and country effects are all averaged and the population size is set to the sample median to obtain the relationship for a "typical" country in the sample. Table 4.1 presents the specifications.

In Section 4.3, I argue that for the debate about the origins of premature deindustrialization as well as for its labor market consequences, it matters which of these occupations account for the "premature" employment losses after 1990. To first establish the facts, columns (2)-(6) of Table 4.2 show that the premature deindustrialization in terms of aggregate manufacturing employment shown in column (1) is driven by machine operator-, elementary- and clerical occupations, as these occupations also experienced significantly decreasing employment shares after 1990 (conditional on income). By contrast, the interaction terms are insignificant for craftsmen and professional occupations (individually as well as jointly).

Figure 4.3 plots the corresponding fitted employment shares by income: it shows that a

[9]For an alternative perspective, Appendix Figure 3.2 plots the corresponding occupational employment shares after normalizing total manufacturing employment to 100 for every country-year, which facilitates answering the question which of the occupations is most important *within manufacturing*. As the Figure highlights, the answer to this question strongly depends on a country´s income level: in the lowest income countries, more than 80 percent of manufacturing workers tend to be craftsmen, and craftsmen remain important also at intermediate income ranges. At the upper end of observed income levels, professionals are the most important group of manufacturing workers, and the employment share of the other occupations within manufacturing increases most strongly at low and intermediate income levels. See Kunst (2019a) for an analysis of labor demand changes *within manufacturing* since the 1950s.

peak only exists for the post-1990 period for elementary occupations (at $10,400), machine operators (at $8,100) and clerks (at $5,800), whereas fitted employment increases almost linearly over the observed income range during the early period. Moroever, the simulated peak employment shares decrease substantially: from 3.4 to 1.6 percent for elementary occupations, 6.9 to 3.9 percent for machine operators, and 2 to 1.3 percent for clerks. By contrast, fitted craftsman and professional employment look very similar for both periods, consistent with the small and insignificant interaction terms in Table 4.2.

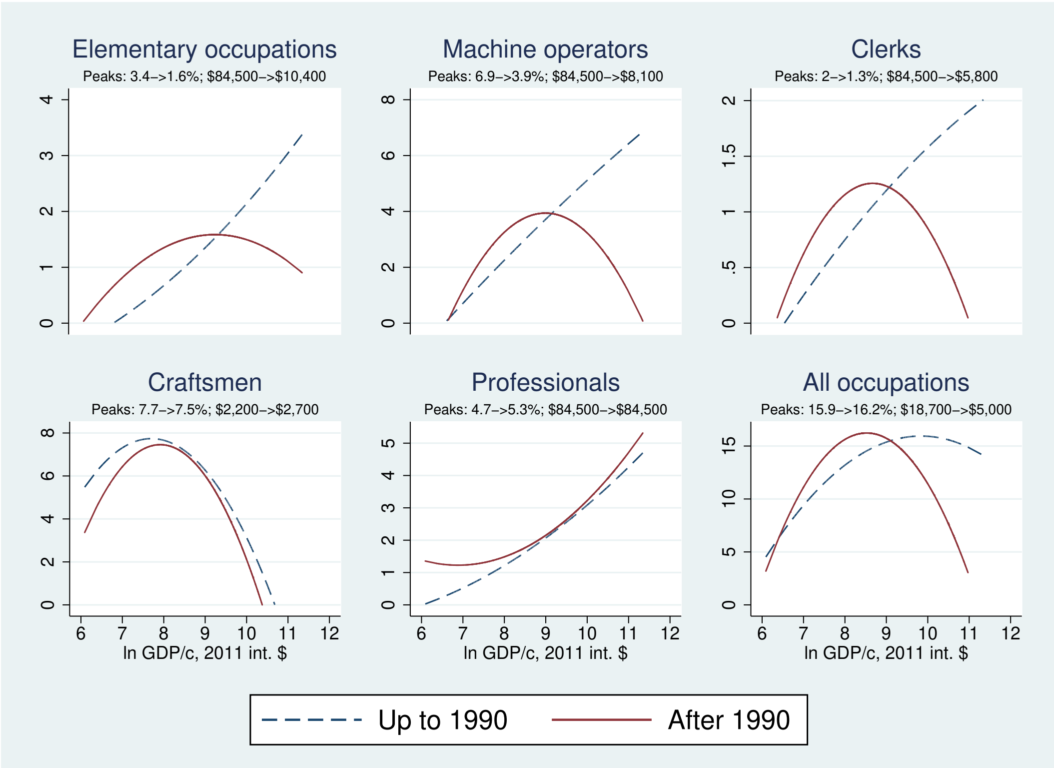

Figure 4.3: Simulated Manufacturing Employment Shares by Occupation: period up to versus post-1990

All simulations are based on the models presented in Table 4.2. The subtitles of each Figure in the panel indicate the highest simulated employment share in the period up to and after 1990, as well as the estimated GDP per capita levels at which this peak employment is reached.

Appendix Table 4.A.1 presents the results of two robustness checks: first, I exclude about 6 percent of the surveys which do not contain manufacturing observations for all five occupations (resulting in an employment share of zero for the respective occupation). This may indicate that some occupations did not play any role in the respective country and year–but could also hint at issues with the sampling, or the harmonization of the occupation classification. However, results are robust to excluding such surveys.

Second, I keep only surveys from the 43 countries for which my sample includes at least one survey for both the period up to and after 1990. Also for this sub-sample, I find a significant shift in the relationship between manufacturing employment and income for total manufacturing as well as elementary, machine operator and clerical occupations, but not for craftsmen and professionals. This suggests that even within *the same* countries, the relationships between changes in income and manufacturing employment has changed.[10]

In summary, the evidence robustly suggests that manufacturing employment in elementary-, machine operator- and clerical occupations has disappeared "prematurely" after 1990, whereas employment in craftsman- and professional occupations did not. In the next Section, I discuss the labor market consequences and origin of these employment trends by proposing four stylized facts about premature deindustrialization.

4.3 Four Stylized Facts about Premature Deindustrialization

Stylized Fact I: It´s mostly about *Unskilled* Jobs

Table 4.3 presents average wage premia, educational attainments and average employment shares–both for non-manufacturing versus manufacturing, and by manufacturing occupation. Not all of the variables are available for surveys from all countries, and column (1) indicates the number of countries across which the sample average has been calculated. Columns (2) and (3) of the first panel show that on average, manufacturing workers tended to be relatively well paid: workers outside of manufacturing earned a 6.6 log points lower wage than those within (for which the wage premium in the second row is zero by construction), and this holds true across all income groups.[11]

My preferred proxy for the skill requirements of manufacturing occupations are wage premia, as they take into account both formal education and skills obtained through training on the job.[12] Columns (4)-(8) present average wage premia by occupation group, relative to the average manufacturing wage: the lowest-paid manufacturing workers were those in machine operator-, craftsman- and in particular elementary occupations, who earned wages 27 log points below the manufacturing average in the pooled sample. Only in low income countries, machine operators commanded wages that were (insignificantly) above-average, and clerks were paid below the manufacturing average only in high income countries. The second and third panel show that also educational attainments of workers in elementary-, machine operator- or craftsman occupation tended to be below or similar to the manufacturing average.

[10] To save space, I present the results from these robustness checks for joint employment in elementary, machine operator and clerical occupations, and for joint employment in craftsmen and professional occupations. However, results are similar to those for the benchmark sample also when running the regressions separately for all occupations.

[11] The corresponding p-values of tests for the equality of means are 0.00 for the pooled sample and high income countries, 0.10 for middle income countries, and 0.09 for low income countries. Since I am interested in comparisons between various pairs of workers, Table 4.3 omits tests for the significance of differences between means for the sake of readability. However, all differences discussed in the text are significant at p-values below 0.10, unless indicated otherwise.

[12] As we argue in Kunst et al. (2020), taking into account skills obtained through informal training is particularly important in developing countries–in which formal educational attainments are often low, and where large wage premia among workers with identical formal educational attainments are common.

Hence, premature deindustrialization is largely driven by relatively unskilled jobs in elementary and operator occupations. Medium-skilled clerks are also affected–but the bottom panel shows that they represent a much smaller share of manufacturing employment, in particular in low and middle income countries. It is worth noting that for most of the sample period, machine operators tended to be even less skilled than their relative wage in Table 4.3 suggests: about 80 percent of the underlying surveys with income data in this Table are from the year 2000 or later, so that the numbers are more representative for the later part of the sample period. Appendix Figure 4.A.2 uses wages from the extended "Occupational Wages around the World" database by Freeman and Oostendorp (2020) to show that in the 1950s, manufacturing operators earned wages that were on average 18 log points *below* those of craftsmen- in contrast to Table 4.3, which suggests somewhat *higher* wages for machine operators than for craftsmen.[13]

This also highlights a potential caveat of inferring changes in the demand for unskilled labor from changes in occupational employment: if machine operator jobs have become not only scarcer, but the remaining operator jobs also require higher skills, occupational employment trends understate the extent to which the demand for unskilled workers by manufacturing has decreased. One way of addressing this is to analyze the evolution of the wage premium that workers with a low *educational attainment* have been able to command in manufacturing, relative to other industries (irrespective of their occupation).

Figure 4.4 plots the evolution of this "manufacturing wage premium" among all workers with less than completed primary schooling for the first and the last available year for the 12 countries with income data in IPUMS: a first observation is that in all surveys, unskilled workers earned substantially higher wages in manufacturing than in other industries. In the first year, they commanded 29 log points higher wages on average when working in manufacturing. However, the manufacturing wage premium decreased in 10 of the 12 countries, and the point estimate from a regression on country fixed effects and a trend suggests an average decrease by 3.7 log points per decade.

Appendix Table 4.A.2 shows that also in a sample of 88 countries–which includes all IPUMS and I2D2 surveys from countries with wage and educational attainment data for at least two years–, the point estimate implies a similar decrease in the manufacturing wage premium among workers with less than completed primary schooling of 3.3 log points per decade. By contrast, there is no significant trend in the relative wage of workers with a higher education (which on average also did not earn higher wages in manufacturing as compared to other industries).

