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Deskilling among Manufacturing Production Workers

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David Kunst[1]

[1] Tinbergen Institute and Vrije Universiteit Amsterdam, School of Business and Economics, Department of Economics

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David Kunst*

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Abstract

I use new occupational wage and employment data from more than 160 countries to document a global decline in the demand for skilled production workers in manufacturing since the 1950s. They tended to work in craftsman occupations, and their declining relative wages and employment have been associated with increasing capital intensities of production. My findings reconcile conflicting characterizations of technological change throughout the 20th century as either 'skill biased' or 'deskilling', and point to a globally decreasing number of manufacturing jobs in which workers with little formal education can acquire significant marketable skills.

JEL: O33, J22, J31, N60

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*Tinbergen Institute and Vrije Universiteit Amsterdam, School of Business and Economics, Department of Economics. Contact: david.m.kunst@gmail.com. I am grateful to Peter F. Lanjouw and Remco Oostendorp for their detailed suggestions which have greatly improved the paper, and to Daron Acemoglu, David Autor, Travers Barclay Child, James Bessen, Richard B. Freeman, David Garces Urzainqui, Dani Rodrik, Anna Salomons, Luca Sandrini, Marcel Timmer, Gaaitzen de Vries, Martin Wiegand, Jan Luiten van Zanden, Wouter Zant and seminar participants at the VU Amsterdam for helpful comments. I am also grateful to Kathleen G. Beegle, Claudio E. Montenegro, David Newhouse and Aditi Mishra for their help in accessing the I2D2 surveys.

1 Introduction

There is mounting evidence that the increasing adoption of ICT has reduced the demand for medium-skilled workers in the labor markets of high income countries.[1] This polarization of labor demand raises concerns about social mobility: is it still possible for workers in unskilled occupations to climb up the occupational wage ladder, when an increasing number of steps in the middle are missing? However, the diagnosis of a polarization or "hollowing out of the middle" leaves open the question whether the displaced workers have moved *up* or *down* in the wage distribution. Goos et al. (2009) for Europe and Autor (2019) for the US show that in the aggregate, labor market polarization appears to have been driven mostly by the middle-class joining the upper-class, which may soothe concerns about declining social mobility.[2]

In this respect, the recent labor market polarization appears to stand in sharp contrast with a historical precedent, the polarization of labor demand in US manufacturing during the nineteenth century. Katz and Margo (2014) document that also the move to more capital-intensive factory production in this period was polarizing by reducing the demand for medium-skilled artisans relative to both low-skilled laborers and operatives and high-skilled white collar workers. However, the literature emphasizes the *deskilling* aspects of this episode: the initially well-remunerated handicraft skills which artisans possessed lost much of their value as production was broken into simple parts that could be carried out by unskilled workers.[3]

A first question this comparison raises is whether the recent episode of labor market polarization really has been fundamentally different in this respect, or whether it has also been deskilling at least for some groups of workers: for the US, Autor (2019) indeed finds strong evidence of

[1] See Autor et al. (2003), Autor et al. (2006) and Autor and Dorn (2013) for evidence from the US, and Goos and Manning (2007), Goos et al. (2009), Goos et al. (2014) and Michaels et al. (2014) for international evidence of labor market polarization.

[2] For instance, Goos et al. (2009) compare employment changes in 16 European countries between 1993 and 2006 for the eight highest paying occupations, the nine middling occupations and the four lowest paying occupations: they find that while the joint employment share in middling occupations decreased by 9 percentage points over this period, employment in the lowest paying occupations increased by only 1.2 percentage points- with the highest paying occupations registering a corresponding increase in employment of 7.8 percentage points.

[3] For evidence of deskilling in US manufacturing during the 19th century, see Field (1980), Goldin and Sokoloff (1982), James and Skinner (1985) and Atack et al. (2004).

deskilling between 1970 and 2016 once restricting his sample to non-college workers: *"almost all occupational change among non-college workers reflects a movement from the middle toward the bottom of the occupational distribution. Thus, not only has technology change been transformational, it has been broadly deskilling–by which I mean that it has narrowed the set of jobs in which non-college workers perform specialized work that historically (...) commanded higher pay levels"* (p. 9). However, it remains unclear whether such deskilling has been a worldwide phenomenon, as the modern literature has tended to base its finding of pervasive *skill-bias* in technological change on aggregate proxies such as an increasing wage bill share of white collar workers.[4] This may hide substantial heterogeneity among blue collar workers.

A second interesting question is whether the "deskilling mechanism" highlighted by the historical literature–namely, an increasing automation of dexterity-intensive artisanal tasks in manufacturing–has continued to operate also in recent decades: Goldin and Katz (1998) argue that technological change in US manufacturing had become skill-biased already by the early twentieth century following the adoption of continuous-process production methods. However, their framework distinguishes between only two skill types, skilled and unskilled workers. Hence, little is said about the fate of manufacturing artisans and their handicraft skills during the twentieth and early twenty-first century, in which artisans have tended to be *medium*-skilled: less skilled than white collar workers, but considerably more skilled than other manufacturing production workers. This omission is particularly salient for developing countries, for which the literature review by Tybout (2000) points to a dominance of small-scale and artisanal manufacturing shops at least until recently.

[4] For instance, see Berman et al. (1994) for US evidence of an increasing wage bill share of white collar workers during the 1980s. Berman et al. (1998) and Berman and Machin (2000) find that this finding generalizes to a large number of countries since the 1970s, and conclude that there has been pervasive skill-biased technological change also on a global scale. Also Autor (2019) notes that this conventional framing of recent technological change as skill-biased is somewhat prone to concealing potential deskilling aspects: *"A foundational assumption of the modern literature on skill demand, dating at least to Tinbergen (1974), is that technological progress complements–and hence raises demand for–educated workers. This framing might suggest that highly-educated workers should see their work transformed by technology. While this transformation has to some degree occurred, a clear takeaway from this descriptive analysis is that changes in the nature of work–many of which are technological in origin–have been far more profound and, arguably, far more disruptive for less-educated workers than they have been for more-educated workers"* (p. 9).

In this paper, I use new occupational wage and employment datasets to show that automation since the 1950s has been deskilling among manufacturing production workers around the world in the sense of Autor (2019): it has narrowed the set of jobs in which manufacturing production workers perform specialized work that commands higher pay levels than more elementary production work. In the beginning of my sample period, most manufacturing employees worked in medium-skilled craftsman occupations, jobs which required handicraft skills and a good understanding of the entire production process. Wages in these skilled production (or "blue collar") occupations even rivalled those in some nonproduction (or "white collar") occupations. I document a pervasive reduction in the relative demand for craftsmen in countries of all income levels and world regions over the subsequent decades, following the adoption of more capital intensive production technologies. By contrast, the relative demand for both unskilled other production workers and skilled white collar workers increased, mirroring the findings by Katz and Margo (2014) for US manufacturing during the nineteenth century. This suggests some continuity over time in the "polarizing" impact of technological change on labor demand, and implies that countries worldwide have been confronted with the associated challenges.

This paper contribute to two literatures. First, my findings add to the literature on the effects of technological change on skill demand: they are consistent with a demand shift favoring white collar workers (Berman et al., 1998; Berman and Machin, 2000), but at the same time highlight that such workers tended to account for less than 20 percent of manufacturing employment in most countries for most of the sample period. For a more refined characterization of global labor demand trends in manufacturing since the 1950s, I combine wages from the extended "Occupational Wages around the World" database (OWW) by Freeman and Oostendorp (2020) with occupational employment data from the "Integrated Public Use Microdata Series" (IPUMS, Minnesota Population Center 2018) and the "International Income Distribution Dataset" (I2D2, Montenegro and Hirn 2009). The resulting sample goes significantly beyond the existing literature in terms of the countries and time period covered and in the level of detail of occupational categories. Moreover, relative occupational wages have the advantage of not only reflecting skill differences related to formal education, but also taking into account skills acquired through informal apprenticeships and learning on the job. This is particularly important when analyzing changes in the demand for skill in countries and time periods where formal educational attainments are low.

Among production workers, I find evidence of *declining* returns to skill: craftsman occupations experienced decreasing wages and employment, relative to other production workers who were considerably less skilled initially. For developing countries with often still mostly artisanal manufacturing sectors (Tybout, 2000), my findings are consistent with the model of manufacturing labor demand by Goldin and Katz (1998). In this model, the first automation step towards larger-scale factory production favors unskilled machine operators and laborers at the expense of the more skilled craftsmen.[5] However, the demand for manufacturing craftsmen continued to decline also in high income countries.

Therefore, my findings reconcile the long-standing view that technological change over the 20th century has been skill-biased with the forceful and widely-discussed claim by Braverman (1974) that it has been *deskilling* for most workers.[6] While employment trends are consistent with an increasing demand for (skilled) white collar workers, my findings suggest that Braverman was correct to point out that the substantial skills that craftsmen in manufacturing possessed lost much of their value following the adoption of more capital intensive production methods.

Second, this paper contributes to a literature initiated by Autor et al. (2003), which analyzes the effects of technological change on labor demand from the perspective of occupational tasks. This perspective highlights that the skill required to perform a specific task does not need to coincide with its susceptibility to automation. The effect of technological change on skill demand will

[5] In the Goldin and Katz-model, automation is skill-biased only when starting from an already high division of labor and high capital intensities, with unskilled workers who operate special purpose machines in each production step. Then, the adoption of continuous-process methods reduces the demand for unskilled operators as well as hauling and conveying operations performed by unskilled laborers, and increases the demand for skilled professionals who attend the more advanced machinery.

[6] For instance, Tinbergen (1974) introduced the metaphor of a *"race between technology and education"* to illustrate the wide-spread idea that technological change is skill-biased and increases skill premia, unless also educational attainments increase sufficiently. By contrast, in his widely-discussed book *"Labor and monopoly capital: The degradation of work in the twentieth century"*, published in the same year, Braverman argued that *"the capitalist mode of production systematically destroys all-around skills where they exist"* (p. 57), and that there had been a *"destruction of craftsmanship"* (p. 94) throughout the 20th century.

therefore often not be monotonic.

To illustrate how a fall in the relative price of capital may account for the observed decline of craftsman wages and employment relative to other production workers, Section 4 presents an adapted version of the task model from Autor et al. (2003): in this model, an increasing use of capital substitutes for automatable tasks, while complementing non-automatable tasks. I find that this capital deepening (defined as the adoption of more capital intensive production methods) has been significantly associated with decreases in the relative wage and employment of craftsmen, consistent with the assumption that craftsmen have tended to perform the most automatable production worker tasks.[7]

Also Bessen (2011) and Katz and Margo (2014) note the parallel between the recent labor market polarization in the aggregate economy and the decline of medium-skilled artisans–however, with respect to US manufacturing in the nineteenth century. By contrast, my findings highlight that the process of substituting craftsmen with capital continued even after 1950. This points to a continuity of manufacturing automation replacing artisanal tasks stretching from the nineteenth to the early twenty-first century. It also suggests that the polarization of labor demand in manufacturing precedes ICT.

Finally, task models highlight that automation not only displaces workers from tasks henceforth performed by capital, but also increases their productivity in the remaining tasks and can create new tasks in which labor has a comparative advantage (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2019). Therefore, a reduction in the market value of craftsman skills does not yet imply deskilling among manufacturing production workers more generally. However, looking at trends in either wage or educational attainment levels relative to the labor market overall, I find little evidence of other production workers acquiring additional marketable skills that would be comparable to the ones that manufacturing craftsmen traditionally possessed.

[7] In a companion paper (Kunst, 2019), I argue that also the tasks of unskilled machine operator and elementary occupations have become increasingly automatable when comparing the 1960-1990 to the post-1990 period. This implies that fewer unskilled jobs have been created to make up for the loss of craftsman employment in recent decades, leading to the phenomenon of "premature deindustrialization" popularized by Rodrik (2016). Since the present paper focuses on the composition of occupational labor demand *within* manufacturing, my argument only requires that craftsmen jobs have tended to be *more automatable* than other production worker jobs over the sample period.

This suggests that any new skill-intensive tasks created by automation have tended to be tasks for white collar workers, requiring significantly higher educational attainments. This is consistent with the deskilling among US non-college workers in recent decades documented by Autor (2019).[8]

In summary, this paper documents a worldwide decline in the demand for skilled manufacturing production workers since the 1950s, which appears to be well explained by a substitution of craftsman tasks with capital. The remainder of this paper is organized as follows: Section 2 introduces the wage and employment data, and uses them to characterize the three groups of manufacturing occupations that guide my analyses throughout the rest of the paper. Section 3 documents the pervasive decline in the wages and employment of manufacturing craftsmen relative to other production workers. Section 4 argues that the declining demand for craftsmen can be understood through the lens of the task-framework introduced by Autor et al. (2003). It also provides empirical evidence supporting the view that it has been related to an increasing automation of tasks previously performed by craftsmen, and addresses the question whether the deskilling of craftsmen has been accompanied by other production workers *gaining* marketable skills. Section 5 discusses implications of these findings.

2 Global Manufacturing through the Lens of Occupations

This Section introduces novel databases of occupational wages and employment that offer two main advantages over those used by existing cross-country studies: first, they allow me to distinguish between different groups of manufacturing *production* workers in a way that is consistent across countries and over time, moving beyond the coarse "white collar versus production" distinction existing papers usually rely on because of data limitations.[9] As I will argue throughout the

[8]Autor writes: *"Labor markets in U.S. cities today are vastly more educated and skill-intensive than they were five decades ago. Yet, urban non-college workers perform substantially less skilled work than decades earlier. This deskilling reflects the joint effects of automation and international trade, which have eliminated the bulk of non-college production, administrative support, and clerical jobs, yielding a disproportionate polarization of urban labor markets"* (p. 1). While this quote focuses on *urban* non-college workers, Figure 5 on page 10 of Autor (2019) suggests that the pattern also holds true for all working age adults.

[9]For instance, the United Nations General Industrial Statistics Database used by Berman et al. (1998) only contains disaggregated data for "operatives", defined as all employees directly engaged in production or related activities of the

rest of this Section, this distinction matters, as production workers are a large and heterogeneous group of manufacturing employees.

Second, they extend the country and time coverage significantly beyond commonly available datasets: my sample includes occupational wages from 169 countries between 1953 and 2008 from OWW and occupational employment from 146 countries between 1960 and 2016 from IPUMS and I2D2. This broad coverage allows me to distinguish global trends from more country- or period specific developments.[10] In particluar, Berman et al. (1998) point out that the *pervasiveness* of labor demand changes can be considered as a testable implication of technological change-based explanations, highlighting the benefits of the broad regional and income level coverage of the sample used in this paper. In all specifications, I include country-occupation fixed effects so that trends are driven by changes within countries and occupations, and I also present results for a balanced panel of 86 countries (OWW) and 44 countries (IPUMS and I2D2).

2.1 Occupational Wage Data from OWW

OWW is based on the "October Inquiry" by the International Labor Organization (ILO)–an annual request to national statistical offices to submit wage data for a number of narrowly and consistently defined occupations, described in more detail in Freeman and Oostendorp (2020). My sample includes average hourly wages for 54 manufacturing occupations from 169 countries between 1953 and 2008. 23 of the occupations were included in the "October Inquiry" for the full sample period, and wages from an additional 21 manufacturing occupations were included from 1983 onwards. See Appendix B for additional information, including a list of all manufacturing occupations and industries included in OWW.[11]

Throughout the paper, I distinguish between three groups of manufacturing occupations which

establishment, next to the data for aggregate manufacturing.

[10] For instance, the EUKLEMS database allows Michaels et al. (2014) to study the polarizing impact of ICT on labor markets only for eleven OECD countries between 1980 and 2004, and Ashenfelter (2012) points out that the lack of internationally comparable wage data over long time periods *"is one of the most serious gaps in our evolving system of economic measurement"* (p. 618).