These findings are consistent with the results by Rodrik (2016): he shows that in a sample of 40 mostly high income countries in the "World Input Output Database", it is the share

[13]However, the difference between average machine operator and craftsman wages in Table 4.3 is significant only for low income countries (pval=0.07). In Kunst (2019a), I document a pervasive decline in the relative wage of initially skilled craftsmen in manufacturing, and show that this convergence of manufacturing wages in the "blue collar"/ production occupations in countries of all income levels has been associated with increasing capital intensities of production.

of low-skilled workers who are employed in manufacturing that has declined after 1995, whereas the shares of medium and high skilled workers have remained relatively constant.[14] In summary, both occupational employment trends and the reduction of the "manufacturing wage premium" among workers with little formal education suggest that premature deindustrialization reflects a reduction in manufacturing´s ability to employ unskilled workers more productively than other industries.

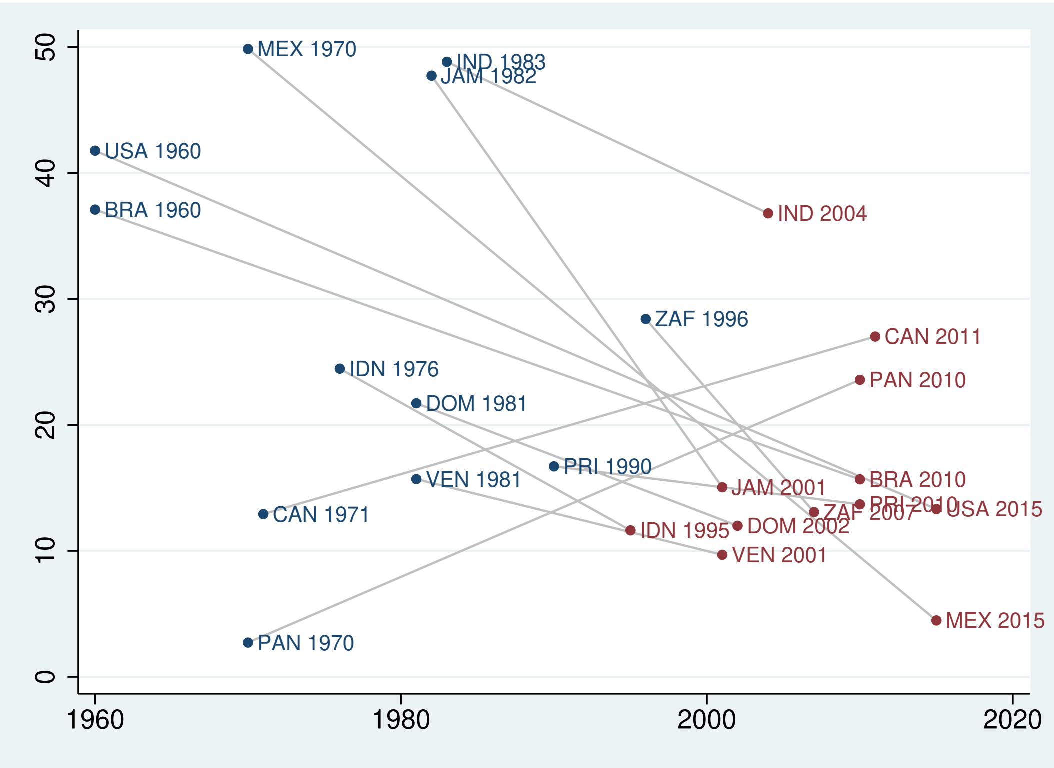

Figure 4.4: "Manufacturing Premium" among Workers with less than Completed Primary Schooling (in log points)

The Figure plots the first and the last year with income data in IPUMS. The manufacturing premium is calculated as 100*the log ratio of income of those with at most incomplete primary schooling who are employed in manufacturing relative to those who work in a different industry. A regression on country fixed effects and a trend suggests an average decline of the the manufacturing premium by 3.7 log points by decade, with a p-value of 0.075 when clustering standard errors at the country level. For samples with missing wage income, I use earned income as a proxy if available, and total income otherwise. For IPUMS surveys which include both wage and earned or total income, correlations between the manufacturing premia calculated using wage income with those based on earned or total income exceed 0.9, suggesting that these are reasonable proxies.

[14] In the World Input Output Database, "low-skilled" is defined as possessing at most lower secondary education. I choose a lower educational attainment-cut off to characterize workers with little formal education since my sample includes earlier years and more developing countries, so that educational attainments tend to be generally lower: among the samples with wage and education data (cf. column (1) of Appendix Table 4.A.2), on average 29 percent of the working-age population had less than completed primary schooling.

Stylized Fact II: It´s about *Formal* Jobs

The benefits of increasing manufacturing employment are particularly large for *formal* manufacturing: Rodrik (2013a) shows that labor productivity in formal manufacturing exhibits "unconditional convergence", closing the gap to the technology frontier at a rate of 2-3 percent per year. By contrast, La Porta and Shleifer (2008) paint a bleak picture of informal firms in developing countries: they are sharply less productive than formal ones, pay lower wages and usually stay informal, consistent with a "dual economy" view of development.[15] Finally, Rodrik (2016) highlights the historical role of organized labor–associated with large, formal manufacturing establishments–in improving wages and employment conditions.

Table 4.4 summarizes various indicators of formality included in the surveys–again comparing total manufacturing with other industries, and distinguishing between the different manufacturing occupations. The most widely available formality indicator is the share of wage employment, presented in the first panel:[16] Columns (2) and (3) show that in all income groups, manufacturing workers were more likely to be in wage employment than those in other industries. The bottom panel shows that manufacturing workers score higher also in terms of other measures of formality such as having an employment contract, and they tended to work in larger establishments that were more often located in urban areas.[17]

However, columns (4)-(8) show that there are large differences between manufacturing occupations: in particular workers in elementary-, machine operator- and clerical occupations were more likely to be wage-employed (84-93 percent on average in the pooled sample, versus only 57 percent for workers outside of manufacturing), whereas the "formality gap" between manufacturing craftsmen and other industries is smaller and insignificant. Differences across manufacturing occupations are particularly striking for low and middle income countries: even compared to the manufacturing average, workers in elementary-, machine operator- and clerical occupations in these countries were between 13-42 percentage points more likely to be wage employed. Also the other formality indicators point in the same direction as craftsmen consistently score the lowest, pulling down the manufacturing average.

Appendix Table 4.A.4 presents the results of regressions of the share of wage employment on country fixed effects and a trend: it suggests that the share of wage employment increased

[15] From this perspective, economic development comes from creating and growing formal manufacturing firms which displace informal manufacturing, rather than from a gradual process of business formalization. Also La Porta and Shleifer (2014) highlight this duality of manufacturing in developing countries, suggesting that some of the advantages of formal manufacturing may not carry over to informal manufacturing: *"although quality is difficult to measure, our visits to furniture and metal-working factories in Kenya and Madagascar revealed extreme crudeness of the products being made, usually with fairly basic tools, even when the raw material (as in the case of furniture) was hardwood. Informal factories appear to sell extremely low-quality goods for low prices to low-income customers."* (p. 113).

[16] Conversely, La Porta and Shleifer (2008) use the share of self-employment as a proxy for informality, and find a strong negative correlation with GDP per capita across countries.

[17] Differences between manufacturing and non-manufacturing averages are significant for the share of wage employment (pval=0.00, also for all income groups individually), as well as for "contract", the firm size variables and "urban" at p-values below 0.10. Differences highlighted in the text below are also significant at p-values below 0.10, unless indicated otherwise.

slightly over time for machine operators and professionals (by 1.6 and 1.0 percentage points per decade, respectively), but did not change significantly for the other occupations. Hence, the cross-sectional ranking of occupations in terms of formality is likely to be representative for the sample period.

In summary, this suggests that premature deindustrialization is slowing down the formalization of labor markets: industrialization has traditionally created formal employment opportunities already at intermediate income levels mostly by creating elementary-, machine operator- and (to a lesser extent) clerical jobs. However, these are precisely the occupations accounting for the "premature" employment losses.

Stylized Fact III: It´s about Jobs that are *Vulnerable to automation by ICT*

Manufacturing occupations differ not only in their skill-, but also in their *task* requirements. Hence, analyzing employment trends through the lens of occupations is informative about the origins of premature deindustrialization: to the extent that it is driven by technological change, one would expect an asymmetric reduction of employment in occupations that are intensive in tasks which have only recently become automatable also in developing countries. Has that been the case for machine operators, clerks and elementary occupations, but not for craftsmen and professionals?

The task descriptions in the definition of the ISCO major groups by the ILO, presented in Appendix 3.C, give a first indication of task differences between occupations. A second widely used measure is the Routine Task Intensity (RTI) index introduced by Autor and Dorn (2013): it summarizes the relative importance of routine- to non-routine tasks in an occupation, and has been used as a proxy for its vulnerability to automation by ICT.[18]

Figure 4.5 presents average RTI scores by occupation, standardized to have a mean of zero and a standard deviation of one for the overall labor market. All manufacturing occupations except for professionals score higher than zero, indicating an above-average vulnerability to automation by ICT. Clerks score particularly high–which is consistent with the ILO´s assessment that their "*main tasks require the knowledge and experience necessary to organise, store, compute and retrieve information*" (quoted from the description of major groups in Appendix 3.C), and the notion that ICT has sharply reduced the need for workers to engage in such tasks.

Quantitatively more important are machine operators: their main tasks consist of "*operating and monitoring (...) production machinery and equipment*". While factory production with mechanically operated machines requires a large number of operators, it appears plausible that a move to more autonomous, digitally controlled machines reduces the need for un-

[18] The task measures underlying the RTI index come from Autor et al. (2003), and are based on the 1977 edition of the US "Dictionary of Occupational Titles". I use the translation of these task scores into sub-major groups of ISCO by Goos et al. (2014). See Appendix Figure 3.A.5 for the individual task scores by occupation, and an explanation for how they are aggregated into the RTI index.

skilled human machine operators.[19] Finally, elementary occupations require "*mostly simple and routine tasks*"- and while the relation to ICT is somewhat less clear than for clerks and machine operators, it is well established that a move to more advanced continuous-process methods reduces the demand for unskilled laborers.[20]

At the other end of the routine task intensity spectrum, professionals engage in "*planning, directing and coordinating*" and "*applying scientific and artistic concepts and theories to the solution of problems*", which are tasks that are arguably more complementary to than substitutable for ICT. Next to professionals, also craftsmen have been spared from premature deindustrialization, although they score high on routine task intensity. One explanation is that manufacturing craftsmen have been vulnerable to automation even before the advent of ICT– as argued already by Jerome (1934) for the US, and documented for a wide range of countries since the 1950s by Kunst (2019a).[21]Hence, while craftsmen jobs continue to disappear with increasing automation already at low levels of income (as is apparent in Figure 4.3), there has not been a sharp reduction in the demand for craftsmen, conditional on income, after 1990.[22]

In summary, the evidence suggests that premature industrialization is characterized by job losses in occupations that appear particularly vulnerable to ICT. This is consistent with evidence of increasing technology adoption in developing countries in recent decades: capital intensities in manufacturing have increased significantly in countries of all income levels (Kunst, 2019a), and Jaumotte et al. (2013) show that also in developing countries, the share of ICT capital in the capital stock has increased rapidly after 1990. Also the World Bank´s 2008 report on technology diffusion in developing countries concludes that the speed at

[19]Appendix Figure shows that machine operators have the second highest score on "set limits, tolerances and standards". Autor et al. (2003) use this task score as a measure for an occupation's demand for routine cognitive tasks, which appear particularly suitable to being taken over by digitally controlled machines.

[20]Continuous process methods take in raw matrials and produce finished goods, with few hands intervening in production. Goldin and Katz (1998) argue that the adoption of such methods reduces the need for elementary occupations by automating hauling and conveying operations.

[21]According to ISCO, craftsmen are *"occupations whose tasks require the knowledge and experience of skilled trades or handicrafts"*. For the US, Jerome (1934) predicts that *"the principal effect of further mechanization of the processing operations will be to decrease the demand for semiskilled workers. (...) On the whole, the shift will continue to be from the emphasis on the trade skill typical of the handicraftsman to, on the one hand, the alertness and intelligence required in handling fast and intricate machinery and, on the other, to the more formal training required in the engineering and production planning departments"* (pp. 402-403).

[22]Because craftsmen score higher in terms of the RTI index than machine operators and elementary occupations, the association between the RTI index of an occupation group and its propensity to experience premature deindustrialization after 1990 is imperfect. Appendix Table 4.A.5 tests whether it is still true that *on average*, occupation groups with a higher RTI score experienced significantly stronger premature deindustrialization: the sample corresponds to the one from Table 4.2, with the difference that it stacks the employment shares in the different occupations. To exploit the full available variation in RTI scores, it distinguishes between major groups 1-3 ("managers", "professionals" and "associate professionals"), which all have RTI scores below 0 and are subsumed into the "professional" category in the rest of this paper. The specification includes country-occupation fixed effecs, in analogy to the country fixed effects of the specifications in Table 4.2. The significant "triple interactions" between the ln GDP per capita terms, the RTI index and the post-1990 dummy show that occupations with a high RTI index did on average experience stronger premature deindustrialization. Therefore, the argument that premature deindustrialization after 1990 has been driven in particular by occupations that are vulnerable to ICT adoption is also robust to considering the RTI index as a perfect proxy for this vulnerability.

which developing countries adopt new technologies has increased since 1990.[23]

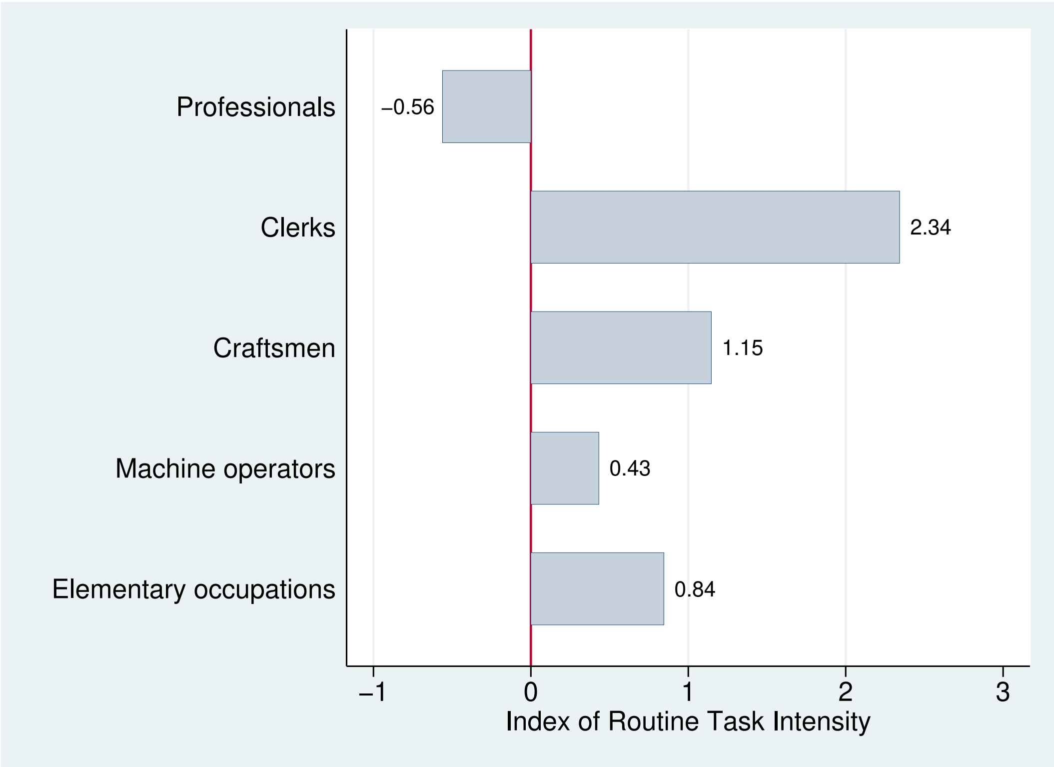

Figure 4.5: Routine Task Intensity Scores by Occupation

The routine task intensity (RTI) scores are calculated as in Autor and Dorn (2013), based on the translation of task scores from the 1977 US "Dictionary of Occupational Titles" into sub-major groups of ISCO-88 by Goos et al. (2014). It is normalized to have a mean of zero and a standard deviation of one across these sub-major groups. The Figure shows occupation group averages constructed from 11 sub-major groups that are relevant to manufacturing, as indicated by representation among the manufacturing occupations in the extended "Occupational Wages Around the World" database (and hence, in the underlying ILO "October Inquiry"- see Freeman and Oostendorp (2020) for more details). This excludes major groups 5 ("Service and sales workers") and 6 ("Skilled agricultural, forestry and fishery workers"), as well as some sub-major groups that do not play a role in manufacturing (for instance, sub-major group 23: "Teaching Professionals").

Stylized Fact IV: Some Manufacturing Jobs also *Appear* at lower Levels of Income

The simulations summarized in Figure 4.3 suggest that while manufacturing employment overall peaked at lower income and employment levels after 1990, low income countries actually saw *more* rather than less manufacturing employment.[24] One concern is that this finding may be driven by the implicitly assumed symmetry when using a quadratic functional

[23] The report concludes that *"since the early 1990s, technological progress in both low- and middle-income countries has increased more rapidly than in high-income countries"* (p. xi), with the effect that *"the technology gap between middle-income and high-income countries has narrowed over the past 10 years"* (p. 52).

[24] The curves intersect around \$9,000 for total manufacturing, \$11,100 for elementary occupations, \$9,100 for machine operators and \$8,700 for clerks–suggesting *higher* manufacturing employment below that income

form. However, Figure 4.6 shows that at least for the joint employment share in machine operator and elementary occupations, also locally weighted regressions on the raw data suggest that low income countries have been spared from premature job losses, and possibly even had higher manufacturing employment after 1990 (conditional on income).[25]

The Goldin and Katz (1998) framework on the effects of technological change in manufacturing on labor demand offers an explanation: in their model, the "first transition" from production in artisanal shops to factories increases the demand for unskilled workers in machine operator and elementary occupations, before further advances of the production technology reduce it.

While the original framework has been used to explain the US experience, it also appears relevant to recent labor demand trends in developing countries: Section 4.2 shows that manufacturing in low income countries still used to be dominated by craftsmen and hence relatively small-scale and artisanal. This is consistent with the characterization of manufacturing in developing countries in the literature review by Tybout (2000). Moroever, the evidence suggests that there has been an acceleration of technology adoption (as argued in the previous Section), which would be expected to change the composition of occupational labor demand towards occupations associated with larger-scale factory production.[26]

For concrete examples of changes in the employment share of machine operators and elementary occupations after 1990, Figure 4.7 plots the employment share from the first and the last year for the 121 countries with at least two surveys from that period. The Figure connects and labels observations from the 10 countries which experienced the largest decrease in machine operators and elementary employment, and the 10 countries experiencing the largest increase. 6 of the 10 countries with the largest decreases were classified as middle income countries in 1990 (such as South Africa/ZAF, Costa Rica/CRI and Jamaica/JAM), whereas 7

level after 1990. In 2014 (the last year in the sample), about 42 percent of the world population lived in countries with a GDP per capita below $9,000 in 2011 international dollars- with China above, yet India below this income threshold. When translating the nominal World Bank income group-thresholds in 1990 to 2011 international dollars using the average Penn World Table price level estimates from the respective income group, the "low income" country-threshold stood at about $2,100, and the "lower middle" income country threshold stood at about $9,900. Hence, the simulations suggest that countries classified as low income countries in 1990, as well as many lower middle income countries, have been spared from premature deindustrialization.

[25] For total manufacturing employment and clerical occupations, the finding of "early *in*dustrialization" in low income countries depends on the quadratic functional form and country fixed effects. However, the evidence robustly suggests that low income countries have at least been spared from premature deindustrialization also for total manufacturing. See Appendix Figure 4.A.4 for plots of the raw data separately for total manufacturing and each occupation, which also include the fitted lines from a locally weighted regression for both periods.