[11] The data are available on the website of NBER under https://data.nber.org/oww/.

are based on the major groups from the ILO's "International Standard Classification of Occupations" (ISCO), and which I argue to have been affected differently by the move towards more capital intensive production technologies: craftsman-, other production-, and white collar occupations.[12] According to the description provided by the ILO, craftsman tasks *"require the knowledge and experience of skilled trades or handicrafts which, among other things, involves an understanding of materials and tools to be used, as well as of all stages of the production process, including the characteristics and the intended use of the final product*" (quoted from the description of major groups, reproduced in Appendix C). Figure 1 presents the wage premia of 8 manufacturing craftsman occupations in the 1950s, relative to the average manufacturing wage report by countries, and shows that handicraft in manufacturing tended to be well remunerated: craftsman wage premia equal 15 log points on average (ranging from close to zero to 39 log points).[13]

Other production occupations include machine operators, whose *"main tasks consist of operating and monitoring (...) production machinery and equipment"*, and elementary occupations, who *"perform mostly simple and routine tasks, involving the use of hand-held tools and in some cases considerable physical effort"*. They commanded wages that were 13 log points *below* the average–though with considerable dispersion around that average, partly due to wage level differences between manufacturing industries.[14]

[12]Craftsmen correspond to major group 7 of ISCO, other production occupations include major groups 8 (*"Plant and machine operators and assemblers"*) and 9 *("Elementary occupations"*), and white collar occupations subsume major groups 1 (*"Legislators, senior officials and managers"*), 2 (*"Professionals"*), 3 (*"Technicians and associate professionals"*) and 4 (*"Clerks"*). In Kunst (2019), I argue that it is insightful to further distinguish between the high skilled white collar occupations in major groups 1-3 and the medium skilled clerks in major group 4 when analyzing the recent impact of ICT on the labor demand in manufacturing. However, this distinction becomes most relevant towards the end of my sample period, and is not the focus of this paper. OWW does not include any manufacturing occupations from major groups 5 (*"Service workers and shop and market sales workers"*) and 6 (*"Skilled agricultural and fishery workers"*), which also do not play an important role in manufacturing in terms of employment.

[13]The occupation fixed effects are similar across countries with different income levels: when estimating them seperately for low-, middle- and high income countries, the correlations of occupation fixed effects by income group with the ones for the pooled sample range between 0.97-0.99.

[14]One may argue that this group hence combines very different occupations. However, the findings presented below also hold true for craftsmen relative to either ony machine operators or only elementary occupations (results available upon request). A second concern is that absent data on employment shares in OWW, I assign equal weight to the underlying occupations when calculating wage premia for these three groups of occupations. However, the three occupational groups differ systematically in their task requirements, so that also reports from occupations with smaller employment shares are informative about task prices. Reassuringly, the ranking of the three occupation groups also holds up within the three more detailed manufacturing industries for which OWW includes occupations from the different groups (see the discussion below, and Appendix Figure A.3). Moreover, craftsmen in the 2000s enjoyed a

For instance, *"printing & publishing"* tended to be a high wage industry in the 1950s, accounting for both the best-paid craftsman occupation (*"machine compositor"*) and other production occupation (*"printing pressman"*). However, Figure 1 shows that within this industry, the craftsman occupation again commanded higher wages than the machine operator occupation. By contrast, *"textiles"* was a low wage industry–and while the occupation *"loom fixer, tuner"* was among the lowest paid craftsman occupations, it still commanded considerably higher wages than *"cloth weavers (machine)"*, a machine operator occupation from the same industry.

The latter example also highlights that manufacturing craftsmen often work together with other production workers, as the description of cloth weavers directly refers to loom fixers and tuners: A cloth weaver *"operates and tends battery of looms to weave yarn into cloth: starts set-up loom and observes weaving operation; (...); reports mechanical faults to loom fixer."* Loom fixers in turn *"set, inspect and repair looms of various kinds: prepare looms for weaving new pattern or different quality of product (...); operate loom manually to check movements (...) and make necessary adjustments; hand loom over to weaver for operation; inspect loom periodically and keep in good working order; make repairs (...); replace empty warp beams with full ones"*.[15] When craftsmen and other production workers work together, craftsmen are hence in charge of setting up machines and taking over production steps that machines operated by unskilled workers cannot (yet) perform on their own.

comparable wage premium over other production workers regardless of whether one looks at OWW wages (which do not weigh the underlying occupations by employment) or the survey wages (which do)- see Figure 3, and the discussion in Section 3. Finally, a challenge to the interpretation of relative occupational wage trends as task price trends is that the former may also reflect changes in worker characteristics within the occupations. However, Böhm et al. (2019) document positive selection effects in declining occupations, i.e. systematically higher wages for "stayers" as compared to "leavers" related to individual characteristics. Hence, the trend of declining relative craftsman wages documented in Section 3 if anything understimates the underlying decline in the relative price of craftsman tasks.

[15]These descriptions are quoted from the detailed description of "October Inquiry" occupations, given to the national statistical offices by the ILO. For the printing industry, the corresponding tasks of the craftsman occupation *"machine compositor"* are described separately by machine type: *"sets and arranges printing type by machine: (a) Linotype operator (...) (b) Monotype keyboard operator (...) (c) Computer keyboard operator (...) (d) Typewriter keyboard operator (...) (e) Filmsetter keyboard operator (...)"*. The tasks of the machine operator occupation *"printing pressman"* are described as follows, again for different machine types: "*Sets and operates various types of machines which print on paper and other materials: (...).*" Additional detailed descriptions are available on request. See Section 3 for references to case studies describing technological changes in the textiles and printing industries over the sample period.

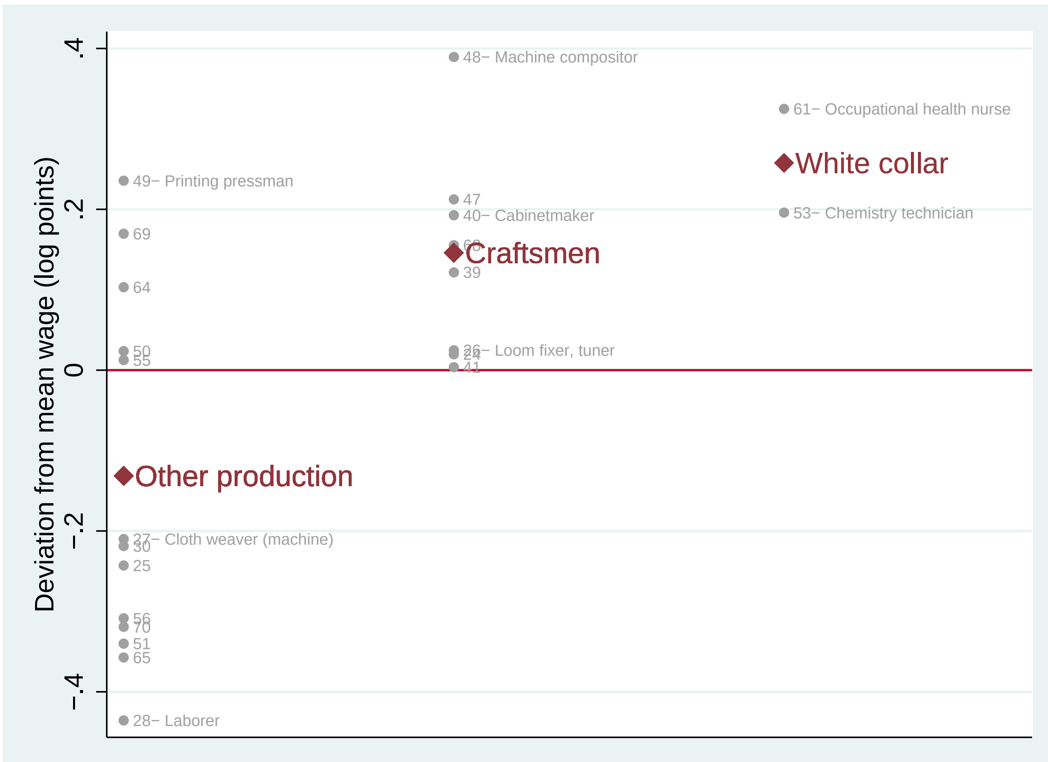

Figure 1: Occupational Wage Premia in Manufacturing in the 1950s in 112 Countries

Source: OWW. The red diamonds represent the occupation group fixed effects from a regression of log wages on country-year fixed effects and occupation group fixed effects. The sample includes 7,950 average annual wages from 23 manufacturing occupations in one of the three occupation groups, reported by 112 countries between 1953-1960. Hence, they represent the average deviation of the wage in an occupation group from the average country-year wage report. The dots in light grey are the corresponding occupation fixed effects from a regression on occupation instead of (coarser) occupation group fixed effects. All occupations are labelled with the occupation code, and selected ones also with the name of the occupation. Appendix B contains a full list of occupations, including occupation codes. Note that there is no reference category because the intercept is instead chosen such that the prediction calculated at the means of the independent variables equal to the mean wage in the sample.

2.2 Occupational Employment Data from IPUMS and I2D2

A drawback of OWW is that it does not include occupational employment data.[16] To complement wages with employment data, I combine census and survey data from IPUMS, hosted by the Minnesota Population Center (2018), with survey data from I2D2. I2D2 is a collection of harmonized and nationally representative household surveys introduced by Montenegro and Hirn (2009) and maintained by the World Bank.[17]

The resulting dataset contains the distribution of manufacturing wage employment across the three occupation groups for 955 country-year observations from 146 countries between 1960 and 2016.[18] However, coverage for the earlier years is scarcer: 90 percent of the surveys are from 1990 or later, and 74 percent are from 2000 or later.

To examine how the occupational employment mix within manufacturing typically varies with a country´s income level, Appendix Table A.1 presents the results from regressing the employment share of craftsmen, other production workers and white collar workers within manufacturing on the best-fitting third order polynomial of ln GDP per capita, decade dummies and country fixed effects.[19] Figure 2 plots the corresponding fitted relationship for a "typical" country in the sample, with averaged period and country fixed effects: it shows that a large majority of manufacturing employees in low income countries tends to work in craftsman occupations. Their share in total manufacturing employment declines with income, with particularly rapid declines at intermediate levels of income. However, it is only after an income level of around $10,000 (in 2011 international

[16] However, the description of the "October Inquiry" states that occupations were chosen with regard to economic relevance*: "the occupations and industry groups covered comprise, as far as possible, those which are important in terms of the number of persons employed in them"*.

[17] 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 their help in accessing the I2D2 surveys.

[18] I hence exclude manufacturing workers classified as self-employed or as non wage-employed/ working in the family business, which represent about 30 percent of manufacturing employees on average. I do this to allow for a cleaner comparison to the wage data from OWW, which does not take account of the earnings of non-wage workers or the self-employed. However, findings are robust to including these non-employed manufacturing workers in the analyses. See Appendix B for a more detailed description of the sample construction.

[19] Using a third order polynomial ensures that the fitted curves could in principle take a large number of possible shapes, and F-test reject the need for even higher order polynomials. The polynomial terms are selected by Stata´s "fp" command (with default settings), which compares 164 models and select the best-fitting one. See the note of Appendix Table A.1 for further details.

$) that they cease to be the most important group of manufacturing employees.

By contrast, the employment share of other production workers tends to increase with income up to an estimated peak of around 39 percent, reached at an income level around $18,000. Afterwards, it also declines. Finally, the employment share of white collar workers in manufacturing is slightly U-shaped, and increases strongly only at higher levels of income.[20]

Table 1 summarizes additional survey information. Not all of the variables are available for all countries, and column (1) indicates the number of countries across which the sample average has been calculated. The average survey is from the year 2002, so that the figures are most representative of the later part of the sample period. The first row indicates that craftsmen and other production workers on average represent more than 70 percent of all manufacturing employees in the sample.

The second row shows that while both groups of production workers earn wages below the manufacturing average in the survey data, craftsmen still tended to be better paid than other production workers–consistent with the ranking of OWW wages in the 1950s shown in Figure 1.[21] However, the middle panel indicates that average educational attainments of craftsmen and other production workers in the surveys are comparable, and much lower than those of white collar workers. The bottom rows show that craftsmen tended to work in smaller establishments than other production and white collar workers.[22]

In summary, OWW wage and survey data consistently characterize craftsmen as the best-paid manufacturing production workers, who likely obtain much of the (handicraft) skills that differ-

[20]The U-shape of white collar employment may reflect economies of scale at intermediate income levels, where expanding factories permit a white collar worker to instruct a larger number of production workers. Table 1 confirms that other production workers, whose employment share expands particularly rapidly at intermediate income levels, tend to work in larger establishments. By contrast, as GDP per capita increases further, the handling of advanced machines increasingly requires "white collar" professionals.

[21]For the sake of readability, Table 1 omits tests for the significance of differences between means. However, the difference between average craftsman and other production worker wages is highly significant (pval=0.00).

[22]For all educational attainments, the differences between both groups of production workers are insignificant. The differences between average firm sizes are insignificant (pval=0.33 for the upper limit, and pval=0.18 for the lower limit). However, this is due to large standard deviations resulting from large cross-country differences in average manufacturing firm sizes across all occupation groups. In 84 percent of countries, the average upper firm size-bracket of other production workers exceeds the one for craftsmen, and this is the case for 90 percent of countries with respect to the lower firm size bracket. Hence, the survey data do robustly suggest that craftsmen tend to work in smaller establishments.

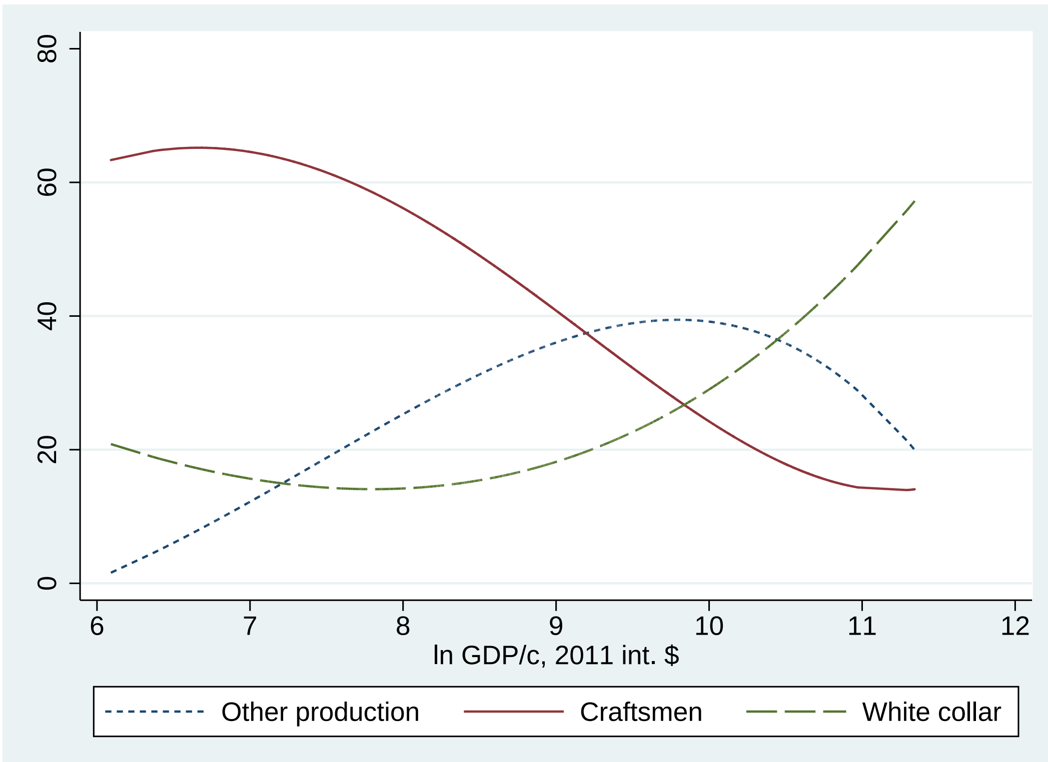

Figure 2: Fitted Occupational Employment within Manufacturing by GDP per Capita

Source: IPUMS and I2D2. The Figure shows the predicted employment shares among all wage employed aged 15-64 from a regression on a third-order polynomial of ln GDP per capita, decade fixed effects and country fixed effects in a sample including surveys from of 123 countries between 1960 and 2014. The best-fitting third order polynomials are selected using Stata´s "fp" command with default settings. Period and country effects are all averaged to obtain the relationship for a "typical" country in the sample. Appendix Table A.1 presents the specifications (which exclude countries with observations from only one year, and country-years for which the Penn World Table do not include data on real GDP per capita). While the three occupation groups cover almost all manufacturing employees (cf. Table 1), I do not impose that the fitted employment shares in the three groups in this Figure always add up to 100.

Table 1: Descriptives by Occupation in Manufacturing: Survey Data

			By occupation		
	Countries	(1) All groups	(2) Other production	(3) Craftsmen	(4) White collar
Employment (%)	146	93.4	30.4	40.1	22.9
Wage premium (log pts)	124	0	-19	-10.8	34.8
Educational attainment: at least completed...					
-primary schooling (%)	127	71.7	69.2	69.1	88.1
-secondary schooling (%)	127	32.9	26	27.1	62.5
-tertiary schooling (%)	127	8.1	3.1	3.7	26.8
Firmsize (number of workers):					
-lower bound	94	31.8	34.6	26.6	39.2
-upper bound	94	34.6	38.2	30.7	40.2

Source: IPUMS and I2D2. Averages across all countries 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 row presents the distribution of manufacturing wage employment of men and women aged 15-64 across occupations. Employment in the "all groups" columns is less than 100 because it excludes manufacturing employees classified as working major group 5 ("service and sales workers") and 6 ("skilled agricultural, forestry and fishery workers"). These major groups are not represented among the manufacturing occupations in OWW, and play a negligible role for manufacturing in surveys from most countries. The second row depicts the wage premium relative to total manufacturing in log points. Firmsizes are reported as "upper" and "lower" bounds of the size category that the establishment falls into. For the "tertiary education" variable, I2D2 surveys include those who started their tertiary education, whereas IPUMS surveys include only those who also completed it.

entiate them from other production workers by means of informal apprenticeships and training on the job rather than formal education. They tend to work in smaller establishments, likely reflecting a lower division of labor, and their importance in manufacturing tends to decline with a country´s income level.

3 The Changing Fortunes of Craftsmen

In this Section, I use the wage and employment data to argue that there has been a pervasive decline in the relative demand for craftsman tasks since the 1950s in countries from all income groups and world regions.

Figure 3 summarizes the evolution of the craftsman wage premium relative to other production workers over a period of six decades for a balanced sample of 86 countries. It reveals a substantial and monotonic decline in the wage premium of craftsmen, from an average of 31.8 log points in the 1950s to 8.3 in the 2000s.[23] The dotted lines split the sample by income group, following the World Bank´s income classification in 1990.[24] They suggest that craftsmen were the most skilled production workers in countries of all income groups, yet enjoyed particularly high wage premia in low and middle income countries.[25] However, craftsmen in these countries also experienced particularly stark declines in their wage premium, and craftsmen in middle income countries earned the *lowest* wage premia by the 2000s.

Appendix Figure A.1 compares the distribution of the craftsman wage premium in the 1950s and the 2000s for the same sample, and confirms that the entire distribution of wage premia has

[23]Note that reassuringly, the OWW wage premium of craftsmen over other production workers in the 2000s corresponds very closely to the corresponding wage premium of 8.2 log points in Table 1, which is calculated from the IPUMS and I2D2 surveys (and which is on average also based on surveys from the early 2000s).

[24]I calculate it as the (max) mode of all available classifications between 1987 (the first year for which World Bank income classifications are available) and 1993, to deal with missing classifications. Using the 1990 income classification has the advantage that the classification broadly corresponds to well established notions about the income status of countries, and is usually representative for most of the sample period. However, given the pervasiveness of the decline of craftsman wage premia documented in this paper, the picture does not change much when using (estimated) income groups from the beginning or end of the sample period instead.

[25]This is consistent with the finding of generally larger skill premia in low and middle income countries in Kunst et al. (2020).

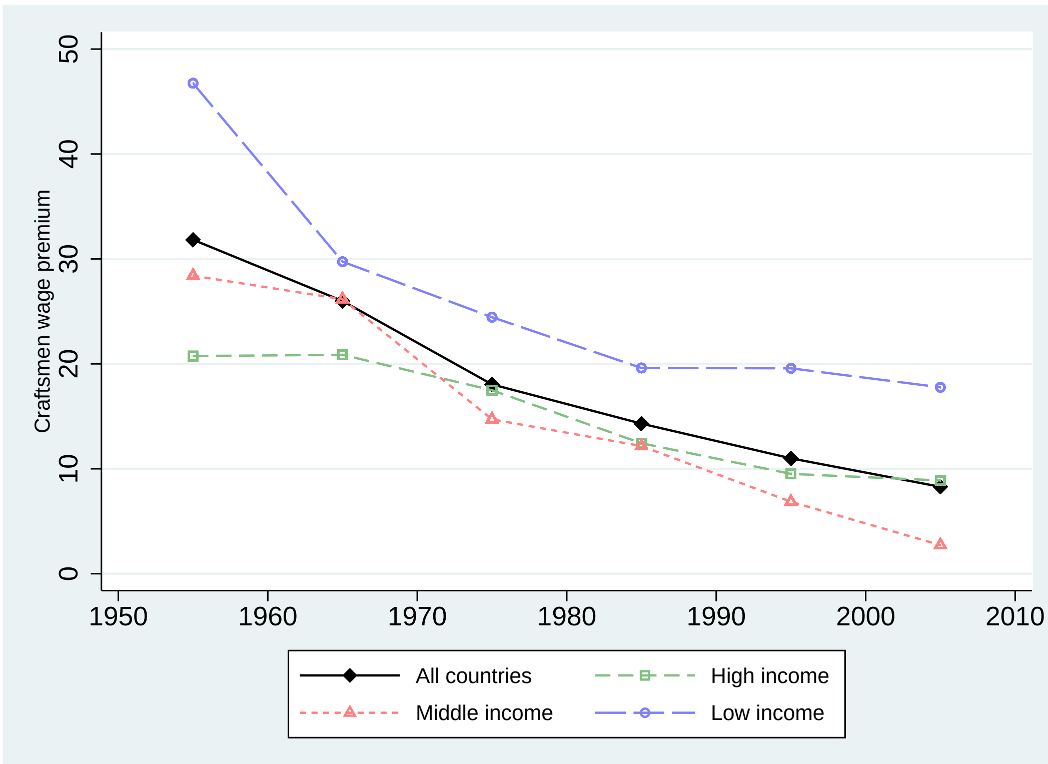

Figure 3: Craftsman Wage Premium relative to Other Production Workers

Source: OWW. The average wage premium of manufacturing craftsmen versus other production occupations is based on 86 countries, of which 19 are classified as high income, 43 as middle income, and 24 as low income. It is calculated as 100 times the difference between the decade average log wages in up to 8 craftsmen and 13 other production occupations. The sample is balanced, and gaps of at most one decade (15 percent of wage reports) have been filled using nearest inter- or extrapolation of reports from neighboring decades. This interpolation procedure is conservative in the sense that it makes it harder to find a trend.

shifted to the left. Appendix Figure A.2 shows that craftsman wages declined relative to both occupation groups subsumed in the "other production" category, machine operators and workers in elementary occupations.

Table 2 presents the results of regressions of all log wages from manufacturing craftsman and other production occupations included in OWW over the full sample period on interactions of decade dummies and a "craftsman" dummy. The specifications include country-occupation fixed effects (so that the identication comes from changes within country-occupation series over time) and country-year fixed effects (to control for changes in wage levels), and cluster standard errors at the country level. Comparing the 1950s to the 2000s, the point estimate for the pooled sample in Column (1) suggests a significant decline of the craftsman wage premium by 20.9 log points, similar to the decline in the balanced sample.

Note that these comparisons include wages from craftsmen and other production occupations in different manufacturing industries. For instance, I may compare wages in the craftsman occupation *"cabinetmaker"* from the *"manufacture of furniture and fixtures"* industry with the other production occupation *"mixing and blending-machine operator"* from the *"manufacture of industrial chemicals"* industry. This should not pose a problem if the task differences between craftsmen and other production occupations are sufficiently general, as the definition of major groups suggests. As a robustness check, I use the fact that OWW includes at least one craftsman and one other production occupation for three 2 digit manufacturing industries, allowing me to track the evolution of the craftsman wage premium within these industries: Appendix Figure A.3 plots the evolution of wage premia calculated separately for each available country-industry (instead of country, as in Figure 3). It shows that the average industry-level craftsman premium declined from 36.4 log points in the 1950s to 11.5 log points in the 2000s. This is in the ballpark of, and slightly exceeds, the decline of the country-level craftsman premium from 31.8 to 8.3 log points over the same period.

At the level of the individual occupations, Figure 4 presents two examples from the textiles and the printing and publishing industries: the left panel plots all wage premia of *"loom fixers, tuners"* (a craftsman occupation) relative to *"cloth weavers (machine)"* in the sample against the year of the report, and the right panel presents all wage premia of *"machine compositors"* (a craftsman occupation) relative to *"printing pressmen"* (see Section 2.1 for a description of these occupations). To help with the interpretation, both panels include a non-parametric local polynomial fit, and the subtitles present the point estimates from a regression of log wages on country fixed effects and a trend. Fitted wage premia in 1953 amount to 17.5 log points for *"machine compositors"* and 24 log points for *"loom fixers, tuners"*, and they declined significantly by on average 3.8-4 log points per decade over the subsequent six decades. This is similar to the decline of average craftsman wage premia in the balanced sample in Figure 3. Hence, fitted wage premia in 2008 amounted to only 2.1 log points for *"loom fixers, tuners"*, and *minus* 3.2 log points for *"machine compositors"*.

These findings are consistent with case studies from the textiles and printing industry: Rasiah (1993) documents rapid automation in a sample of Malaysian textile firms during the 1980s. By the end of the decade, nine of the eleven fibre-making, spinning and weaving firms in his study had switched to using shuttleless air-jet looms, reducing the demand for some skilled craftsmen: *"skilled menders who spot and swiftly mend breaks in the weaved and knitted cloth became redundant as the automated machines enabled break free weaving and knitting"* (p. 18). Rasiah reports that in particular skills requiring dexterity had become less important due to the adoption of the new machines.[26] Wallace and Kalleberg (1982) review how technological changes in the US printing industry have changed labor demand over time: they argue that *"by all accounts, printers have enjoyed a privileged status among manufacturing workers since the early 1800s"*, and that well into the twentieth century, *"printers were expected to be proficient in all phases of printing production from composition to presswork"* (pp. 308-309). They then document how the new technology of teletypesetting (TTS) reduced the demand for skilled craftsmen in the composing room over the 1931-1978 period: *"The TTS machine produces a perforated tape which can be transmitted from shop to shop, virtually bypassing the services of local compositors. (...) TTS contributed*

[26]He writes: *"In 1980 when none of the textile and garment firms had automated machinery, dexterity was the prime skill. (...) Indeed, new recruits had to pass dexterity tests. The most dexterous recruits were trained into sewers (in garment firms) and menders (in weaving and knitting firms). Automation has gradually reduced the importance of dexterity. The fall in dexterity appears sharpest in textile firms"* (p. 17).

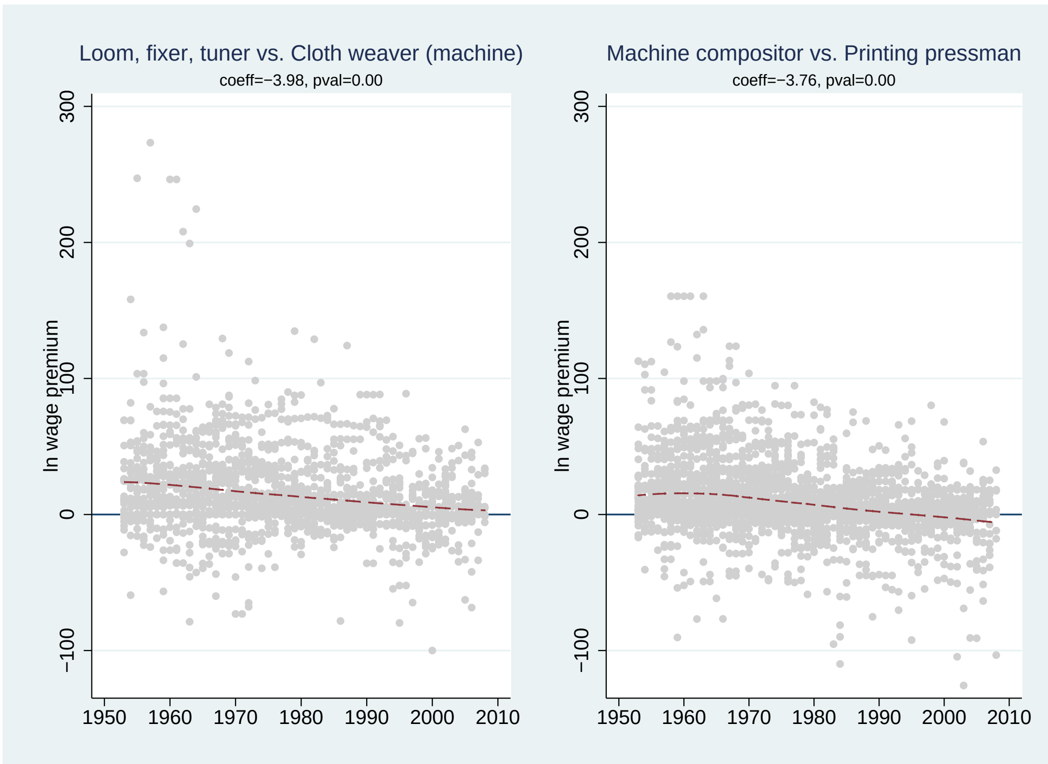

Figure 4: Craftsman Wage Premia: Examples from the Textiles and Printing Industries

Source: OWW. The left panel plots the (log point) wage premium of *"loom fixers, tuners"* (a craftsman occupation) over *"cloth weavers (machine)"* (a machine operator occupation) in the textiles industry over time, along with a non-parametric local polynomial fit (using Stata´s "lowess" command). The wage premium could be calculated for 133 countries and 1,798 country-year observations in OWW. The sub-header shows the point estimate and p-value of a regression of the wage premium on a linear trend (year/10) and country fixed effects, with standard errors clustered at the country level. The right panel plots all wage premia of *"machine compositors"* (a craftsman occupation) over *"printing pressmen"* (a machine operator occupation) in the printing industry over time. Wage premia could be calculated for 156 countries and 2,615 country-year observations.

in a significant way to the de-skilling of composing room operators. (...) It greatly diminished the training time required to set the type, thus obviating the need for long apprenticeships required of compositors and linotype operators. (...) While these occupational titles have remained intact (...) the tasks performed by occupational incumbents have been drastically simplified and routinized" (pp. 310-311).[27]

As Berman et al. (1998) point out, a testable prediction of technological change-based explanations of the wage structure is that changes should be *pervasive*, and hence visible in countries with different income levels, policies and macroeconomic experiences.[28] Columns (2)-(4) of Table 2 confirm that while declines in relative craftsman wages were about double as strong in low and middle income countries, they are significant in countries of all income groups. Columns (5)-(7) compare the evolution of relative craftsmen wages in Africa and Latin America–for which Rodrik (2016) finds declining shares of manufacturing employment and value added since the 1980s–and Asia, which has tended to experience significant industrialization. In all country groups, there has been a significant decline of craftsman wage premia.

This highlights that the trends described in this Section are consistent with very different performances of the manufacturing sector in the aggregate economy: craftsmen lose out in an expanding, export-oriented manufacturing sector that switches to a more capital intensive production technology in response to falling costs of capital or to comply with increasing consumer demands. They also lose out in a contracting, import-competing manufacturing sector in which firms that use older, more labor intensive production technologies exit disproportionately.[29]

A second testable implication of a technological change-induced demand shift against craftsmen is a pervasive decline also in their employment share in manufacturing. For a first impression, Figure 5 plots the number of craftsmen per other production worker, comparing the first available year with data before 1990 with the last available year after 1990 for 44 countries with data for

[27] Note that *"linotype operator"* is a type of machine compositor, whose declining wages relative to *"printing pressmen"* are plotted in the right panel of Figure 4.

[28] With the caveat that technology adoption lags across countries are often substantial (Comin and Hobijn, 2010).

[29] See Section 4 for an illustration of how increasing capital intensities can reduce relative craftsman wages, and evidence that this has actually been the case.