[26] The World Bank report on technology adoption (World Bank, 2008) highlights that technological change in developing countries has mostly taken the form of adopting technologies that had already been well established in high income countries, as opposed to innvations from developing countries themselves: *"while a strong correlation exists between scientific innovation and invention and income in high-income countries, almost none of this kind of activity is being performed in developing countries. As a result, virtually all technological progress in developing countries comes from the adoption and adaptation of preexisting technologies"* (p. 52). Often, these are the same machines that had previously been used in high income countries, and which are imported as "vintage capital" (Navaretti et al., 2000).

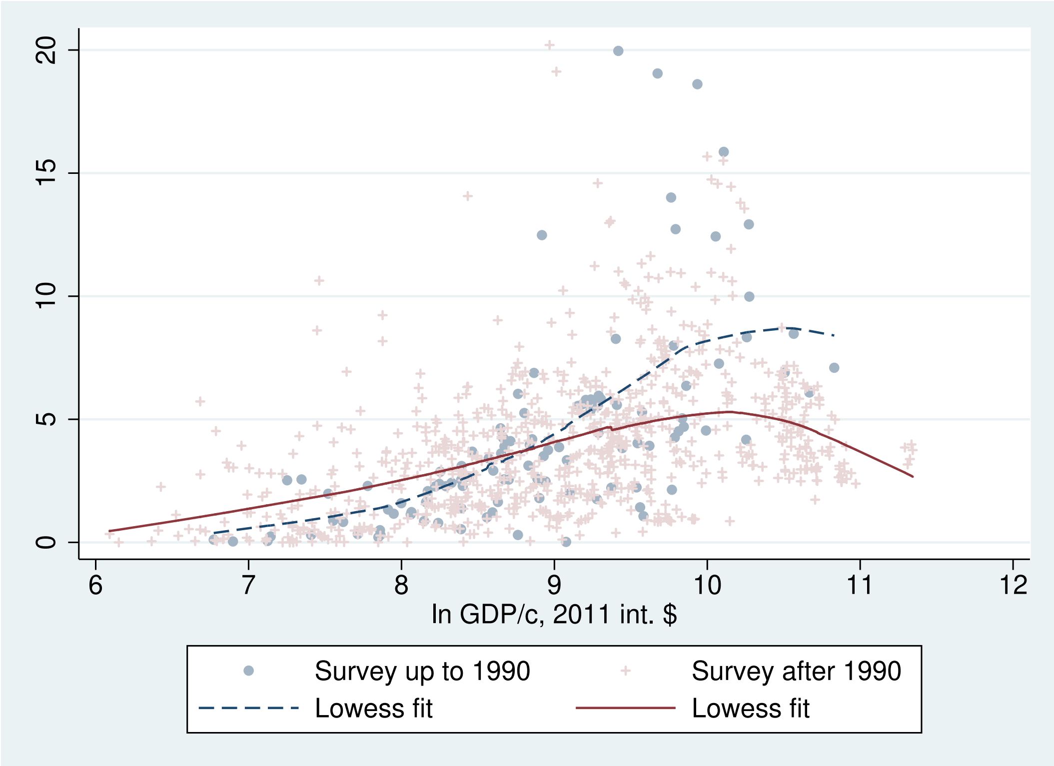

Figure 4.6: Manufacturing Employment in joint Machine Operator and Elementary Occupations

Every dot represents the joint manufacturing employment share in machine operator or elementary occupations from a country-year up to or after 1990. Moreover, the Figures include non-parametric estimates of the employment shares by GDP per capita in both periods, produced using the "lowess" command in Stata, using the default bandwidth.

of the 10 countries with the largest increases were classified as low income countries (such as China/CHN, Cambodia-/KHM and Ethiopia/ETH).[27]

Diao et al. (2017b) argue that in Ethiopia, employment gains in light manufacturing since the early 1990s have been based on the processing of agricultural products, and are the result of successful efforts of the Ethiopian government to attract foreign investors. McMillan et al. (2014) and Diao et al. (2017a) point to recent manufacturing employment gains in several additional African low-income countries, also suggesting that such gains have not been limited to Asia.[28] Finally, Appendix Table 4.A.3 shows that also the decrease of the manufacturing wage premium among unskilled workers has been driven by middle income countries, whereas the point estimate is smaller and insignificant (though still negative) for low income countries.

[27] Moroever, the data for Bangladesh ("BGD"), a low income country for which the Figure suggests strongly decreasing manufacturing employment in elementary or operator occupations, appears dubious: the surveys suggest increasing *total* manufacturing employment between both years (2000 and 2013), driven by strongly increasing craftsman employment. However, there is no evidence of such a shift from elementary or operator to craftsman occupations in the previous available survey from 2010.

[28] Diao et al. (2017a) conclude that *"although the employment share in manufacturing is not expanding rapidly, in most of the low-income African countries the employment share in manufacturing has not peaked and is still expanding, albeit from very low levels"* (p. 28).

Figure 4.7: Employment Changes after 1990 in joint Machine Operator and Elementary Employment

For 121 countries with at least two surveys after 1990, the Figure plots the joint manufacturing employment share in machine operator or elementary occupations for both the first and the last year in the sample (on average, these years are 1998 and 2010). For the 10 countries with the largest employment gains or losses in these occupations, I connect both observations and assign a country label. The employment share in the bottom 10 countries on average decreased by 5.1 percentage points, and 6 of them were classified as middle income countries in 1990. The top 10 countries on average increased their employment share by 4.7 percentage points between both years, and 7 of them were classified as low income countries in 1990.

In summary, the evidence suggests that premature deindustrialization has to date spared low income countries. There are even some signs of increasing manufacturing employment conditional on income for poorer developing countries, most clearly in elementary and machine operator occupations. This is consistent with the view that the move from artisanal to more modern, larger-scale production creates opportunities for employment industrialization in low income countries–in particular if they follow the example of countries like Cambodia or China by tapping into foreign demand for consumer goods in relatively low-tech manufacturing industries such as garments, footwear or electronics assembly.

4.4 Concluding Remarks

Occupational employment trends paint a nuanced picture of the future prospects for manufacturing-led growth in developing countries: on the one hand, the trend towards more open goods and capital markets appears to facilitate some employment industrialization in low income countries by increasing technology transfer and export opportunities.[29] At the same time, this technology transfer appears to have markedly reduced employment opportunities in unskilled, yet formal, machine operator and elementary occupations even in middle income countries in recent decades, resulting in much lower peak manufacturing employment shares in these occupations.

It is useful to compare this account with Akamatsu´s (1962) "flying geese paradigm" of development: in his metaphor, the technologically most advanced countries are "chased" by exporters of consumer goods, which are in turn chased by exporters of raw materials, the least advanced countries. The occupational employment pattern can then be understood as resulting from a reduction in the technological distance between countries (or as "geese flying closer together"): low income countries move towards the export of consumer goods such as garments, creating employment in the more formal manufacturing occupations, whereas middle income countries adopt the capital- and skill-intensive production technologies of the most advanced countries, resulting in employment losses in the occupations that are most vulnerable to ICT adoption.[30]

The notion of a convergence of manufacturing production technologies is consistent with China, a middle income country, being the largest buyer of high-tech industrial robots in 2017, accounting for more than a third of global robot sales (International Federation of Robotics, 2018). It is also consistent with the findings of a companion paper (Kunst, 2019a), which documents that capital intensities in manufacturing have increased substantially over recent decades also in developing countries–with profound impacts on the structure of occupational employment and wages. Finally, it is in line with both stylized facts emerging from the historical account of technology adoption by Comin and Hobijn (2010): while there are large cross-country differences in the extent to which new technologies are adopted, the adoption lag length has decreased over time.

From this perspective, premature deindustrialization is the result of a global shift of the frontier separating manufacturing tasks that are automated from those that are still performed by human labor. Therefore, it appears unlikely that China further moving up the development ladder will bring back unskilled manufacturing employment on a large scale to other developing countries, as suggested by Haraguchi et al. (2017). Rather, the question is whether further shifts of the "automation frontier" will reduce the scope for even the moderate increases in unskilled manufacturing employment that still prevails today in low income countries.

[29] See Jaumotte et al. (2013) for an illustration of the increases in various measures of trade and financial openness by income group since 1980.

[30] In the notation of Akamatsu (1962), low income countries are moving from stages one and two (import of consumer goods and production for the domestic market) to stage three (export of consumer goods), whereas middle income countries join high income countries by moving from stage three to stage four (product differentiation and export of capital goods). Akamatsu also acknowledges that the distance between the "flying geese" can vary over time: *"however, these countries, advanced and less advanced, do not necessarily go forward at the same speed in their development of a wild-geese-flying pattern, nor do they always make gradual progress, but they are at times dormant and at other times make leaping advances"* (p. 18).

Note that this account does not negate the role of globalization in creating premature deindustrialization: first, because increasing openness has facilitated technology transfer–and has also increased the pressure to adopt more advanced production technologies via stronger import competition, as well as increased the benefits of doing so by facilitating the access to the markets of high income countries (featuring higher quality standards). Second, because the emergence of global value chains with consecutive and interdependent production steps has reduced the scope of manufacturing firms in developing countries to substitute capital with unskilled labor, as argued by Rodrik (2018). This is consistent with the decrease in the "manufacturing premium" of unskilled workers documented in this paper.[31] And finally, because the manufacturing employment gains in some low income countries (stylized fact number IV) leave open the possibility that increasing labor cost competition from these countries has also contributed to the premature deindustrialization-phenomenon.

250 years after the beginning of the Industrial Revolution, it appears that manufacturing is losing its ability to employ unskilled workers more productively than other industries. As Rodrik (2018) points out, this implies that developing countries, abundant in unskilled labor, lose their comparative advantage in producing an increasing range of manufactured goods.[32] Hence, future growth in developing countries may have to rely more on improvements in "fundamentals" such as education and governance, and policy makers need to focus on a broader range of sectoral policies than in the past (Stiglitz, 2018). Absent a reduction in the "formality gap" between manufacturing and other industries, it will also create employment that is less formal.

[31]Global value chains may also have affected manufacturing occupations asymmetrically, as they entail the relocation of specific production tasks–as opposed to entire production processes–across countries. However, Reijnders and de Vries (2018) decompose the changes in routine versus non-routine jobs in thirty-seven advanced and emerging countries over the period 1999–2007 into those that are due to technological change and those that are due to task relocation, and find that the contribution of technological change has been an order of magnitude larger (cf. their Figure F.2). This suggests that technological change within countries has been the main *proximate* driver of the asymmetric deindustrialization trends across manufacturing occupations documented in this paper.

[32]This is also evidenced by the increasing attention to the phenomenon of "reshoring" of production to high income countries (Gray et al., 2013).

Table 4.1: Manufacturing Employment as a Function of Income

Dependent variable: manufacturing employment in total employment, ages 15-64 (percentage points)

	Total	Occupation split				
	(1)	(2) Elementary	(3) Operators	(4) Craftsmen	(5) Clerks	(6) Professionals
ln GDP/c	41.01**	4.97**	12.74**	16.58**	5.17**	-1.28
	(8.08)	(1.72)	(3.97)	(5.58)	(1.20)	(1.27)
ln GDP/c squared	-2.26**	-0.27**	-0.65**	-1.02**	-0.28**	0.13+
	(0.43)	(0.09)	(0.23)	(0.30)	(0.07)	(0.07)
ln population	5.49*	0.22	4.02+	0.18	0.54	0.16
	(2.43)	(0.57)	(2.14)	(2.44)	(0.34)	(0.56)
ln pop. squared	0.19	0.01	-0.26	0.55*	-0.05	-0.07
	(0.31)	(0.10)	(0.16)	(0.26)	(0.05)	(0.07)
1970s	-2.07*	0.41+	-2.78*	0.08	0.10	-0.05
	(0.99)	(0.23)	(1.33)	(1.02)	(0.15)	(0.19)
1980s	-3.89*	0.45	-3.65+	-1.18	-0.07	0.32
	(1.57)	(0.37)	(1.96)	(1.62)	(0.22)	(0.30)
1990s	-5.58**	0.53	-4.36+	-2.48	-0.24	0.52
	(1.70)	(0.39)	(2.26)	(1.72)	(0.28)	(0.33)
2000s	-7.50**	0.44	-5.01+	-2.83	-0.47	0.45
	(2.03)	(0.46)	(2.53)	(1.98)	(0.33)	(0.37)
2010s	-9.68**	0.38	-5.80*	-3.59+	-0.67+	0.23
	(2.23)	(0.52)	(2.73)	(2.14)	(0.36)	(0.43)
R^2	0.259	0.031	0.136	0.181	0.185	0.142
Country FE	✓	✓	✓	✓	✓	✓
F-test joint GDP/c	0.00	0.01	0.00	0.00	0.00	0.00
Mean dep. var.	13.79	1.40	2.62	6.10	0.79	2.16
Countries	125	125	125	125	125	125
Observations	925	925	925	925	925	925

Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$,* $p < 0.05$,** $p < 0.01$. Employment data are taken from IPUMS and I2D2 (see Section 4.2), and data on GDP per capita in 2011 International Dollars are taken from the Penn World Table 9.0. The “mean dependent variables” in columns (2)-(6) not exactly add up to the number for total manufacturing in column (1), as the total include some manufacturing workers in major group 5 (“service and sales workers”) and 6 (“skilled agricultural, forestry and fishery workers”). However, these major groups tend to play a negligible role in manufacturing employment. “F-test joint GDP/c” in the bottom panel presents the p-value of an F-test for joint significance of ln GDP per capita and its square.

Table 4.2: Manufacturing Employment as a Function of Income: Period up to versus post-1990

Dependent variable: manufacturing employment in total employment, ages 15-64 (percentage points)

	Total	Occupation split				
	(1)	(2) Elementary	(3) Operators	(4) Craftsmen	(5) Clerks	(6) Professionals
ln GDP/c	16.00	-0.29	2.12	13.41	0.93	-0.50
	(13.22)	(3.45)	(6.17)	(8.15)	(1.86)	(1.71)
ln GDP/c squared	-0.81	0.06	-0.04	-0.87^{+}	-0.03	0.08
	(0.76)	(0.20)	(0.36)	(0.46)	(0.11)	(0.10)
post-1990	-81.00^{+}	-11.03	-40.22^{+}	-25.59	-11.01^{+}	10.80
	(45.74)	(13.22)	(23.00)	(36.54)	(6.01)	(8.46)
ln GDP/c x post-1990	21.54^{*}	3.16	10.43^{+}	6.03	3.02^{*}	-2.32
	(10.64)	(3.17)	(5.62)	(8.42)	(1.43)	(1.94)
ln GDP/c squared x post-1990	-1.39^{*}	-0.21	-0.66^{+}	-0.36	-0.20^{*}	0.13
	(0.61)	(0.19)	(0.34)	(0.48)	(0.08)	(0.11)
ln population	-2.42	-0.17	-0.01	-2.21	-0.28	0.27
	(2.32)	(0.49)	(0.79)	(2.32)	(0.21)	(0.40)
ln population squared	0.24	0.01	-0.18	0.53^{*}	-0.04	-0.08
	(0.31)	(0.09)	(0.14)	(0.26)	(0.04)	(0.06)
Country fixed effects	✓	✓	✓	✓	✓	✓
F-test joint GDP/c	0.21	0.11	0.01	0.03	0.02	0.01
F-test joint GDP/c x post-1990	0.00	0.02	0.06	0.71	0.00	0.43
Mean dep. var.	13.79	1.40	2.62	6.10	0.79	2.16
Countries	125	125	125	125	125	125
Observations	925	925	925	925	925	925

Standard errors in parentheses, clustered at the country level. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$. The mean dependent variables in column (1) slightly exceeds the sum of columns (2)-(6) because it also includes manufacturing workers classified into major group 5 (“Service and sales workers”) or major group 6 (“Skilled agricultural, forestry and fishery workers”). These occupations are omitted from the analyses by occupation group as they tend to represent a negligible share of manufacturing employment. The rows “F-test joint GDP/c” in the bottom panel present the p-values of F-tests for joint significance of ln GDP/c and its square, with and without the post-1990 interaction.

Table 4.3: Wages, Education and Employment by Industry and Manufacturing Occupation

		Total		Manufacturing, by occupation				
	(1) Countries	(2) Non-manuf.	(3) Manuf.	(4) Elementary	(5) Operators	(6) Craftsmen	(7) Clerks	(8) Professionals
Wage premium (log points)								
-all	121	-6.6	0	-27	-5.7	-10.9	6.6	47.6
-high income	20	-10.4	0	-29.7	-13.2	-9.1	-14.5	26.4
-middle income	64	-3.7	0	-30.7	-11.5	-12.4	8	51.3
-low income	37	-9.6	0	-19.3	8.3	-9.4	15.4	52.7
Share with at least completed primary schooling (%)								
-all	124	62.8	68.4	64.8	70.4	66.2	86.7	86
-high income	11	95	95	90.9	93.8	95.3	95.7	98.8
-middle income	70	69.7	74.2	70.1	73.9	71.8	88	88.7
-low income	43	43.2	52.3	49.5	58.9	49.6	82.2	78.3
Share with at least completed secondary schooling (%)								
-all	124	32.3	30.8	22.3	27.6	25.5	56.7	62.6
-high income	11	62.4	56.4	38.6	47.3	50.9	67	78.9
-middle income	70	37.9	35.7	26.7	32.1	30.4	58.6	67.2
-low income	43	15.5	16.3	10.9	15.2	11.2	50.9	51
Employment (%)								
-all	148	87.9	12.1	1.2	2.2	5.4	.7	1.9
-high income	21	83.1	16.9	1.4	3.5	5.1	1.7	4.6
-middle income	79	86.9	13.1	1.3	2.5	6	.6	1.9
-low income	48	91.7	8.3	.9	1	4.5	.2	.7

The Table presents averages across countries, for all countries in the combined IPUMS and I2D2 sample with available data. For countries with data for several years, I take the average across available years. Hence, all countries have the same weight. The first panel depicts the wage premium relative to total manufacturing in log points. The second and third panel present the average share with at least completed primary and secondary schooling, respectively. The last panel presents the share of manufacturing employment, or manufacturing employment in a specific occupation, in total civilian employment of men and women aged 15-64. Income groups are based on the World Bank classification in 1990.

Table 4.4: Formality Indicators by Industry and Manufacturing Occupation

		Total		Manufacturing, by occupation				
	(1) Countries	(2) Non-manuf.	(3) Manuf.	(4) Elementary	(5) Operators	(6) Craftsmen	(7) Clerks	(8) Professionals
Share of wage employment (%)								
-all	139	57.3	69.1	84.4	84	61.5	93	77.3
-high income	20	85.7	93.3	98.1	97.7	89.1	98	91.1
-middle income	76	63.7	75.3	88.6	90.2	67.3	93.7	79.5
-low income	43	32.9	47	70.7	66.7	38.4	89.5	66.8
Other formality indicators and workplace characteristics								
Contract (%)	56	45.4	55.6	57.8	62.6	48.9	75.8	76.2
Social security (%)	60	29.5	37	39	44.2	29.8	60.3	60.6
Health insurance (%)	44	31.2	36.1	38	45.2	28.5	60	56.9
Union member (%)	36	14.8	18.3	20.7	23.7	15.5	30.3	25.3
Firmsize (lower bracket)	91	16.8	26.7	30.1	35.4	22.1	35.9	34.2
Firmsize (upper bracket)	92	19.7	29.9	33.9	38.3	25.9	38.2	36.5
Urban (%)	122	50.5	62.3	60.5	64.8	60.8	76.7	75.4

The Table presents averages across countries, for all countries in the combined IPUMS and I2D2 sample with available data. For countries with data for several years, I take the average across available years. Hence, all countries have the same weight. The top panel presents the the share of employment that is classified as wage employment, as opposed to non-wage/family or self-employment, the most widely available indicator of formality, for the pooled sample and by income group. The bottom panel presents other formality indicators and workplace characteristics for the pooled samples of all available countries. Firmsizes are reported as the "upper" and the "lower" bracket of the size category that the establishment falls into, which is given as a range in the number of workers. Information for the last five dummy variables come from I2D2 surveys only. "Urban" is a dummy variable taking a value of one if the establishment is located in an urban area, whereby also "semi-urban" has been coded as "urban".