Table 2: Craftsman Wage Premium by Income Group and Region

Dependent variable: ln hourly wage

	By income				By region			
	(1) Pooled	(2) High	(3) Middle	(4) Low	(5) Africa	(6) Latin Am.	(7) Asia	(8) ECA
Craftsman x 1960s	-0.036**	-0.028^{+}	-0.043^{+}	-0.063	-0.054	-0.033	-0.093*	0.018
	(0.014)	(0.016)	(0.022)	(0.041)	(0.038)	(0.035)	(0.039)	(0.020)
Craftsman x 1970s	-0.102**	-0.068**	-0.119**	-0.169**	-0.141**	-0.113**	-0.218**	0.018
	(0.016)	(0.021)	(0.027)	(0.041)	(0.036)	(0.036)	(0.051)	(0.023)
Craftsman x 1980s	-0.159**	-0.089**	-0.185**	-0.268**	-0.259**	-0.151**	-0.306**	-0.056^{+}
	(0.020)	(0.024)	(0.033)	(0.048)	(0.052)	(0.043)	(0.036)	(0.030)
Craftsman x 1990s	-0.181**	-0.124**	-0.220**	-0.248**	-0.281**	-0.176**	-0.296**	-0.079*
	(0.022)	(0.027)	(0.038)	(0.046)	(0.048)	(0.058)	(0.048)	(0.031)
Craftsman x 2000s	-0.209**	-0.122**	-0.272**	-0.268**	-0.470**	-0.211**	-0.305**	-0.132**
	(0.026)	(0.028)	(0.043)	(0.053)	(0.088)	(0.065)	(0.040)	(0.031)
Country-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Country-occup. FE	✓	✓	✓	✓	✓	✓	✓	✓
Countries	158	30	84	44	52	33	23	20
Occupations	21	21	21	21	21	21	21	21
Observations	49153	16297	22584	10272	10814	10893	6579	4570

Source: OWW. Standard errors in parentheses, clustered at the country level. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$. The samples include average annual wages for up to 8 manufacturing craftsman occupations and up to 13 other production occupations by country-year. Income groups are based on the World Bank income classification in 1990 (calculated as the mode over the years 1987-1993 to deal with missing classifications in 1990, using the maximum mode to break ties). All region groups exclude high income countries, and "ECA" in column (8) stands for "Europe and Central Asia". Appendix Table A.2 presents the corresponding specifications for the sample of occupations available from 1983 onwards. I use Stata´s "reghdfe" command based on Guimaraes and Portugal (2011) and Gaure (2013) to deal with the large number of fixed effects in these regressions.

both periods:[30] in the first year (on average, 1974), there were on average 4.9 craftsmen per other production worker. In the last year (on average, 2009), this number had decreased to 1.4 craftsmen per other production worker in the same countries. While a few countries (such as PRY-Paraguay or HND-Honduras) experienced particularly large decreases, the number of craftsman per other production worker decreased in 38 of the 44 countries, consistent with a pervasive demand shift against craftsmen.

For a more systematic illustration of trends in the occupational employment mix within manufacturing, Table 3 regresses the employment shares of other production workers ("O"), craftsmen ("C") and white collar workers ("WC") on country fixed effects and a trend. While the focus of this paper is on the two groups of production workers, I include the results for white collar workers to allow for a direct comparison to the "production worker versus white collar"-distinctions that is common in the existing literature. The first panel in the top row shows that in the pooled sample, craftsmen experienced strong and significant employment share decreases of 4 percentage points per decade, whereas the employment shares of both other production and white collar occupations both increased by 2 percentage points per decade. An analysis through the "blue collar versus white collar" lens would hence lead us to conclude that there has been skill-biased technological change, as the white collar occupations increased their employment share by 2 percent per decade, mirrored by a decline of blue collar employment. However, it would miss the equally large employment shift towards the less skilled production occupations.

The other panels show that across all income groups and regions, point estimates suggest a decreasing employment share of manufacturing craftsmen, with particularly large decreases in middle income and Asian countries. By contrast, employment shares in other production and white collar occupations either show no significant change or increased.[31]

[30] The choice of 1990 as demarcation-year is somewhat arbitrary–but it ensures that there is a reasonable number of countries in the comparison, and that their first and last years in the sample are a reasonable number of years apart from each other. See Table 3 for an alternative representation of employment trends that makes use of the full employment dataset.

[31] Notably, the point estimate of other production occupations in high income countries is (insignificantly) negative, and of the same size as the point estimate for craftsmen: in Kunst (2019), I argue that the demand for other production workers declines with the following automation step towards digitally controlled machines. Such machines require less unskilled human operators, and also reduce the need for hauling and conveying operations performed by unskilled

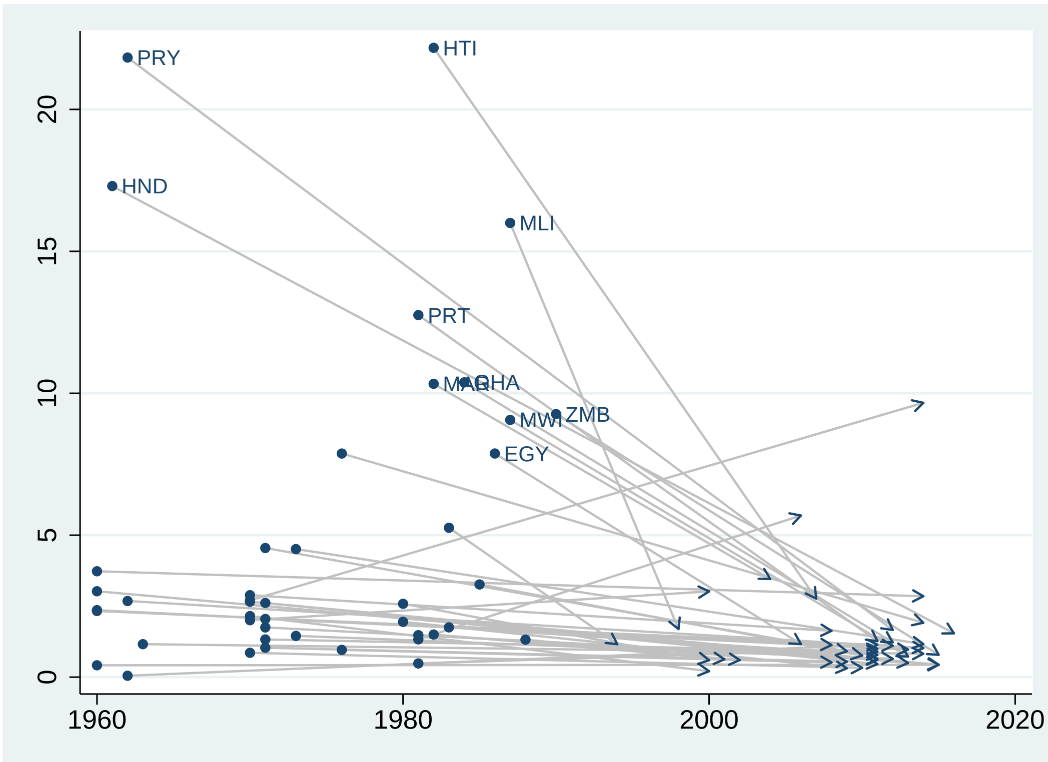

Figure 5: Craftsmen per Other Production Worker in Manufacturing

Source: IPUMS and I2D2. The Figure compares the number of craftsmen per other production worker in manufacturing for the *first* available year before 1990, and the *last* available year after 1990, and labelling the 10 countries which experienced the largest decreases. Of 45 countries with employment data from both periods, 38 experienced a reduction in the number of craftsmen per other production worker. The Figure omits the outlier Benin, in which manufacturing was dominated by craftsmen throughout the sample period. Among the remaining 44 countries, the average selected first years is 1974, the average selected last years is 2009, and the average number of craftsmen per other production worker decreased from 4.9 to 1.4 (median: from 2.6 to 0.9) during this 35 year-period.

Table 3: Employment Trends within Manufacturing by Occupation and Country Group

Dependent variable: share of manufacturing employment

	Pooled			High income			Middle income			Low income		
	(1) O	(2) C	(3) WC	(4) O	(5) C	(6) WC	(7) O	(8) C	(9) WC	(10) O	(11) C	(12) WC
Linear trend/10	2.0*	-4.0**	2.0**	-2.6	-2.6	5.2**	2.7*	-4.6**	1.9**	3.7*	-3.4+	-0.3
	(0.9)	(1.0)	(0.4)	(2.2)	(2.4)	(0.6)	(1.1)	(1.3)	(0.5)	(1.6)	(1.8)	(0.8)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Countries	133	133	133	20	20	20	71	71	71	42	42	42
Mean dep. var.	34.7	41.4	23.9	32.6	27.8	39.6	36.0	42.4	21.7	33.0	47.4	19.6
Observations	942	942	942	146	146	146	552	552	552	244	244	244
	Africa			Latin America			Asia			ECA		
	(1) O	(2) C	(3) WC	(4) O	(5) C	(6) WC	(7) O	(8) C	(9) WC	(10) O	(11) C	(12) WC
Linear trend/10	4.4*	-3.2	-1.2	2.0	-3.4*	1.4**	5.4**	-7.7**	2.2*	2.3	-5.9**	3.6**
	(2.0)	(1.9)	(0.9)	(1.2)	(1.4)	(0.5)	(1.2)	(1.4)	(0.8)	(1.7)	(1.1)	(1.0)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Countries	40	40	40	24	24	24	26	26	26	23	23	23
Mean dep. var.	35.5	42.1	22.5	33.8	45.3	20.9	36.6	47.0	16.4	34.7	38.7	26.7
Observations	179	179	179	285	285	285	202	202	202	130	130	130

Source: IPUMS and I2D2. Standard errors in parentheses, clustered at the country level. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$. "O" stands for "other production workers", "C" for "craftsmen", and "WC" for "white collar". Manufacturing employment shares in these three groups are standardized to sum to 100 in each survey, so that the point estimates in the three groups sum to zero. All region groups exclude high income countries, and "ECA" in the bottom panel stands for "Europe and Central Asia".

In summary, the initially well-paid manufacturing craftsmen experienced strong and global declines in their relative wages and employment since the 1950s. An increasing supply of craftsmen could account for the decline in their relative wages, but would be accompanied by increasing rather than declining employment shares. By contrast, both wage and employment trends are consistent with a pervasive decline in the demand for craftsman tasks in manufacturing.[32]

4 An Interpretive Framework

In this Section, I borrow the model from Autor et al. (2003) to show how increasing capital intensities in manufacturing may account for the observed reduction in the relative demand for craftsmen. While Autor et al. (2003) use this model to study the effect of *computer* capital on task demand, I argue that it is equally useful to illustrate the mechanism behind the reduction in the demand for tasks that can be performed by capital more generally.

4.1 Capital Deepening and the Demand for Craftsmen

Following the previous discussions, I think of craftsmen as the production workers performing the most automatable tasks: as the examples of *"loom fixers, tuners"* and *"cloth weavers (machine)"* in the textiles industry illustrates, craftsmen tend to be engaged in handicraft tasks that cannot yet be performed cost-effectively by machines (cf. the task descriptions in Section 2.1)–a range of tasks that has narrowed over time, as machines have become increasingly wide-spread and capable (cf. the case studies in Section 3).

laborers. Since such technologies were first adopted in high income countries, the reduction in the employment share of other production workers is already apparent for these countries. In Kunst (2019), I show that once conditioning on GDP per capita, employment in such occupations has decreased also in middle income countries when comparing the 1960-1990 to the post-1990 period.

[32] An alternative test to rule out a supply-side explanation of the declining craftsman wages is to control for the average educational attainment by country-year in the relative wage-regressions and its interaction with a craftsman-dummy (which requires dropping the then collinear country-period fixed effects). The finding of a prevasive decline of relative craftsman wages is robust to controlling for a variety of different educational attainment measures in this way (results available upon request). However, note that skill differences among manufacturing production workers are likely in large part due to on-the-job training in most countries and years in my sample (cf. Table 1), which is not captured by measures of formal educational attainments.

To avoid possible confusion with the literature on routine-biased technological change–which studies the effects of computer/ICT capital rather than "old school" total capital–, I refer to "automatable" rather than "routine" tasks. However, Appendix Figure A.4 shows that craftsmen also score higher than both groups of other production workers and white collar occupations on the "routine task intensity index" (RTI) introduced by Autor and Dorn (2013). Hence, the demand shift against manufacturing craftsmen can already be characterized as "routine biased" when using a measure of the relative importance of routine to non-routine tasks that is widely used in the recent literature on labor market polarization.[33]

By contrast, the move towards more capital-intensive factory production increased the demand for other production workers, namely machine operators and laborers for hauling and conveying operations. This is the case especially in the earlier part of my sample period and in developing countries with technologically less advanced manufacturing industries, prior to the adoption of more advanced and digitally controlled machines (cf. Goldin and Katz 1998, and Kunst 2019).

This informal discussion of typical craftsman and other production tasks and their interaction with capital can be summarized in three assumptions:

- **A1.** In manufacturing, capital tended to be more substitutable for tasks performed by craftsmen ("automatable tasks") than for tasks performed by other production workers.
- **A2.** Automatable and other production task inputs are imperfect substitutes.
- **A3.** A greater use of automatable task input increases the marginal productivity of other production tasks.

More specifically, suppose the production function in manufacturing is given by Equation 1. L_c is craftsman labor input, K is capital input, and L_o is other production labor input, all measured in efficiency units. For simplicity, this production function implies a perfect substitutability between

[33] Moreover, Appendix Figure A.5 presents the disaggregated task scores that enter in the calculation of the RTI index. It confirms that craftsmen score highest in terms of "finger dexterity" and "setting limits, tolerances and standards", consistent with the view that manufacturing automation reduced the demand for dexterity and the need to manually set limits, tolerances and standards.

craftsmen and capital inputs, and an elasticity of one between automatable and other production inputs. However, the only substantive model requirement is that capital input is more substitutable for craftsmen than for other production labor input (cf. A1. and A2.). Moreover, automatable and other production task inputs are complements with this production function, consistent with A3. I abstract from nonproduction/white collar labor input here, but A1-A3 remain reasonable also if we instead assume L_o to include white collar workers.[34]

$$Q = (L_c + K)^{1-\beta} L_o^{\beta} \tag{1}$$

I further assume that there is a large number of income-maximizing workers, each of whom inelastically supplies one unit of labor to the manufacturing industry.[35] Workers have heterogeneous productivity endowments $E_i = [c_i, o_i]$ in both automatable (craftsmen) and other production tasks, with $c_i, o_i \in (0,1]$ $\forall i$. A worker can choose to supply c_i efficiency units of craftsmen input or o_i efficiency units of other production input. These assumptions imply that workers will choose tasks according to their comparative advantage as in Roy (1951). The framework hence allows for changes in craftsmen versus other production task supplies in reaction to changes in the relative wage, and hence for changes in the relative employment of craftsmen and other production workers. I assume that capital is supplied perfectly elastically at price r. Since craftsmen and capital inputs are perfect substitutes, the craftsmen wage is pinned down by the price of capital (Equation 2).[36] Given r, the self-selection of workers into craftsmen and other production jobs clears the labor market.

$$w_c = r \tag{2}$$

To characterize the relative employment of craftsmen versus other production workers, I de-

[34] In Section 4.2, I show that also the empirical tests of the model are robust to including white collar occupations in L_o.

[35] Since I am concerned with labor demand changes *within* manufacturing, I abstract from employment flows between industries.

[36] I implicitly assume that the shadow wage of craftsmen absent capital exceeds r so that Equation 2 holds with equality.

fine the relative productivity of individual i in performing automatable versus craftsmen tasks as $\eta_i = \frac{o_i}{c_i}$. The assumptions above imply that $\eta_i \in (0, \infty)$. At the labor market equilibrium, the marginal worker with relative efficiency units η^* is indifferent between performing craftsmen and other production tasks when $\eta^* = \frac{w_c}{w_o}$. Individual i works as a craftsman if $\eta_i < \eta^*$, and works as an other production worker otherwise. Functions $g(\eta)$ and $h(\eta)$ characterize the total labor supply of craftsmen and other production labor, respectively. $g(\eta) = \sum_i c_i \cdot I[\eta_i < \eta^*]$, and $h(\eta) = \sum_i o_i \cdot I[\eta_i \geq \eta^*]$, where $I[\cdot]$ is the indicator function. Moreover, productive efficiency requires that craftsmen and other production workers wages equal their marginal productivities (Equations 4 and 5), where θ is the ratio of automatable to other production input in production (Equation 3):

$$\theta \equiv \frac{g(\eta^*) + K}{h(\eta^*)} \tag{3}$$

$$w_c = \frac{\partial Q}{\partial L_c} = (1-\beta)\theta^{-\beta} \tag{4}$$

$$w_o = \frac{\partial Q}{\partial L_o} = \beta \theta^{1-\beta} \tag{5}$$

One can use Equations 1-5 to study the effect of a decrease of the price of capital on θ and the relative craftsmen versus other production wage and employment: first, Equation 6 shows that a decrease in the price of capital will increase the ratio of automatable input to other production input in production.[37]

[37] This follows from Equations 2 and 4.

$$\frac{\partial ln\,\theta}{\partial ln\,r} = -\frac{1}{\beta} < 0 \qquad (6)$$

From the perspective of producers, this increase in automatable input could come either from increasing K or from increasing L_c. However, Equation 7 shows that the increasing use of automatable inputs will be met entirely by increasing K, since η^* decreases alongside r so that L_c *declines* (as more workers choose to become other production workers instead of craftsmen).[38] Since $\eta^* = \frac{w_c}{w_o}$, also the wage of craftsmen relative to other production workers declines.

$$\frac{\partial ln\,\eta^*}{\partial ln\,r} = \frac{\partial ln\,\frac{w_c}{w_o}}{\partial ln\,r} = \frac{1}{\beta} > 0 \qquad (7)$$

In summary, an exogenous decline in the price of capital raises the marginal productivity of other production tasks, incentivizing craftsmen to work in other production occupations. Although craftsman labor input declines, an inflow of capital more than compensates, yielding a net increase in the intensity of automatable (and in fact, increasingly automated) task input in production. Hence, relative employment of craftsmen decreases alongside their relative wage.[39]

4.2 Has Capital Deepening Reduced the Demand for Craftsmen?

To assess the hypothesis that the declining demand for manufacturing craftsmen is the result of craftsman tasks being taken over by capital, the top panel of Table 4 regresses log wages from manufacturing occupations on alternative measures of the log capital stock per worker (both expressed in 2011 prices). While the value of the capital stock per worker need not be perfectly correlated

[38] This follows from Equations 4, 5, and 6.

[39] Note that for wages, this is true for wages per efficiency unit of task that is supplied, which may differ from observed wages. For example, if there is a positive correlation between worker's abilities to carry out automatable (craftsman) and non-automatable (other production) tasks, the flow of craftsmen into other production jobs in response to a decline in the price of capital reduces the average ability among workers in both occupations. Then, observed craftsman wages unambiguously fall, but observed other production wages may not rise. See Section 4.3 for a discussion of the evolution of craftsman and other production wages relative to a "numeraire"–namely, relative to wages outside of manufacturing. A decrease in the average ability of workers to carry out non-automatable task could be another reason for the absence of a clear increase in their observed relative wage documented in that Section. However, this mechanism hinges on displaced craftsmen having a lower average innate productivity when carrying out the mostly simple non-craftsman production worker tasks, and hence appears unlikely to play an important role in practice.

with the extent to which machines are able to take over tasks previously performed by craftsmen, I consider it as a reasonable proxy.[40] All specifications include an interaction of the capital intensity with a dummy taking a value of one for craftsman occupations, to test for an effect of capital intensity on the relative wage of craftsmen. Since specifications include country-occupation fixed effects, identification comes from wage variation within country-occupation specific wage series. Moreover, specifications include year fixed effects to control for global time trends, and cluster standard errors at the country level.

Column (1) uses the most widely available capital intensity measure, the economy-wide capital stock per worker from the Penn World Table. Unsurprisingly, wages are positively associated with the capital stock per worker, with an elasticity of 0.58. However, the significantly negative craftsman-interaction suggests that craftsman wages increased more slowly with capital intensity than the wages in other production occupations.[41] Since the economy-wide capital stock per worker need not be a good proxy for the capital intensity in manufacturing, I construct manufacturing-specific capital intensities using investment and employment data from the INDSTAT2 database by the United Nations Industrial Development Organization (UNIDO, 2018): I deflate the investment data using the price level of capital formation from the Penn World Table, and use the perpetual inventory method to estimate capital stocks, following Caselli (2005) in assuming a 6 percent depreciation rate (see Appendix B for more details). INDSTAT2 allows to estimate capital intensities both for aggregate manufacturing and by 2-digit manufacturing indus-

[40] An alternative test of the model in Section 4.1 would be to check whether relative craftsman wages and employment have been associated with changes in the *price* of capital. While it is well established that the relative price of investment to consumption goods has declined globally since the 1950s (cf. Karabarbounis and Neiman (2014)), factors other than the relative price of investment goods–such as openness to foreign direct investment, exports to high income markets, increasing import competition, or factor market imperfections (as argued by Hasan et al. (2013))–are likely to have also influenced the extent to which more capital intensive production methods have been adopted. I do not attempt to gauge the relative importance of these potential drivers of capital deepening in this paper, and the model hence uses a declining price of capital as a "catch-all" driving force for simplicity. However, I acknowledge that factors other than the relative price of capital are likely to also have played a role in bringing about the observed increases in capital intensity.

[41] For simplicity, the model assumes that craftsman wages are pinned down by the (declining) price of capital, as it is concerned with the demand for craftsman relative to other production workers. In a model that is more informative about *absolute* craftsman wages, it would appear reasonable to assume that an increasing capital intensity also enhances the productivity of the remaining craftsmen, which could explain the (observed) positive association between capital intensities and absolute craftsman wages.

try.[42] Columns (2) and (3) shows that using either measure of capital intensity, the point estimates of the craftsman-interactions are also significantly negative, and in the ballpark of the estimate for the economy-wide capital intensity.[43]

While the main focus of this article is on demand changes among manufacturing production workers, the literature suggests that also white collar workers tend to be more complementary to capital than craftsmen. Columns (4)-(6) therefore replace the other manufacturing production occupations with white collar occupations, and results suggest that increasing capital intensities tend to be associated with decreasing craftsman wages also relative to this reference group (with significant point estimates for the economy-wide and the industry-specific capital intensity measures). This is consistent with the view that one may consider the framework in the previous Section as being informative about the demand for manufacturing craftsmen relative to other manufacturing workers more generally (including other production as well as white collar workers).

The bottom panel of Table 4 presents results from corresponding regressions in which the dependent variable is the occupational *employment share* in manufacturing. This panel omits the results for the industry-level capital stock estimates, since I do not have employment data at this disaggregated level. Increasing capital intensities are also significantly associated with decreasing employment shares of craftsmen–relative to other production workers in columns (1)-(2), and relative to white collar workers in columns (4)-(5). In summary, these results corroborate the view that the adoption of more capital intensive production methods has been behind the demand shift against manufacturing craftsmen.

To illustrate the economic significance of these point estimates, one can compare the actually

[42]National statistical offices sometimes made reports to UNIDO jointly for several industries. In such cases, I aggregate investment data to the most detailed level for which I could construct a consistent investment series (see Appendix B for details). This hints at challenges encountered by some statistical offices in assigning capital formation to a unique 2-digit industry. Moreover, note that my investment price deflator from the Penn World Table is only available for aggregate manufacturing. While the industry-specific capital intensities are conceptually preferrable, the capital intensities for aggregate manufacturing are hence likely to be measured with less measurement error.

[43]Point estimates become insignificant once also allowing for a linear time trend of craftsman wages (not shown). However, they remain negative, and are not significantly different from the point estimates of the time trends. Since both the decline in relative craftsman wages and capital deepening have been pervasive (see Section 3 for craftsmen wages, and Appendix Table A.4–which I introduce in more detail at the end of this Section–for capital deepening), it is perhaps not surprising that it is empirically challenging to disentangle the effects of capital deepening from a pure time trend of relative craftsman wages.

Table 4: Capital Intensity and the Demand for Craftsmen

Craftsmen...	...vs. Other production			...vs. White collar		
	(1)	(2)	(3)	(4)	(5)	(6)
Capital intensity:	Total	Manuf.	By ind.	Total	Manuf.	By ind.
Dependent variable: ln hourly wage (in constant national prices)						
ln capital/employee	0.576^{**}	0.140	0.075^{+}	0.681^{**}	0.172^{*}	0.129^{**}
	(0.084)	(0.087)	(0.039)	(0.096)	(0.084)	(0.048)
x craftsman	-0.076^{**}	-0.067^{*}	-0.042^{*}	-0.120^{**}	-0.069	-0.081^{*}
	(0.016)	(0.027)	(0.019)	(0.044)	(0.046)	(0.033)
Country-occ. FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Countries	138	84	85	138	84	85
Occupations	46	46	46	26	26	26
Observations	57386	30644	31122	29712	15977	16250
Dependent variable: share of manufacturing employment						
ln capital/employee	9.17^{*}	6.93^{**}		7.91^{**}	3.51^{*}	
	(3.83)	(1.47)		(2.54)	(1.33)	
x craftsman	-23.54^{**}	-11.22^{**}		-23.77^{**}	-8.26^{**}	
	(6.79)	(2.89)		(3.31)	(2.58)	
Country-occ. FE	✓	✓		✓	✓	
Year FE	✓	✓		✓	✓	
Countries	122	74		122	74	
Occupations	2	2		2	2	
Observations	1766	1064		1766	1064	

Source: OWW (top panel) and I2D2 and IMPUMS (bottom panel), as well as INDSTAT2 and Penn World Table for data on capital intensity (both panels). Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$,* $p < 0.05$,** $p < 0.01$. Top panel: Specifications in the first three columns include only other manufacuring production occupations next to craftsmen, whereas specifications in columns (4)-(6) compare manufacturing craftsman to white collar occupations. “Total” denotes the capital stock per worker in the total economy, taken from the Penn World Table. “Manuf.” stands for the capital stock per worker in aggregate manufacturing, estimated from the INDSTAT2 database as described in Appendix B. “By ind.” stands for industry-level capital stock estimates, seperately by 2-digit ISIC manufacturing industry. Bottom panel: specifications in the first two columns include the stacked employment shares of two groups of production occupations from each survey, “craftsmen” and “other production workers”. In columns (4) and (5), specifications include the employment shares of craftsmen and white collar workers. The capital intensity variables are defined analogously. Since occupational employment shares are only available for total manufacturing, the bottom panel does not include regressions at the level of disaggregated manufacturing industries.

observed change of the average relative craftsman wage and employment in the sample with the change that would be predicted from the capital intensity changes, based on the point estimates in Table 4. For the countries in the wage sample, Figure 6 compares the distributions of the capital intensity in aggregate manufacturing for the *first* and the *last* year from each country: these are the years 1975 and 1997 on average, and the distribution of capital intensities shifted markedly to the right between both years.[44]

The average capital stock per worker more than doubled from $43,200 to $95,600 during this 22 year period. Using the point estimate from column (2), this implies a reduction of the craftsman wage premium by 4.4 percentage points, or by 2 percentage points when scaled to one decade. When regressing wages in the same sample on country-occupation fixed effects, country-period fixed effects and a linear trend (as in Table 2 when replacing the decade dummies with a linear trend), the point estimate implies an average decrease by 3.6 percentage points per decade.[45] When doing the corresponding calculations for relative craftsman employment, the capital intensity-changes suggest a reduction in relative craftsman employment by about 4.1 percentage points per decade, as compared to a trend decline of 7.8 percentage points.

Hence, these back-of-the-envelope calculations suggest that capital deepening in manufacturing can account for more than half of the observed reductions of both relative craftsman wages and employment. In summary, the pervasive decline in the demand for manufacturing craftsmen has been accompanied by pervasive capital deepening. Panel regressions suggest that both trends have been related, consistent with the framework in Section 4.1.

[44] Also for the full sample of estimated manufacturing capital intensities, Appendix Table A.4 shows significant increases in all income and region groups (with the exception of Latin America, where point estimates are insignificant).

[45] The precise calculations go as follows: The average increase in the log capital stock per worker between the first and the last year in the sample is 0.685. Since (exp(-0.067*0.685)-1)*100=4.5 percentage points, and both years are on average 22 years apart, this corresponds to a (10/22)*4.4=2.0 percentage point decline in the craftsman wage premium when scaled to a 10 year-period. In the same sample, the point estimate of the "craftsman x trend"-term from a regression of log wages in this sample on country-occupation and country-period fixed effects is -0.037 (not shown), and (exp(-0.037)-1)*100=3.6 percentage points.

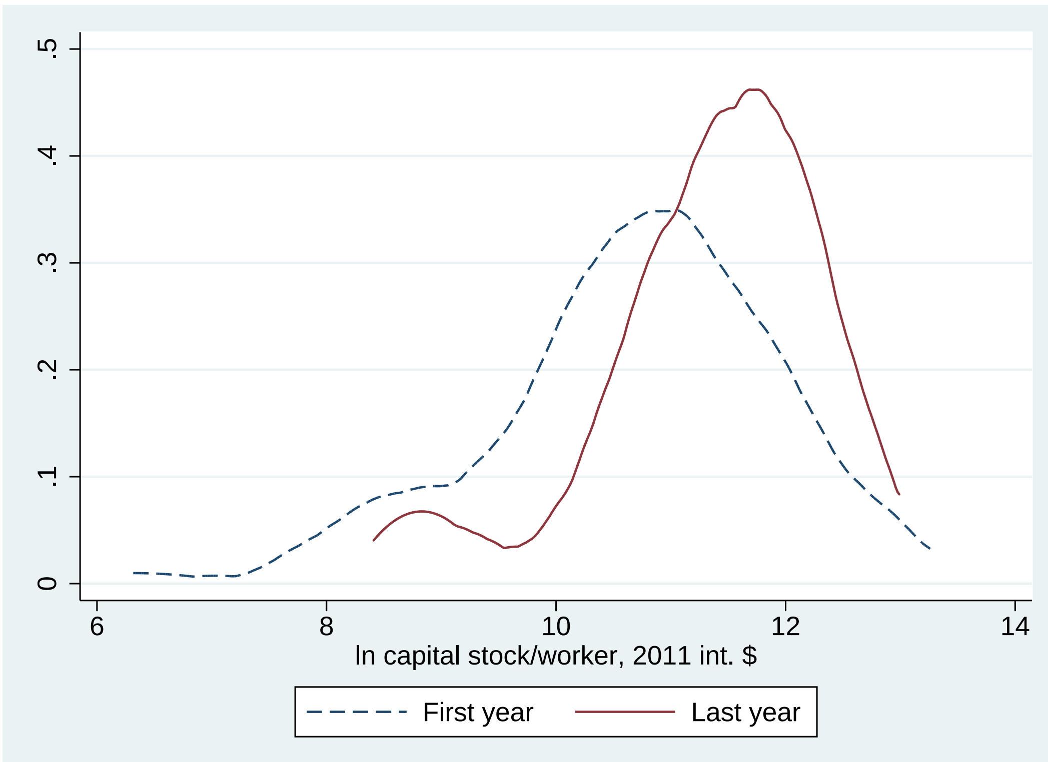

Figure 6: Evolution of Manufacturing Capital Stock per Worker in the Sample

Source: INDSTAT2. The Figure compares the kernel densities of the estimated capital stocks per worker for the first and last year in the sample from the specification in column (2) of Table 4. On average, the first year is 1975, and the last year is 1997. Over this 22 year period, the average capital intensity increased from $43,200 to $95,600 (median: $47,300 to $103,800), and 65 of the 84 countries in the sample experienced increasing capital intensities. Capital stocks per manufacturing worker are estimated from the INDSTAT2 database as described in Appendix B.

4.3 Deskilling of Craftsmen- or Upskilling of other Production Workers?

From the perspective of manufacturing production workers, the model from Section 4.1 offers a silver lining: while automation reduces the demand for craftsmen, it increases the marginal productivity of other production tasks, creating the scope for higher wages in other production occupations. Also Autor (2015) highlights that while workplace automation has always made some tasks carried out by human labor obsolete, it has tended to increase the value of the remaining tasks which could not be automated. In addition, increasing automation may have created new and more skill-intensive tasks for other production workers, allowing them to acquire marketable skills comparable to those that craftsmen possessed traditionally.

While Braverman (1974) agreed that automation increased the demand for highly skilled production tasks, he believed that these tasks would be performed by white collar workers (with much higher educational attainments, cf. Table 1). By contrast, he did not believe in a compensating increase in the value of the remaining tasks carried out by production workers: *"The mass of workers gain nothing from the fact that the decline in their command over the labor process is more than compensated for by the increasing command on the part of managers and engineers. On the contrary, not only does their skill fall in an absolute sense (in that they lose craft and traditional abilities without gaining new abilities adequate to compensate), but it falls even more in a relative sense"* (pp. 294-295).

The question is hence whether the decline in the relative wage of manufacturing craftsmen reflects first and foremost a decline in the value of craftsman skills (as Braverman forcefully argued), or at least in part increasing wages for other production workers (which may arise either from complementarity to the increasingly abundant capital, or from newly acquired skills). From the perspective of task models, this is an empirical question. Since OWW includes wages for occupations outside of manufacturing, one can shed light on this question by comparing wage trends of manufacturing craftsmen and other production workers with wage trends in occupations from industries other than manufacturing in the same country-years. This comparison controls for general wage growth trends at the national level affecting all occupations symmetrically.