Appendices

4.A Appendix Tables and Figures

Table 4.A.1: Robustness Checks: period up to versus post-1990

Dependent variable: manufacturing employment in total employment, ages 15-64 (percentage points)

	Benchmark			All occupations			Both periods		
	(1) All	(2) E+O+Cl	(3) C+P	(4) All	(5) E+O+Cl	(6) C+P	(7) All	(8) E+O+Cl	(9) C+P
ln GDP/c	16.00	2.76	12.91^{+}	15.97	2.57	12.80	23.53	10.45	16.78^{+}
	(13.22)	(7.77)	(7.78)	(13.57)	(8.33)	(8.15)	(16.63)	(11.23)	(9.77)
ln GDP/c squared	-0.81	-0.01	-0.79^{+}	-0.81	0.01	-0.79^{+}	-1.23	-0.44	-0.98^{+}
	(0.76)	(0.45)	(0.44)	(0.78)	(0.48)	(0.46)	(0.93)	(0.65)	(0.53)
post-1990	-81.00^{+}	-62.27^{*}	-14.79	-96.24^{*}	-63.13^{*}	-24.90	-84.89^{+}	-66.20^{*}	-15.53
	(45.74)	(23.87)	(33.98)	(39.53)	(24.96)	(28.27)	(46.77)	(24.56)	(36.04)
ln GDP/c x post-1990	21.54^{*}	16.61^{**}	3.72	24.75^{**}	16.89^{**}	5.75	22.28^{*}	17.22^{**}	3.87
	(10.64)	(5.66)	(7.83)	(9.29)	(5.86)	(6.63)	(10.82)	(5.82)	(8.18)
ln GDP/c squared x post-1990	-1.39^{*}	-1.07^{**}	-0.23	-1.56^{**}	-1.09^{**}	-0.34	-1.42^{*}	-1.09^{**}	-0.24
	(0.61)	(0.33)	(0.45)	(0.54)	(0.34)	(0.39)	(0.62)	(0.34)	(0.46)
ln population	-2.42	-0.46	-1.94	-2.04	-0.58	-1.36	-2.91	-0.59	-2.39
	(2.32)	(0.99)	(2.29)	(2.17)	(1.06)	(2.22)	(2.78)	(1.18)	(2.84)
ln population squared	0.24	-0.21	0.45^{+}	0.19	-0.22	0.43^{+}	0.15	-0.27	0.37
	(0.31)	(0.17)	(0.24)	(0.30)	(0.17)	(0.22)	(0.36)	(0.19)	(0.29)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
F-test joint GDP/c	0.21	0.00	0.13	0.23	0.00	0.15	0.27	0.00	0.13
F-test joint GDP/c x post-1990	0.00	0.00	0.73	0.00	0.00	0.69	0.00	0.00	0.77
Mean dep. var.	13.79	4.81	8.26	14.09	4.97	8.44	14.21	4.69	8.59
Countries	125	125	125	118	118	118	43	43	43
Observations	925	925	925	872	872	872	439	439	439

Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. Columns (1)-(3) are for the benchmark sample also used in the main text. The dependent variable in column (2) is the joint employment share in elementary, machine operator and clerical occupations, whereas the dependent variable in column (3) is the joint employment share in craftsman and professional occupations. In columns (4)-(6), I exclude 53 samples from 30 countries which do not include manufacturing employment in all five occupation categories. In columns (7)-(9), I keep ony countries with at least one survey for both the period up to and after 1990 in the sample. The rows "F-test joint GDP/c" in the bottom panel present the p-values of F-tests for joint significance of ln GDP/c and its square, with and without the post-1990 interaction.

Table 4.A.2: Trends in the Manufacturing Wage Premium

Dependent variable: Manufacturing premium in log points

	(1) Less than primary completed	(2) At least primary completed
Trend/10	-3.29^{+}	-1.58
	(1.90)	(1.38)
Country fixed effects	✓	✓
Mean dep. var.	13.24	-3.05
Countries	88	88
Observations	601	601

The manufacturing premium is calculated as 100*the log ratio of income of those with at most incomplete primary schooling who are employed in manufacturing relative to those who work in a different industry. Wage data are taken from IPUMS and I2D2. Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$,* $p < 0.05$,** $p < 0.01$.

Table 4.A.3: Trends in the Manufacturing Wage Premium by Income Group

Dependent variable: Manufacturing premium in log points

	Less than primary completed, by income			
	(1) Pooled	(2) Low	(3) Middle	(4) High
Trend/10	-3.29^{+}	-2.53	-4.37*	-0.11
	(1.90)	(5.75)	(1.99)	(4.38)
Country fixed effects	✓	✓	✓	✓
Mean dep. var.	13.24	15.41	11.14	18.48
Countries	88	27	46	15
Observations	601	143	369	89

The manufacturing premium is calculated as 100*the log ratio of income of those with at most incomplete primary schooling who are employed in manufacturing relative to those who work in a different industry. Wage data are taken from IPUMS and I2D2. Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$,* $p < 0.05$,** $p < 0.01$.

Table 4.A.4: Trends in the Share of Wage Employment in Manufacturing

Dependent variable: Wage employment in manufacturing (%)

	(1) All	(2) Elementary	(3) Operators	(4) Craftsmen	(5) Clerks	(6) Professionals
Trend/10	0.47	-0.61	1.57^{+}	-0.48	0.46	0.95^{+}
	(0.52)	(0.54)	(0.83)	(0.79)	(0.92)	(0.52)
Country fixed effects	✓	✓	✓	✓	✓	✓
Mean dep. var.	73.17	88.00	87.17	64.98	93.54	77.84
Countries	122	122	122	122	122	122
Observations	921	915	912	912	899	919

Data are taken from IPUMS and I2D2. The number of surveys included differes slightly across columns because not all surveys include manufacturing workers in all occupations. Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Table 4.A.5: Manufacturing Employment as a Function of Income: period up to versus post-1990, by RTI

Dependent variable: manufacturing employment by occupation (percentage points)

	(1)
ln GDP/c	0.98
	(1.67)
ln GDP/c squared	-0.04
	(0.10)
ln GDP/c x RTI	2.91**
	(0.71)
ln GDP/c squared x RTI	-0.17**
	(0.04)
post-1990	-11.01^{+}
	(6.09)
ln GDP/c x post-1990	2.83*
	(1.41)
ln GDP/c squared x post-1990	-0.18*
	(0.08)
ln GDP/c x RTI x post-1990	0.16^{+}
	(0.09)
ln GDP/c squared x RTI x post-1990	-0.02^{+}
	(0.01)
Country-occupation fixed effects	✓
Population controls	✓
F-test joint GDP/c x RTI x post-1990	0.10
Mean dependent variable	1.87
Countries	125
Observations	6,475

Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$,* $p < 0.05$,** $p < 0.01$. The sample corresponds to the one from Table 4.2, with the difference that it stacks the employment shares in seven occupation groups: “managers”, “professionals”, “associate professionals”, “clerks”, “craftsman”, “machine operators” and “elementary occupations”. The number of observations hence results from multiplying the 925 country-years with the 7 occupations. “RTI” stands for the index of Routine Task Intensity. “Population controls” in the bottom panel stands for ln population and its square, as well as interactions with the RTI score. The row “F-test joint GDP/c” presents the p-values of an F-test for joint significance of ln GDP/c and its square, interacted with the RTI score and a “post-1990” dummy.

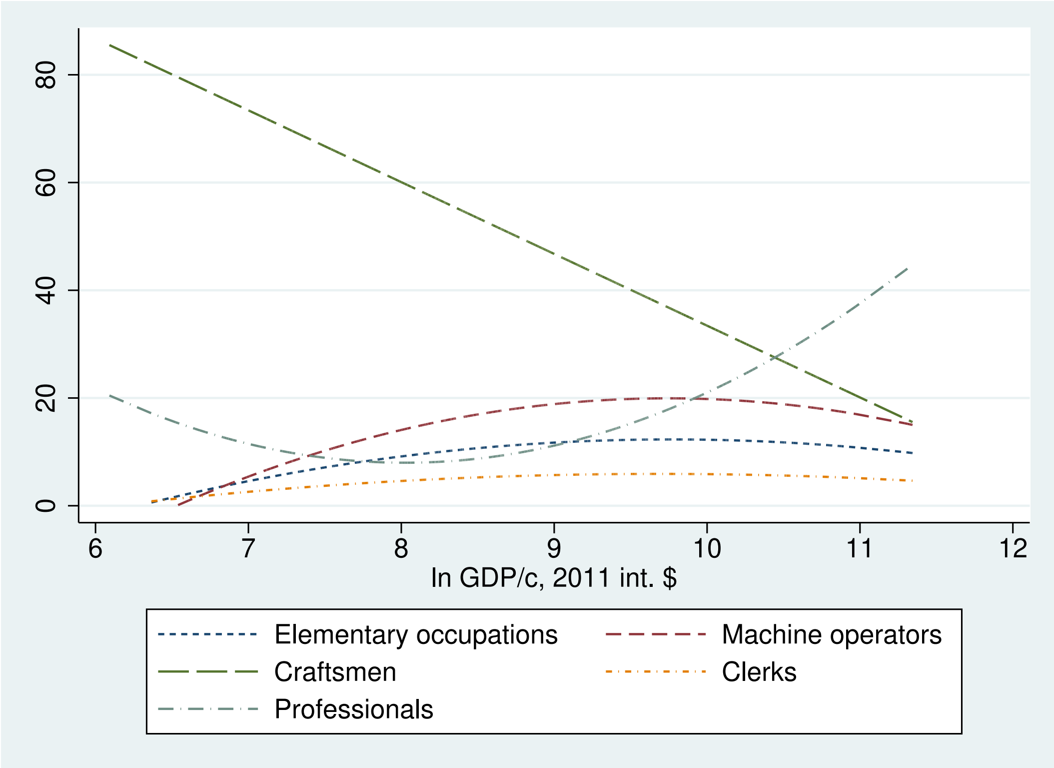

Figure 4.A.1: Simulated Employment *within Manufacturing*, by Occupation (Percentage Points)

The Figure corresponds to Figure 4.2 in the main text- with the difference that the dependent variable in the regression is the occupational employment shares *within manufacturing*.