The first two columns of Table 5 make this comparison for manufacturing craftsmen: the specifications correspond to those from Table 2 (and hence include country-occupation and country-year fixed effects), with the difference that the reference group is wages from all non-manufacturing occupations in column (1), and from all non-manufacturing occupations excluding white collar occupations in column (2). The case for excluding white collar occupations is that they tend to be considerably more skilled than manufacturing craftsmen (cf. the wage premia in Figure 1 and Table 1). Hence, they may be less informative as a comparison group than "production" occupations from other industries that require similar formal qualifications as manufacturing production workers.[46] However, columns (1) and (2) show that the wages of manufacturing craftsmen decreased considerably regardless of whether one includes white collar occupations in the reference group, by 7.9-10.9 log points when comparing the 1950s to the 2000s.

By contrast, columns (3) and (4) show that the increase of other production wages up to the 1980s becomes insignificant once excluding white collar occupations from the reference group.[47] Appendix Table A.3 presents the corresponding specifications when including the occupations available since 1983: in this extended sample, craftsman wages declined significantly since the 1980s, whereas wages in other production occupations did not increase–regardless of whether one includes white collar occupations in the reference group. Hence, wage trends robustly point to a decline in the wages of manufacturing craftsmen relative to the wages paid in other industries, but not to an increases in the wages of other production workers.

To approach the same question from a different perspective, Table 6 compares the evolution of educational attainments of manufacturing craftsmen and other production workers to those among all wage employed (regardless of occupation or industry). All samples hence include three observations per survey, and specifications include country fixed effects to ensure that identification

[46] For example, samples include the non-manufacturing, non-white collar occupations *"bricklayer", "bus conductor"* and *"plumber"*. See Freeman and Oostendorp (2020) for a complete list of the occupations included in the OWW database.

[47] When including white collar occupations in the reference category, column (3) suggests increasing other production wages up to the 1980s. In Kunst et al. (2020), we show that the 1950s-1980s were a period of strongly declining skill premia, driven by increasing educational attainments. Hence, when the reference group includes white collar occupations, the increasing relative wage of other production workers over this period reflects decreasing skill premia of white collar workers, as opposed to an upskilling of other manufacturing production workers.

Table 5: Wage Trends: Craftsmen and Other Production Workers vs. Other Occupations

Dependent variable: ln hourly wage

Group:	Craftsmen		Other production	
	(1) vs. all	(2) excl. WC	(3) vs. all	(4) excl. WC
group x 1960s	-0.023	-0.025	0.015	0.017
	(0.015)	(0.015)	(0.011)	(0.011)
group x 1970s	-0.040*	-0.034^{+}	0.063**	0.025
	(0.017)	(0.019)	(0.019)	(0.016)
group x 1980s	-0.059**	-0.048*	0.098**	0.012
	(0.019)	(0.022)	(0.023)	(0.017)
group x 1990s	-0.055*	-0.031	0.107**	0.018
	(0.024)	(0.026)	(0.025)	(0.023)
group x 2000s	-0.109**	-0.079**	0.096**	0.029
	(0.026)	(0.026)	(0.026)	(0.020)
Country-year FE	✓	✓	✓	✓
Country-occup. FE	✓	✓	✓	✓
Countries	165	163	165	162
Occupations	32	20	37	21
Observations	78434	52458	87274	47359

Source: OWW. Standard errors in parentheses, clustered at the country level. $^{+}p < 0.1,^{*} p < 0.05,^{**} p < 0.01$. "Group" is a dummy taking a value of one for manufacturing craftsman occupations in columns (1)-(2), and for other manufacturing production occupations in columns (3)-(4). Column (1) compares wages in manufacturing craftsman occupations to all other occupations in OWW, except for other manufacturing production occupations. Column (2) excludes white collar occupations. Column (3) compares wages in other manufacturing production occupations to all other occupations in OWW, except for manufacturing craftsman occupations, and column (4) again excludes white collar occupations.

comes from within country-variation, as well as fixed effects for each population group to control for differences in the average educational attainment. The first row shows that unsurprisingly, educational attainments increased strongly over time among all wage-employed: most strongly for the share with at least completed secondary education (plus 9.1 percentage points per decade), followed by the share with completed primary education (plus 7.7 percentage points) and the share with completed tertiary education (plus 4.4 percentage points).[48]

The second and third row present the point estimates of interaction terms with a "craftsman" and "other production worker" dummy. The first column shows that for primary schooling, there are no significant differences, suggesting that attainments of manufacturing craftsmen and other production workers increased at roughly the same pace as for employees overall. By contrast, the share of both groups of workers with tertiary education in the third column increased significantly more slowly than for the wage employed overall, reflecting the fact that both are production occupations that do not usually require tertiary education. Interestingly, column (2) shows that the share of manufacturing craftsmen with completed secondary education increased significantly more slowly than among all wage employed, whereas the corresponding share of other manufacturing production workers did not increase more rapidly.

This corroborates the view that the primary effect of automation on production workers in manufacturing has been to reduce the value of craftsman skills, as opposed to increasing the value of–or need for–other skills that they possessed or acquired.[49] This account is consistent with both the argument made by Braverman (1974), and with the recent US evidence of deskilling among non-college workers by Autor (2019).

[48] While the first two educational attainment categories are perfectly comparable across surveys from IPUMS and I2D2, the "tertiary" variable from I2D2 surveys includes those who started their tertiary education, whereas it includes only those who also completed it for IPUMS surveys. However, point estimates are similar (and significant) also when running the regression in column (3) seperately for observations from both sources, which is why I report results from the pooled specification for the sake of brevity.

[49] This is also true when further distinguishing between the two sub-groups of other production workers, machine operators and elementary occupations. Results are available upon request.

Table 6: Trends in the Relative Educational Attainment

Dependent variable: share with at least completed...

	(1) ...primary	(2) ...secondary	(3) ...tertiary
Trend/10	7.72**	9.11**	4.41**
	(1.02)	(0.69)	(0.32)
x Craftsmen	-0.30	-1.17**	-2.95**
	(0.50)	(0.43)	(0.29)
x Other production	0.67	-0.37	-2.79**
	(0.47)	(0.46)	(0.29)
Country + pop. group FE	✓	✓	✓
Countries	127	127	127
Samples	734	734	734
Mean dep. var.	72.61	31.96	7.19
Observations	2202	2202	2202

Source: IPUMS and I2D2. Standard errors in parentheses, clustered at the country level. $^{+}\ p < 0.1,^{*}\ p < 0.05,^{**}\ p < 0.01$. Each survey enters the sample with three observations: the reference category is the share with at least the respective educational attainment level among all wage-employed. In addition, the sample includes the corresponding shares for manufacturing craftsman and other production workers. For the "tertiary education" variable, I2D2 surveys include those who started their tertiary education, whereas IPUMS surveys include only those who also completed it.

5 Concluding Remarks

It is widely accepted that today´s labor markets are more skill-intensive than in the past, and that increasing human capital investments are necessary to seize the opportunities offered by the new technologies. The findings of this paper highlight that while increasing human capital investments may be necessary, they do not guarantee success on the labor market: in spite of the substantial skills that they had acquired, manufacturing craftsmen have experienced pervasive declines in relative wages and employment opportunities since the 1950s, following the adoption of more capital-intensive production methods. At the same time, I do not find evidence of other manufacturing production workers acquiring marketable skills comparable to those that craftsmen traditionally possessed. Rather, newly emerging skill-intensive production tasks were taken over by white collar workers with considerably higher formal educational attainments.

Declines in the demand for manufacturing craftsmen have been strongest in developing countries, where the scope for the adoption of capital-intensive production technologies was greatest in the beginning of my sample period. This is consistent with the model of manufacturing labor demand by Goldin and Katz (1998), in which the automation of handicraft-intensive production tasks is deskilling. It is also consistent with the historical account of technology adoption by Comin and Hobijn (2010), which points to substantial technology adoption lag lengths across countries, and with studies showing that imported "vintage capital" plays an important role in developing countries.[50]

However, the demand for manufacturing craftsmen continued to decline also in high income countries, suggesting that the experience of a declining market value of acquired craftsman skills has been shared by manufacturing production workers around the world. Deskilling of manufacturing production work can hence be considered as a an additional contributor to the wide-spread perception that "good" blue collar jobs–those in which even workers with little formal education can acquire valuable, marketable skills–have been lost in recent decades, which is corroborated by

[50] See Navaretti et al. (2000) and Raveh and Reshef (2016) for studies on the role of vintage capital in developing countries. Moreover, Verhoogen (2008) presents the case study of a German "Volkswagen" production line from the 1950s being used in Mexico to produce original "Beetle" cars for the domestic market up until 2003.

the finding of Autor (2019) that non-college workers in the US nowadays perform substantially less skilled work than they did in the past. This mechanism is distinct from the *displacement* of production workers by local trade shocks studied by Autor et al. (2013), which has been linked to political polarization and social problems in the affected US communities (Autor et al., 2017, 2019).

Absent individual-level panel data, this paper cannot provide direct evidence on the subsequent labor market outcomes of the craftsmen displaced by automation. However, indirect evidence suggests that the displacement from a manufacturing craftsman job was usually associated with lower wages: the results in this paper show that this tended to be the case when transferring to another manufacturing production job. Transfers to white collar jobs have likely been limited, given their scarcity at most income levels (Figure 2) and their higher educational requirements (Table 1).[51] Further, the results from the companion paper Kunst (2019) suggest that transitions to industries other than manufacturing have become more frequent in recent decades, as fewer "compensating" other production jobs have been created to make up for the loss of craftsman jobs. That paper also documents substantial wage premia for low-educated workers in manufacturing compared to other industries, consistent with the development literature (Rodrik, 2013a). For the US, Ebenstein et al. (2014) use individual-level panel data to confirm that the displacement from a manufacturing job tends to be associated with substantial wage losses.

Recent case studies from China suggest that deskilling is likely to remain a possible outcome of workplace automation also in the future: Huang and Sharif (2017; 2019) document how the adoption of advanced production technology, supported by the Chinese government in an effort to move up in manufacturing value chains, has affected labor demand in five manufacturing industries, and find that the primary effect has been deskilling in two of them.[52]They also argue that the

[51]A theoretical caveat is that they may have moved into newly created craftsman occupations that are not included in the OWW. However, the evidence does not suggest that there are important growing craftsman occupations which are omitted from the analysis: relative craftsman wages decline also among the manufacuring occupations available from 1983 onwards (among which any growing craftsman occupations should be overrepresented), and the employment data, which would include any newly crated craftsman occupations, shows declining craftsman employment.

[52]For instance, they report reduced training times for production workers in the "bicycle and motorcycle helmet" industry, following the adoption of industrial robots: *"In our visit to Factory H, the manager explained to us that previously it took six months to train a novice operator to become proficient in cutting venting holes in a bicycle*

new technologies have reduced the bargaining power of experienced production workers in these industries by allowing factory managers to rely on younger and cheaper workers.[53]

While recent studies find little evidence of an economy-wide polarization of labor markets in developing countries (Maloney and Molina, 2016; Das and Hilgenstock, 2018), my results suggest that within manufacturing, the polarization of labor demand has been a global phenonemon which has started already before the advent of ICT. Braverman (1974) points to two possible consequenses: a reduction in the bargaining power of production workers since shorter training periods make them more easily replaceable (as is also highlighted in one of the Chinese case studies), and an increase in the "knowledge distance" between production and white collar workers, which makes transitions of production workers to management positions less likely.[54]

Moreover, it is insightful to interpret the findings of this paper through the lens of the task-model presented in Acemoglu and Restrepo (2019): in their framework, automation may or may not increase total labor demand (depending on whether the demand for non-automatable tasks increases sufficiently to compensate for the displacement of labor from tasks henceforth performed by capital), and always decreases the labor share in value added.[55] This raises the question whether the displacement of production workers from production tasks documented in this paper has contributed to the global decline of the labor share since the early 1980s shown by Karabarbounis and Neiman (2014).[56]Also for developing countries in recent decades, the evidence points to an accel-

helmet. Now, the same worker who is assigned to operate the robotic arm can finish the tasks very effectively in only three days" (Huang and Sharif 2017, p. 67).

[53]They give the example of an unsuccessful strike of experienced production workers in one of the factories in their study, specialized in manufacturing doors: *"The veteran workers suddenly realized that they were no longer the backbone of the factory and their skills no longer automatically granted them workplace bargaining power. In their 40s, most feared that they would have great difficulty finding other jobs if they were fired, and quickly returned to their positions. Each striking worker was fined 100 yuan as punishment."* (Huang and Sharif 2017, p. 70).

[54]Braverman described the widening of the "knowledge gap" between production and white collar occupations as follows: *"The more science is incorporated into the labor process, the less the worker understands of the process; the more sophisticated an intellectual product the machine becomes, the less control and comprehension of the machine the worker has. In other words, the more the worker needs to know in order to remain a human being at work, the less does he or she know"* (p. 295).

[55]A countervailing force is the introduction of new tasks in which labor has a comparative advantage, which increases the labor share.

[56]Karabarbounis and Neiman (2014) find that manufacturing exhibited the third strongest decrease of ten industries since 1975 (cf. their Figure V). One may wonder why the global labor share decline started later than the displacement of skilled manufacuring production workers by capital, if both trends are related. For US manufacturing, Acemoglu and Restrepo (2019) argue that what distinguishes the period after 1987 from the previous four decades (during which

erating pace of technology adoption (cf. World Bank (2008) and Kunst (2019)) accompanied by a strong reduction of labor shares, and Bessen (2015) argues that historically, technological changes which reduced the returns to experience had a tendency to also reduce labor shares for extended periods.[57]

It is interesting to compare the recent experience of developing countries with automation to the US experience between the 1950s and 1970s: in the US, labor market prospects remained favorable during this period in spite of rapid automation, as rising incomes increased labor demand across a broad range of non-tradable sectors (Autor, 2015). Also Acemoglu and Restrepo (2019) suggest that the net impact of automation on labor demand depends on the broader labor market context, and that it is particularly prone to reducing labor demand when wages are low and labor is abundant.[58] From that perspective, labor markets in developing countries may be most strongly affected by further automation, and the future effect of automation on total labor demand in developed and developing countries alike will depend on how widely the associated productivity gains are shared.

Finally, the accelerating pace of changes in labor markets around the world in recent years suggests that the phenomenon of specific human capital investments losing their market value is increasingly relevant also beyond manufacturing. The findings of this paper do not imply that workers should abstain from making specific human capital investments. Rather, they highlight that in a technologically dynamic environment, such investments are inherently risky. Social safety

the labor share remained roughly constant) is a slower pace at which new tasks have been created to compensate for the displacement of labor from automated tasks (cf. their Figures 3 and 5).

[57]For instance, a regression of the labor shares from the Penn World Table between 1980-2014 on country fixed effects and a linear trend yields a significant decline of 1.13 percentage points by decade in high income countries. For developing countries, the corresponding point estimate is 65 percent larger (-1.86), and the difference is only marginally insignificant when clustering standard errors at the country level (pval=0.147). Bessen (2015) gives the examples of two previous instances of falling labor shares in times of disruptive technological change: the stagnation of manufacturing wages during the introduction of steam power in the early period of the British Industrial Revolution, and falling average real wages in US manufacturing between 1899-1919 during the electrification of manufacturing plants.

[58]This is because the productivity effect of automation is proportional to the cost-savings due to automation: *"because the productivity gains of automation depend on the wage, the net impact of automation on labor demand will depend on the broader labor market context. When wages are high and labor is scarce, automation will generate a strong productivity effect and will tend to raise labor demand. When wages are low and labor is abundant, automation will bring modest productivity benefits and could end up reducing labor demand"* (p. 11).

nets and subsidized (re-)training programs then have insurance features, and may be necessary to incentivize workers to invest sufficiently in their human capital.

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A Supplementary Tables and Figures

Table A.1: Occupational Employment in Manufacturing as a Function of Income

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

	Other production	Craftsmen	White collar
	(1)	(2)	(3)
<fpfit polynomial term 1>	-2.31	6.67	459.39
	(7.02)	(7.03)	(1963.24)
<fpfit polynomial term 2>	2.15	-5.32	-0.39
	(5.47)	(5.48)	(0.34)
<fpfit polynomial term 3>	-0.49	1.07	0.17
	(1.09)	(1.09)	(0.12)
Country fixed effects	✓	✓	✓
Decade fixed effects	✓	✓	✓
F-test joint polynomial terms	0.06	0.00	0.00
Mean dep. var.	32.55	39.16	22.21
Countries	123	123	123
Observations	901	901	901

Source: IPUMS and I2D2. 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 B), and data on GDP per capita in 2011 International Dollars are taken from the Penn World Table 9.0. To allow for flexible relationships between occupational employment shares and ln GDP per capita, the best-fitting third order polynomials of ln GDP per capita are selected using Stata´s "fp" command (with default settings). For other production workers in column (1) and craftsmen in column (2), this polynomial consists of the terms x^3, $x^3 * ln(x)$, and $x^3 * ln(x)^2$(denoting ln GDP per capita as "x" for simplicity). For white collar workers in column (3), the terms are x^{-2},x^3 and $x^3 * ln(x)$. Due to collinearity, the polynomial terms are not individually significant. However, the p-values of the F-tests for joint significance in the third row of the bottom panel of the Table show that they are jointly significant. The "mean dependent variables" do not exactly add up to 100, as the total include some manufacturing employees 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.

Table A.2: Craftsman Wage Premium by Income Group and Region after 1982 in the Extended Sample

Dependent variable: ln hourly wage

		By income			By region			
	(1) Pooled	(2) High	(3) Middle	(4) Low	(5) Africa	(6) Latin Am.	(7) Asia	(8) ECA
Craftsman x 1990s	-0.019^{+}	-0.016	-0.045*	0.023	-0.016	-0.055	0.010	-0.033*
	(0.010)	(0.009)	(0.019)	(0.022)	(0.030)	(0.032)	(0.025)	(0.015)
Craftsman x 2000s	-0.041**	-0.018	-0.070**	-0.028	-0.125**	-0.054^{+}	-0.010	-0.072**
	(0.012)	(0.016)	(0.021)	(0.037)	(0.040)	(0.032)	(0.031)	(0.021)
Country-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Country-occup. FE	✓	✓	✓	✓	✓	✓	✓	✓
Countries	132	26	71	35	39	28	19	20
Occupations	46	46	46	46	46	46	46	46
Observations	34588	10656	17456	6476	5444	6950	5418	6120

Source: OWW. Standard errors in parentheses, clustered at the country level. $^{+}p < 0.1,^{*}p < 0.05,^{**}p < 0.01$. Specifications correspond to those in Table A.2 with the difference that they include wages from 10 additional craftsman occupations and 15 additional other production occupations which are not available for the 1953-1982 period. All region groups exclude high income countries, and "ECA" in column (8) stands for "Europe and Central Asia".

Table A.3: Wage Trends: Craftsmen and Other Production Workers vs. Other Occupations

Dependent variable: ln hourly wage

Group:	Craftsmen		Other production	
	(1) vs. all	(2) excl. WC	(3) vs. all	(4) excl. WC
group x 1990s	-0.004	-0.011	0.012	-0.001
	(0.017)	(0.013)	(0.014)	(0.013)
group x 2000s	-0.057*	-0.042*	-0.015	0.004
	(0.026)	(0.016)	(0.020)	(0.014)
Country-year FE	✓	✓	✓	✓
Country-occup. FE	✓	✓	✓	✓
Countries	142	139	142	137
Occupations	131	54	141	67
Observations	95761	40498	102077	45464

Source: OWW. Standard errors in parentheses, clustered at the country level. $^{+}\,p < 0.1,^{*}\,p < 0.05,^{**}\,p < 0.01$. "Group" is a dummy taking a value of one for manufacturing craftsman occupations in columns (1)-(2), and for other manufacturing production occupations in columns (3)-(4). Column (1) compares wages in manufacturing craftsman occupations to all other occupations in OWW, except for other manufacturing production occupations. Column (2) excludes white collar occupations. Column (3) compares wages in other manufacturing production occupations to all other occupations in OWW, except for manufacturing craftsman occupations, and column (4) again excludes white collar occupations.

Table A.4: Capital Stock per Employee by Income Group and Region

Dependent variable: ln capital stock/employee in manufacturing (in 2011 int. $)

		By income			By region			
	(1) Pooled	(2) High	(3) Middle	(4) Low	(5) Africa	(6) Latin Am.	(7) Asia	(8) ECA
1970s	0.230^{**}	0.179^{*}	0.253^{+}	0.290	0.273	-0.060	0.605^{+}	0.058
	(0.074)	(0.072)	(0.145)	(0.234)	(0.164)	(0.114)	(0.328)	(0.151)
1980s	0.437^{**}	0.493^{**}	0.427^{*}	0.461	0.524^{*}	0.014	0.715^{+}	0.087
	(0.087)	(0.086)	(0.168)	(0.280)	(0.207)	(0.152)	(0.364)	(0.108)
1990s	0.679^{**}	0.782^{**}	0.574^{**}	0.847^{**}	0.909^{**}	0.155	0.989^{*}	0.126
	(0.100)	(0.098)	(0.202)	(0.297)	(0.244)	(0.132)	(0.381)	(0.133)
2000s	1.105^{**}	1.023^{**}	0.887^{**}	1.881^{**}	1.571^{**}	0.238	1.466^{**}	0.776^{**}
	(0.130)	(0.139)	(0.243)	(0.377)	(0.368)	(0.263)	(0.442)	(0.122)
2010s	1.438^{**}	1.295^{**}	1.177^{**}	2.624^{**}	2.096^{**}	-0.077	1.730^{**}	1.275^{**}
	(0.149)	(0.152)	(0.270)	(0.400)	(0.482)	(0.214)	(0.464)	(0.174)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Countries	116	30	63	23	26	16	21	23
Mean dep. var.	11.266	11.714	11.248	10.506	10.765	11.319	11.031	11.167
Observations	3639	1217	1744	678	695	450	704	573

Source: INDSTAT2. Standard errors in parentheses, clustered at the country level. $^{+}\ p < 0.1,^{*}\ p < 0.05,^{**}\ p < 0.01$. Income groups are based on the World Bank income classification in 1990 (calculated as the mode over the years 1987-1993 to deal with missing classifications in 1990, using the maximum mode to break ties). All region groups exclude high income countries, and "ECA" in column (8) stands for "Europe and Central Asia". Capital stocks per manufacturing worker are estimated from the INDSTAT2 database as described in Appendix B.

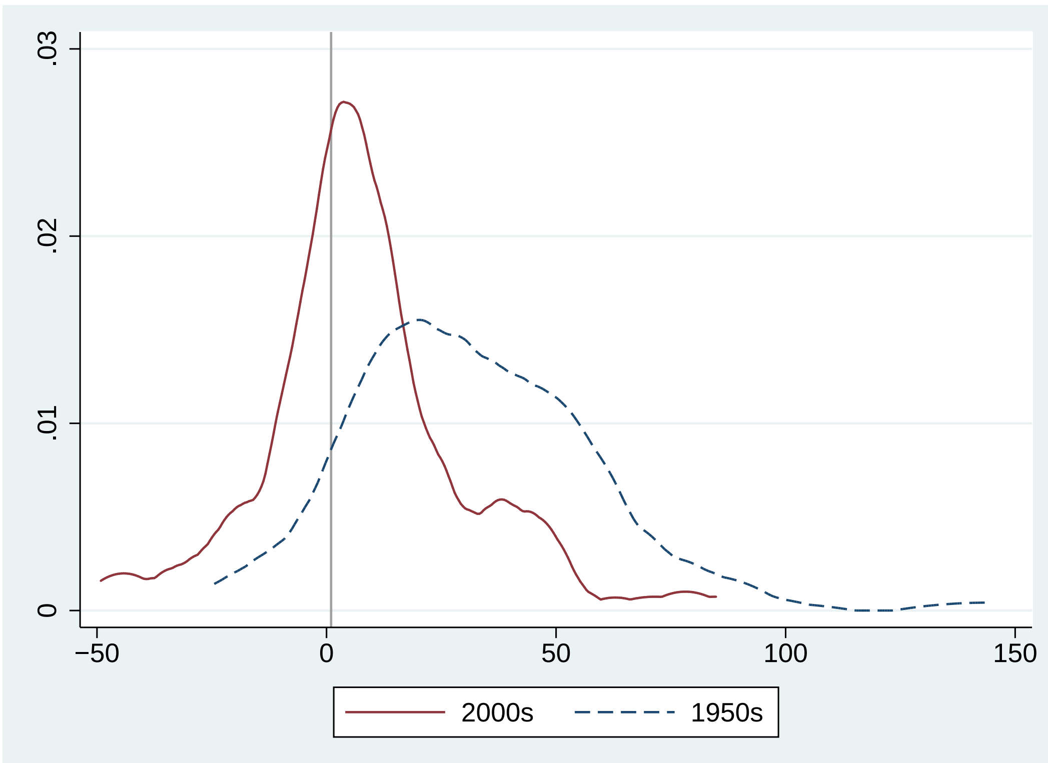

Figure A.1: Distribution of the Craftsman Wage Premium in the 1950s versus 2000s

Source: OWW. The Figure plots the kernel densities of craftsman wage premia in the 1950s and the 2000s. The sample and the calculation of wage premia are explained in the note of Figure 3.

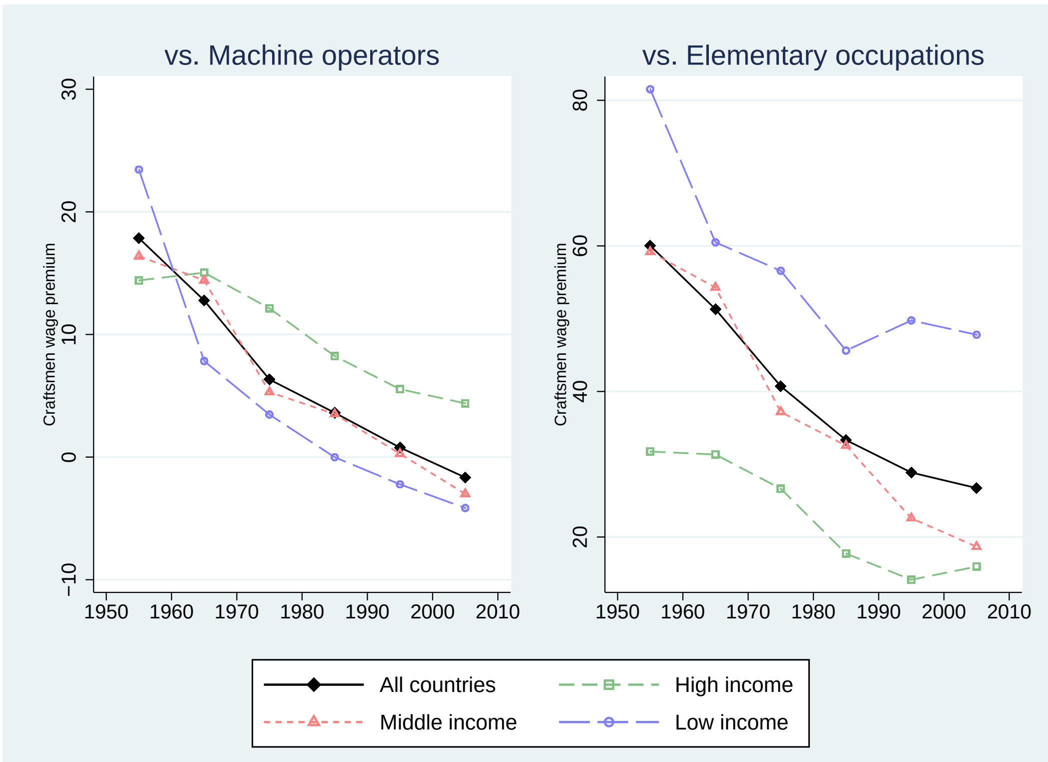

Figure A.2: Wage Premium of Manufacturing Craftsmen by Category of Other Production Workers

Source: OWW. Wage premia are calculated as described in the note of Figure 3- with the difference that the left panel only used the wages in up to 9 machine operator occupations as the reference category, whereas the right panel uses only the wages in up to 4 elementary occupations as the reference category.

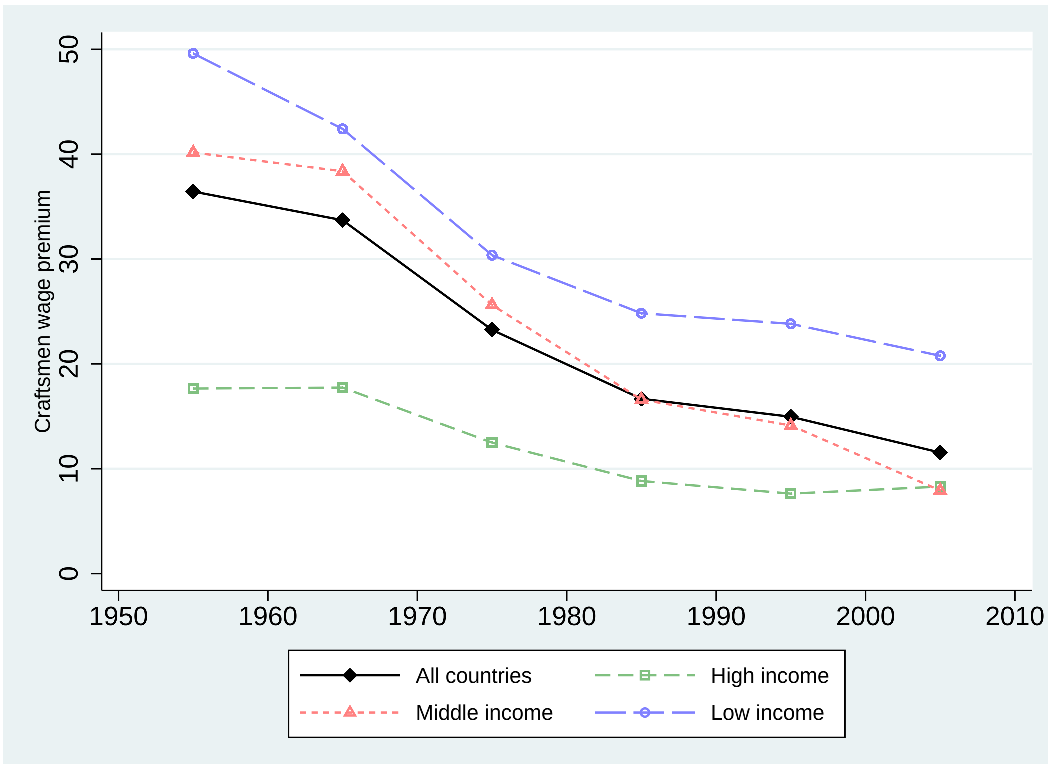

Figure A.3: Wage Premium of Manufacturing Craftsmen relative to Other Production Workers within Industries

Source: OWW. Wage premia are calculated as described in the note of Figure 3- with the difference that for each country, craftsmen wage premia are calculated seperately for up to three ISIC Rev. 3 2 digit industries for which OWW includes wages from both occupation groups. These industries are "Manufacture of textiles", "Printing & Publishing", and "Manufacture of machinery and equipment". The Figure is based on 76 countries with both craftsmen and other production wages in at least one of these industries.

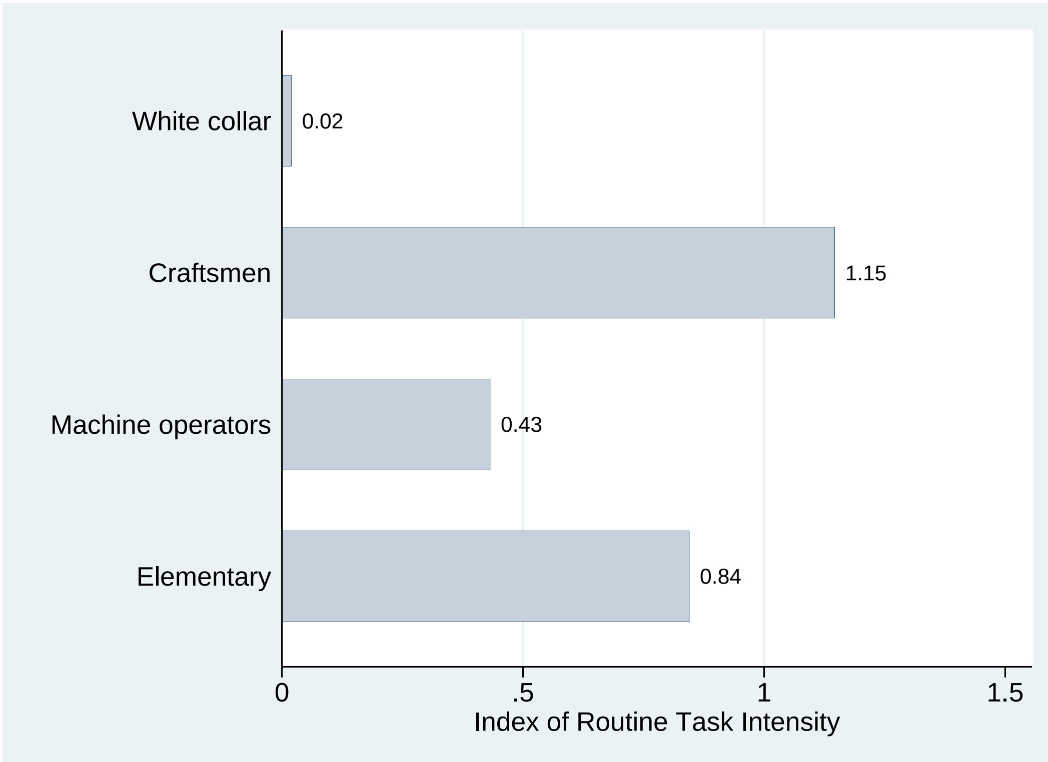

Figure A.4: Routine Task Intensity Scores by Occupation

Source: Goos et al. (2014). 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 OWW. 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").