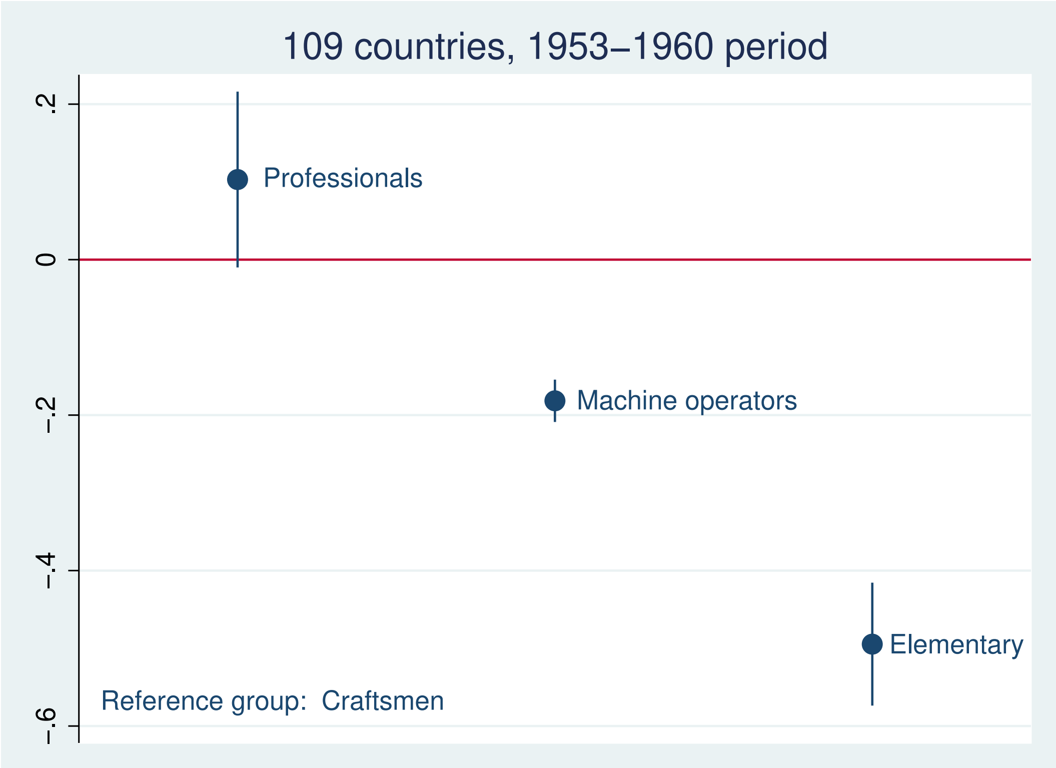

Figure 4.A.2: Occupational Wage Premia in Manufacturing in the 1950s (in log points)

Source: the extended "Occupational Wages Around the World" (OWW) database as described by Kunst et al. (2020). The Figure plots the average deviations of manufacturing wages in the respective major group from craftsman wages, in a sample of 109 countries between 1953-1960, along with the 95 percent confidence intervals. Coefficients are obtained from a regression of 8,258 average annual log wages from 24 manufacturing occupations that belonging to one of the 4 occupation groups on country-year dummies and major group dummies. The sample does not include wages from clerical occupations. See Kunst (2019a) for an analyses of trends in occupational wage premia in manufacturing over time.

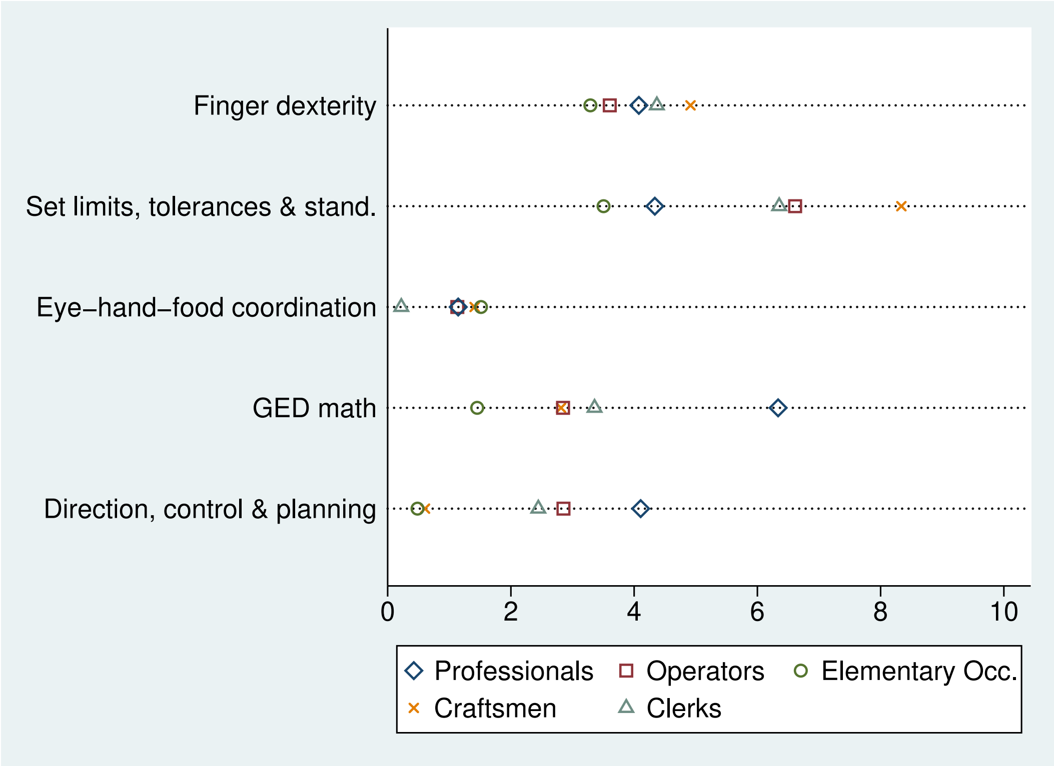

Figure 4.A.3: Task Scores by Occupation

Task measures come from the 1977 US "Dictionary of Occupational Titles", and are based on the ranking of occupations in the 1960 distribution of task input in the USA. They range between 0 and 10. See Autor et al. (2003) for a detailed description. I make use of a translation of these US scores into sub-major groups of ISCO-88 by Goos et al. (2014). The Figure shows occupation group averages constructed from 11 sub-major groups that are relevant to manufacturing, as indicated by representation among the manufacturing occupations in the extended "Occupational Wages Around the World" database (and hence, in the ILO "October Inquiry", which it is based on- see Freeman and Oostendorp (2020) for a description). This excludes major groups 5 ("Service and sales workers") and 6 ("Skilled agricultural, forestry and fishery workers"), as well as some sub-major groups that appear not relevant for manufacturing (for instance, sub-major group 23: "Teaching Professionals"). The RTI indices of occupations in Figure 3.A.4 are calculated from the individual task indices as follows, following Autor et al. (2003): first, they are combined to produce three task aggregates: the *Manual* task measure corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination"; the *Routine* task measure is a simple average of two DOT variables, "set limits, tolerances and standards" measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks; and the *Abstract* task measure is the average of two DOT variables: "direction control and planning," measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning requirements. Second, the RTI index is constructed from these aggregates as the difference between the log of Routine task score and the sum of the log of Abstract and the log of Manual tasks scores.

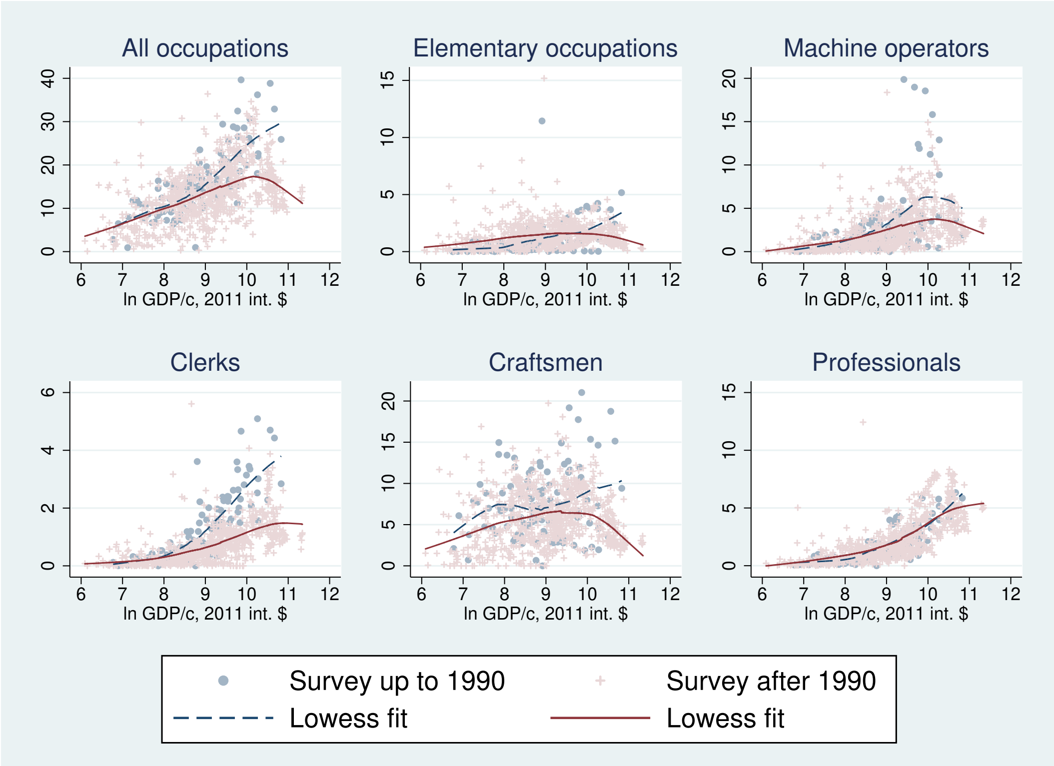

Figure 4.A.4: Manufacturing Employment Shares by Period: Raw Data and Non-Parametric Fit

Every dot represents a survey from a country-year up to or after 1990. Moreover, the Figures include non-parametric estimates of the employment shares by GDP per capita in both periods, produced using the "lowess" command in Stata, using the default bandwidth.

4.B Sample Construction and Coverage

The first data source is the "International Income Distribution Dataset" (I2D2), which is a harmonized collection of nationally representative and harmonized household surveys maintained by the World Bank. It is first described in Montenegro and Hirn (2009), but has been extended significantly since then. The data in this paper are based on the full I2D2 database as of March 2019. I2D2 draws on a variety of surveys such as labor force surveys, budget surveys, and the World Bank´s Living Standards Measurement Surveys. Industry and occupation codes are harmonized to the 1-digit level of ISIC and ISCO, respectively. I calculate employment shares for all men and women aged 15-64 in civilian employment, using the survey weights. If several surveys are available for a country-year, I take the average values across surveys, using the square root of the number of manufacturing observations as weight. I2D2 includes surveys from 139 countries, but has very limited coverage for years before 1990.

I hence complement I2D2 with the surveys of the Integrated Public Use Microdata Series (IPUMS), provided by the Minnesota Population Center (2018). IPUMS contains data with 1-digit level of ISIC and ISCO codes from 76 countries, the large majority of which are census extracts. I again calculate employment shares for all men and women aged 15-64 in civilian employment, using the person weights. Finally, I combine the IPUMS and I2D2 surveys. If a country-year observation is available from both sources, I give preference to the IPUMS data, as IPUMS census extracts tend to contain a larger number of observations and the sampling is likely to be more harmonized.[33] I did not engage in any further “cleaning” of the resulting dataset.

The combined sample includes manufacturing employment shares from 148 countries and 980 country-years between 1960 and 2016. The main sample used in the regression analyses excludes countries for which the Penn World Table 9.0 (Feenstra et al., 2015) does not include data on real GDP per capita, or for which data are available for only a single year. This sample includes data for 925 country-years between 1960 and 2014. 112 of the country-years are from the period up to 1990. For 43 countries, at least one survey from both up to and after 1990 is available. Table 4.B.1 summarize the data availability by country in the main sample.

The additional 23 countries, which enter into the calculations in Table 4.3, are: Afghanistan, Bahamas, Barbados, Belarus, Burundi, Chad, Croatia, Côte d’Ivoire, Djibouti, Guyana, Kiribati, Kosovo, Marshall Islands, Micronesia, Papua New Guinea, Puerto Rico, Solomon Islands, South Sudan, Sudan, St. Lucia, Timor-Leste, Togo, Tonga.

Table 4.B.1: Sample Coverage

43 Countries with Data in Both Periods (up to and post-1990)					
	First year	Last year	Total surveys	-to 1990	-post 1990
ARG - Argentina	1970	2014	12	2	10
AUT - Austria	1971	2008	9	2	7
BEN - Benin	1979	2013	4	1	3
BOL - Bolivia	1976	2014	16	1	15
BRA - Brazil	1960	2014	27	13	14
CAN - Canada	1971	2011	5	2	3
CHE - Switzerland	1970	2000	4	3	1
CHL - Chile	1960	2013	16	5	11
CRI - Costa Rica	1973	2012	15	2	13
DEU - Germany	1970	2008	6	2	4
DOM - Dominican Republic	1960	2013	10	3	7
ECU - Ecuador	1962	2014	12	3	9
EGY - Egypt, Arab Rep.	1986	2006	7	2	5
ESP - Spain	1981	2011	11	1	10
FJI - Fiji	1976	2008	4	1	3
FRA - France	1962	2011	12	5	7

[33] For 47 country-years from 30 countries, I have estimates from both IPUMS and I2D2. The correlation between the estimated employment shares for total manufacturing from both sources is 0.88.

GHA - Ghana	1984	2012	7	1	6
GIN - Guinea	1983	1994	2	1	1
GRC - Greece	1971	2011	10	2	8
HND - Honduras	1961	2014	22	2	20
HTI - Haiti	1982	2007	3	1	2
IDN - Indonesia	1971	2009	19	5	14
IND - India	1983	2011	8	2	6
IRL - Ireland	1971	2011	13	3	10
JAM - Jamaica	1982	2002	7	2	5
MAR - Morocco	1982	2004	5	1	4
MEX - Mexico	1970	2010	15	3	12
MLI - Mali	1987	2009	4	1	3
MWI - Malawi	1987	2013	5	1	4
MYS - Malaysia	1970	2000	4	2	2
NIC - Nicaragua	1971	2009	7	1	6
PAK - Pakistan	1973	2014	15	1	14
PAN - Panama	1960	2012	22	5	17
PRT - Portugal	1981	2011	9	1	8
PRY - Paraguay	1962	2012	9	3	6
SEN - Senegal	1988	2001	3	1	2
THA - Thailand	1981	2011	18	9	9
TTO - Trinidad and Tobago	1980	2000	3	2	1
TUR - Turkey	1985	2010	13	2	11
URY - Uruguay	1963	2014	21	2	19
USA - United States	1960	2010	7	4	3
VEN - Venezuela, RB	1981	2006	9	3	6
ZMB - Zambia	1990	2014	9	1	8
TOTAL	1960	2014	439	110	329

82 Countries with Data in One Period (up to or post-1990)

	First year	Last year	Total surveys	-to 1990	-post 1990
AGO - Angola	2000	2014	3	0	3
ALB - Albania	2002	2008	3	0	3
ARM - Armenia	2011	2013	2	0	2
AUS - Australia	2001	2010	10	0	10
BEL - Belgium	2004	2011	8	0	8
BFA - Burkina Faso	1996	2014	4	0	4
BGD - Bangladesh	2000	2013	5	0	5
BGR - Bulgaria	2003	2010	5	0	5

BIH - Bosnia and Herzegovina	2001	2007	2	0	2
BLZ - Belize	1993	1999	6	0	6
BTN - Bhutan	2003	2012	3	0	3
BWA - Botswana	1991	2011	5	0	5
CHN - China	2002	2013	4	0	4
CMR - Cameroon	2001	2014	5	0	5
COL - Colombia	1964	1973	2	2	0
COM - Comoros	2004	2013	2	0	2
CPV - Cabo Verde	2000	2007	2	0	2
CYP - Cyprus	2005	2008	4	0	4
CZE - Czech Republic	2005	2008	4	0	4
DNK - Denmark	2004	2008	5	0	5
EST - Estonia	2000	2008	9	0	9
ETH - Ethiopia	1995	2014	12	0	12
FIN - Finland	2004	2008	5	0	5
GBR - United Kingdom	1991	2008	6	0	6
GEO - Georgia	2008	2013	6	0	6
GMB - Gambia, The	1998	2010	3	0	3
GTM - Guatemala	2000	2006	5	0	5
HUN - Hungary	2001	2011	7	0	7
IRN - Iran, Islamic Rep.	2006	2011	2	0	2
IRQ - Iraq	1997	2012	3	0	3
ISL - Iceland	2004	2008	5	0	5
ITA - Italy	2001	2011	7	0	7
JOR - Jordan	2000	2014	14	0	14
KEN - Kenya	1999	2005	2	0	2
KGZ - Kyrgyz Republic	1999	2011	2	0	2
KHM - Cambodia	1997	2012	8	0	8
LBN - Lebanon	2004	2011	2	0	2
LBR - Liberia	2008	2014	3	0	3
LKA - Sri Lanka	1992	2014	20	0	20
LSO - Lesotho	2002	2010	3	0	3
LTU - Lithuania	2003	2008	6	0	6
LUX - Luxembourg	2004	2011	8	0	8
LVA - Latvia	2005	2008	4	0	4
MDA - Moldova	1998	2014	16	0	16
MDG - Madagascar	2001	2012	3	0	3
MDV - Maldives	1998	2009	4	0	4
MMR - Myanmar	2005	2010	2	0	2
MNE - Montenegro	2006	2010	2	0	2

MNG - Mongolia	2000	2011	7	0	7
MOZ - Mozambique	1996	2014	4	0	4
MRT - Mauritania	2004	2014	3	0	3
MUS - Mauritius	1999	2012	13	0	13
NAM - Namibia	1993	2014	6	0	6
NER - Niger	2007	2014	3	0	3
NGA - Nigeria	1993	2012	6	0	6
NLD - Netherlands	2001	2011	7	0	7
NOR - Norway	2004	2008	5	0	5
NPL - Nepal	1995	2010	5	0	5
PER - Peru	1993	2014	19	0	19
PHL - Philippines	1997	2014	15	0	15
POL - Poland	1997	2011	14	0	14
PSE - West Bank and Gaza	1997	2008	12	0	12
ROU - Romania	1992	2013	12	0	12
RUS - Russian Federation	2004	2009	5	0	5
RWA - Rwanda	2002	2013	3	0	3
SLE - Sierra Leone	2003	2014	2	0	2
SLV - El Salvador	1991	2014	16	0	16
SVK - Slovak Republic	2005	2008	4	0	4
SVN - Slovenia	2002	2011	10	0	10
SWE - Sweden	2004	2011	8	0	8
SWZ - Swaziland	1995	2000	2	0	2
SYC - Seychelles	2006	2013	2	0	2
SYR - Syrian Arab Republic	1997	2003	2	0	2
TJK - Tajikistan	1999	2009	3	0	3
TUN - Tunisia	1997	2011	5	0	5
TZA - Tanzania	2000	2014	7	0	7
UGA - Uganda	1999	2012	5	0	5
UZB - Uzbekistan	2000	2003	3	0	3
VNM - Vietnam	1997	2010	8	0	8
YEM - Yemen, Rep.	1998	2005	2	0	2
ZAF - South Africa	1995	2014	12	0	12
ZWE - Zimbabwe	2001	2011	3	0	3
TOTAL	1964	2014	486	2	484