The RTI scores are calculated from the individual task scores shown in Figure A.5 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.

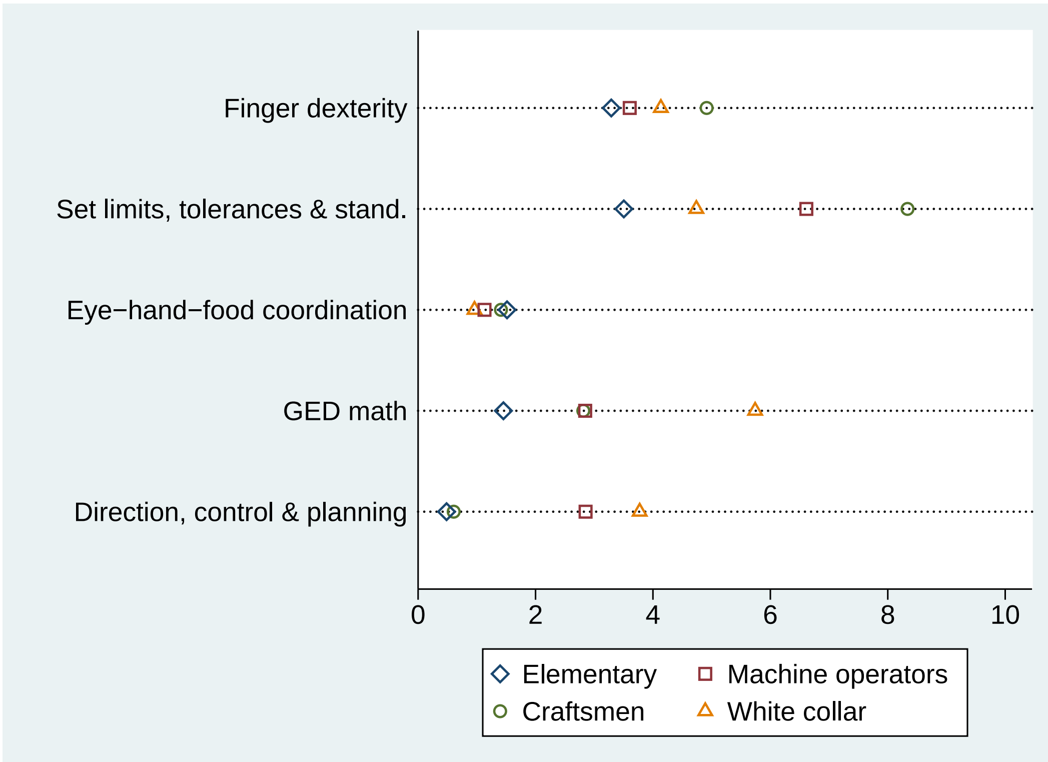

Figure A.5: Task Scores by Occupation

Source: Goos et al. (2014). 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").

B Details on Wage, Employment and Capital Data

Wage data

See Freeman and Oostendorp (2020) for a description of the "Occupational Wages around the World" database, and the underlying "October Inquiry" by the ILO. While the broad country and time coverage of the database likely comes at the cost of measurement error stemming from the varying capabilities of the national statistical offices submitting the reports as well as the standardization of reports in different formats to hourly wages, there is no reason to believe that this affects the key finding of declining relative wages of manufacturing craftsmen as the occupations are narrowly and consistently defined over time. Moreover, results are robust to keeping only wage reports without imputations in the sample (see Freeman and Oostendorp (2020) for details, and results available upon request).

For the analyses in this paper, I exclude the wage reports from 21 non-sovereign countries with populations below one million (such as Guadeloupe or La Reunion). All results are robust to including them. The analysis sample contains reports from 168 countries, of which Puerto Rico is the only non-sovereign country. Table B.1 presents the OWW manufacturing occupations by ISIC-industry and occupation group, using the correspondence Table by the ILO.

Table B.1: Overview of Manufacturing Occupations in OWW

Manufacturing Occupations Available 1953-2008		
Industry (ISIC-88)	Occupation group (ISCO-88)	Occupation name
(15) food products	(7)Craftsmen	Baker (ovenman)
(17) textiles	(7)Craftsmen	Loom fixer, tuner
(17) textiles	(8-9)Other prod.	Cloth weaver (machine)
(17) textiles	(8-9)Other prod.	Thread and yarn spinner
(17) textiles	(8-9)Other prod.	Labourer

(18) wearing apparel and fur	(8-9)Other prod.	Sewing-machine operator
(22) publishing and printing	(7)Craftsmen	Hand compositor
(22) publishing and printing	(7)Craftsmen	Machine compositor
(22) publishing and printing	(8-9)Other prod.	Bookbinder (machine)
(22) publishing and printing	(8-9)Other prod.	Printing pressman
(22) publishing and printing	(8-9)Other prod.	Labourer
(24) chemicals and chemical prod.	(2)-(4)White collar	Chemistry technician
(24) chemicals and chemical prod.	(8-9)Other prod.	Mixing, blending-machine oper.
(24) chemicals and chemical prod.	(8-9)Other prod.	Labourer
(27) basic metals	(2)-(4)White collar	Occupational health nurse
(27) basic metals	(8-9)Other prod.	Labourer
(27) basic metals	(8-9)Other prod.	Metal melter
(29) machinery and equipment	(7)Craftsmen	Bench moulder (metal)
(29) machinery and equipment	(8-9)Other prod.	Machine fitter-assembler
(29) machinery and equipment	(8-9)Other prod.	Labourer
(36) furniture; manufacturing	(7)Craftsmen	Cabinetmaker
(36) furniture; manufacturing	(7)Craftsmen	Furniture upholsterer
(36) furniture; manufacturing	(7)Craftsmen	Wooden furniture finisher
Additional Manufacturing Occupations Available 1983-2008		
(15) food products	(7)Craftsmen	Butcher
(15) food products	(8-9)Other prod.	Dairy product processor
(15) food products	(8-9)Other prod.	Grain miller
(15) food products	(8-9)Other prod.	Packer
(18) wearing apparel and fur	(7)Craftsmen	Garment cutter
(19) leather, luggage, footwear	(7)Craftsmen	Clicker cutter (machine)
(19) leather, luggage, footwear	(7)Craftsmen	Laster
(19) leather, luggage, footwear	(7)Craftsmen	Leather goods maker

(19) leather, luggage, footwear	(7)Craftsmen	Show sewer (machine)
(19) leather, luggage, footwear	(8-9)Other prod.	Tanner
(20) wood prod. except furniture	(8-9)Other prod.	Plywood press operator
(20) wood prod. except furniture	(8-9)Other prod.	Sawmill sawyer
(20) wood prod. except furniture	(8-9)Other prod.	Veneer cutter
(21) paper and paper products	(8-9)Other prod.	Paper-making-machine operator
(21) paper and paper products	(8-9)Other prod.	Wood grinder
(22) publishing and printing	(2)-(4)White collar	Journalist
(22) publishing and printing	(2)-(4)White collar	Office clerk
(22) publishing and printing	(2)-(4)White collar	Stenographer-typist
(23) coke, petroleum products	(8-9)Other prod.	Controlman
(24) chemicals and chemical prod.	(2)-(4)White collar	Chemical engineer
(24) chemicals and chemical prod.	(8-9)Other prod.	Supervisor or general foreman
(24) chemicals and chemical prod.	(8-9)Other prod.	Packer
(27) basic metals	(8-9)Other prod.	Blast furnaceman (ore smelting)
(27) basic metals	(8-9)Other prod.	Hot-roller (steel)
(28) fabricated metal products	(7)Craftsmen	Metalworking machine setter
(28) fabricated metal products	(7)Craftsmen	Welder
(31) electrical machinery & apparatus	(2)-(4)White collar	Electronics draughtsman
(31) electrical machinery & apparatus	(2)-(4)White collar	Electronics engineering technician
(31) electrical machinery & apparatus	(7)Craftsmen	Electronics fitter
(31) electrical machinery & apparatus	(8-9)Other prod.	Electronic equipment assembler
(35) other transport equipment	(7)Craftsmen	Ship plater

Employment data

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 occupational employment shares for all men and women aged 15-64 in manufacturing wage employment, using the survey weights. I exclude non-wage (family) employed and self-employed manufacturing workers in order to match the OWW wage data. 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 with information on wage-employment by occupation and industry from 137 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 occupational employment shares for all men and women aged 15-64 in manufacturing wage 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. The combined sample includes manufacturing employment shares by occupation for 955 country-years from 146 countries and between 1960 and 2016. 10 percent of the observations are from before 1990, a further 16 percent from the 1990s, and the remaining 74 percent from the 2000-2016 period. I did not engage in any further "cleaning" of this dataset. The surveys from 133 countries for which the sample includes surveys from at least two years enter in the regressions with country fixed effects.

Capital data

INDSTAT2 is a database maintained by the United Nations Industrial Development Organization (UNIDO, 2018) which contains data on employment and gross fixed capital formation in current US dollar for total manufacturing and by 2-digit manufacturing industry, mostly derived from industrial surveys. It is the largest database of its kind. Often, countries made reports jointly for several industries for at least some years–for instance, jointly for industries 18 (*"manufacturing of wearing apparel and fur"*) and 19 (*"Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear"*). In such instances, I aggregate all reports to the level of combined industries. To ensure consistency of the time series, I exclude observations from years for which only reports for a subset of the industries are available.

To prepare the investment data for the capital stock estimation, I deflate the investment data to 2011 international prices, using the price level of capital formation from the Penn World Table 9.0, and fill any gaps in the investment series by means of log-linear interpolations. Next, I use the "perpetual inventory method" to estimate capital stocks: as is commonly done in the literature, I estimate the initial capital stock as $K_0 = \frac{I_0}{g+\delta}$, with I_0 being the initial investment, g being the growth rate of investment, and δ being the depreciation rate. I calculate I_0 as the average of the investments in the first three years to reduce the impact of measurement error, and follow Caselli (2005) in calculating g as the geometric average of growth rates in the (up to) first 20 years and in assuming a depreciation rate of 6 percent. Then, the capital stock in period t can be estimated as $K_t = (1-\delta) * K_{t-t} + I_t$, and the corresponding capital intensity results from dividing the estimated capital stock by the number of employees. The final resulting dataset contains estimated capital intensities from 125 countries between the 1963 and 2014.

I have verified that both the finding of a pervasive increase in manufacturing capital intensities since the 1960s, and its negative association with relative craftsman wages and employment, are robust to making a number of alternative assumptions: first, it is robust to being more conservative in the interpolations of missing investment data by only interpolating gaps of up to 5 consecutive observations (and by keeping the longest spell for each investment series where this results in gaps). Second, it is robust to using the US investment price deflator from PWT for all countries (similar to Rodrik (2013b), who justifies the use of a common deflator for manufacturing value added with the tradability of manufacturing goods. This argument arguably also applies to many investment goods).

Finally, results for the capital intensity in aggregate manufacturing are robust to assuming a higher depreciation rate of 12.6 percent (instead of 6 percent), which corresponds to the depreciation rate for the investment category *"other machinery and assets"* in the Penn World Table. By contrast, the point estimates of the craftsman-interactions in the wage regressions turn insignificant (yet remain negative) when using industry-level capital stock estimates with a 12.6 percent depreciation rate (cf. the specifications in columns (3) and (6) of the top panel of Table 4). However, the 6 percent depreciation rate taken from Caselli (2005) that I use for my benchmark results appears conceptually preferrable: it lies in between the 2 percent depreciation rates for *"structures (residential and non–residential)"* and the 12.6 percent depreciation rate for *"other machinery and assets"* assumed by Inklaar and Timmer (2013). Also Glitz and Meyersson (2017) assume a depreciation rate of 6 percent when estimating manufacturing industry-level capital stocks.

C Description of ISCO major groups

1. **Legislators, senior officials and managers:** This major group includes occupations whose *main tasks consist of determining and formulating government policies, as well as laws and public regulations, overseeing their implementation, representing governments and acting on their behalf, or planning, directing and coordinating the policies and activities of enterprises and organisations, or departments.* Reference to skill level has not been made in defining the scope of this major group, which has been divided into three sub-major groups, eight minor groups and 33 unit groups, reflecting differences in tasks associated with different areas of authority and different types of enterprises and organisations.

2. **Professionals:** This major group includes occupations whose *main tasks require a high*

level of professional knowledge and experience in the fields of physical and life sciences, or social sciences and humanities. The main tasks consist of increasing the existing stock of knowledge, applying scientific and artistic concepts and theories to the solution of problems, and teaching about the foregoing in a systematic manner. Most occupations in this major group require skills at the fourth ISCO skill level. This major group has been divided into four sub-major groups, 18 minor groups and 55 unit groups, reflecting differences in tasks associated with different fields of knowledge and specialisation.

3. **Technicians and associate professionals:** This major group includes occupations whose *main tasks require technical knowledge and experience in one or more fields of physical and life sciences, or social sciences and humanities. The main tasks consist of carrying out technical work connected with the application of concepts and operational methods in the above-mentioned fields, and in teaching at certain educational levels.* Most occupations in this major group require skills at the third ISCO skill level. This major group has been divided into four sub-major groups, 21 minor groups and 73 unit groups, reflecting differences in tasks associated with different fields of knowledge and specialisation.

4. **Clerks:** This major group includes occupations whose *main tasks require the knowledge and experience necessary to organise, store, compute and retrieve information. The main tasks consist of performing secretarial duties, operating word processors and other office machines, recording and computing numerical data, and performing a number of customer-oriented clerical duties, mostly in connection with mail services, money-handling operations and appointments.* Most occupations in this major group require skills at the second ISCO skill level. This major group has been divided into two sub-major groups, seven minor groups and 23 unit groups, reflecting differences in tasks associated with different areas of specialisation.

5. **Service workers and shop and market sales workers:** *(omitted)*

6. **Skilled agricultural and fishery workers:** *(omitted)*

7. **Craft and related trades workers:** This major group includes occupations whose *tasks require the knowledge and experience of skilled trades or handicrafts which, among other things, involves an understanding of materials and tools to be used, as well as of all stages of the production process, including the characteristics and the intended use of the final product. The main tasks consist of extracting raw materials, constructing buildings and other structures and making various products as well as handicraft goods.* Most occupations in this major group require skills at the second ISCO skill level. This major group has been divided into four sub-major groups, 16 minor groups and 70 unit groups, reflecting differences in tasks associated with different areas of specialisation.

8. **Plant and machine operators and assemblers:** This major group includes occupations whose *main tasks require the knowledge and experience necessary to operate and monitor large scale, and often highly automated, industrial machinery and equipment. The main tasks consist of operating and monitoring mining, processing and production machinery and equipment, as well as driving vehicles and driving and operating mobile plant, or assembling products from component parts.* Most occupations in this major group require skills at the second ISCO skill level. This major group has been divided into three sub-major groups, 20 minor groups and 70 unit groups, reflecting differences in tasks associated with different areas of specialisation.

9. **Elementary occupations:** This major group covers *occupations which require the knowledge and experience necessary to perform mostly simple and routine tasks, involving the use of hand-held tools and in some cases considerable physical effort, and, with few exceptions, only limited personal initiative or judgement. The main tasks consist of selling goods in streets, doorkeeping and property watching, as well as cleaning, washing, pressing, and working as labourers in the fields of mining, agriculture and fishing, construction and manufacturing.* Most occupations in this major group require skills at the first ISCO skill level. This major group has been divided into three sub-major groups, ten minor groups and 25

unit groups, reflecting differences in tasks associated with different areas of work.

Source: ILO