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ABSTRACT

Firms hire workers to undertake tasks and activities associated with particular occupations, which makes occupations a fundamental unit in economic analyses of the labor market. Using a unique set of data on pay in identically defined occupations in developing and advanced countries, we find that occupational pay differentials narrowed substantially from the 1950s to the 1980s, then widened through the 2000s in most countries, creating a U-shaped pattern of change. The narrowing was due in part to the huge worldwide increase in the supply of educated workers. The subsequent widening was due in part to the weakening of trade unions and a shift in demand to more skilled workers associated with rising trade. The data indicate that supply, demand, and institutional forces are all drivers of occupational differentials, ruling out simple single factor explanations of change. The paper concludes with a call for improving the collection of occupational wage data to understand future changes in the world of work.

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A data appendix is available at
http://www.nber.org/data-appendix/w26863
The Occupational Wages around the World 1953-2008 Database is available at
https://data.nber.org/oww/

1 Introduction

Occupations, defined by what people do at work and the knowledge required to do those work tasks, are a fundamental unit in labor market analysis. They are a major determinant of wages, accounting for a greater share of the variance of log wages or earnings than education, arguably because occupations better signal what workers do at a job than does education. The greater number of occupational than educational categories in survey data adds to the explanatory power of occupations.[1]

Despite recognition of substantial differences in labor outcomes across countries even in an era of globalization, analyses of occupational differentials worldwide are rare – a gap that Ashenfelter (2012) attributes to the paucity of internationally comparable data on occupational pay. This paper fills this gap by introducing and analyzing an extended version of the "Occupational Wages around the World" (OWW) database (Freeman and Oostendorp, 2000) that reports wages in many detailed occupations in 192 countries, and is based on the International Labor Organization's "October Inquiry" of pay. From 1953 to 2008, the October Inquiry gathered wages from national statistical offices on more identically defined detailed occupations in more countries than any other data source, and then was abandoned.[2]

To examine the determinants of occupational pay differentials in the OWW, we supplement the wage data with country level data on the distribution of workers by education across occupations, which allows us to estimate the effect of the expansion of education on the supply of workers by occupation in a country, country level data on GDP per worker and merchandise exports plus imports over GDP as measures of the level and trade orientation of aggregate demand, and country union density to reflect the effect of institutions on wages. Since we lack measures of demand and unionization at the country-occupation level, we need a different strategy to assess whether these country level variables impact the wages of more versus less skilled workers differently and thus have an impact on occupational differentials. Our strategy is to estimate separate equations for occupations with differing skill levels. All of our regression analyses include country-occupation and period dummy variables so that estimates rely on within country-occupation changes over time.

Section 2 documents the major finding in our data: surprisingly similar patterns of

[1]Appendix table A.1.1 shows that in the US in 2010, the nine one digit major occupation categories account for a slightly greater share of the variance of ln wages than the nine main education categories. Including 487 occupation dummies adds an additional 12.5 percentage points to the explained variance, whereas including all 23 education dummies does not increase the explained variance. Autor and Handel (2013) find that occupation dummies give an R-squared of 0.61 in accounting for variation of wages (column 3 of table 5), compared to 0.39 for education and demography variables (column 1), and that both sets of variables give an R-square of 0.65. See also Bessen (2015).

[2]Freeman and Oostendorp (2020) give a detailed description of this updated data set. The data are available for download at https://data.nber.org/oww/.

change in occupational differentials among countries at different levels of economic development. Differentials narrowed substantially in most countries from the 1950s to 1980s and then widened through the mid 2000s. Section 3 uses country data on the distribution of workers by educational attainment among occupations to estimate how increased levels of education altered the supply of workers to occupations. Section 4 presents our regressions of log wages by country-occupation on supply, demand and union drivers of wages. The estimates indicate that shifts in labor supply narrowed wage differentials between high and low skill occupations, while labor demand, reflected in increases in trade orientation, raised wages more in skilled than in less skilled occupations. The fall in union density in most countries from the 1980s through the 2000s lowered pay primarily for less skilled workers.[3] Section 5 shows that our estimates of the effect of demand, supply, and unionism on occupational pay explain part but not all of the pattern of skill differentials. Section 6 reviews wage data on occupational differentials from the period after the OWW terminated through the mid-2010s and makes a case for new detailed occupation data to aid analysis of the impact of new technologies on work. The appendices detail the sources of the data and probe the robustness of results.

2 Measuring a Half Century of Occupational Skill Premia, 1950s-2000s

To analyze the evolution of occupational skill premia around the world, we use the updated 2020 OWW database, originally developed from the ILO's "October Inquiry" by Freeman and Oostendorp (2000). Beginning in 1953, the Inquiry asked the statistical offices of member states to report wages in 48 narrow (essentially 4-digit ISCO) occupations.[4] In 1983, it asked the offices to report on 161 occupations in all major industries.[5] Forty-five occupations appear in both periods, although two of them are reported at a more disaggregated industry level since 1983.[6] Because the 45 occupations include only two of

[3]The trade result is consistent with Goldberg and Pavcnik (2007) for developing countries, Wood (1995) and Krugman (2008) for high income countries, Autor et al. (2013) on the China trade impact on the US, and consistent with an increased recognition of the distributional effects of trade. The union result is consistent with the finding that unions reduce pay differentials in both advanced and developing economies (Freeman, 1998).

[4]For a smaller number of occupations, the data collection of the "October Inquiry" started already in 1924.

[5]The ILO collects information on 159 occupations, but occupation 139 ('government executive official') has subsequently been split in three administrative levels (central, regional/provincial, local) (see Appendix C in Freeman and Oostendorp, 2020).

[6]The occupations "Mixing- and blending-machine operator" and "Labourer" are reported for the entire chemical industry in 1953-1982, and for the "industrial chemicals" and "other chemical products" industries separately since 1983.

the university-level professional occupations that became more important in the 1980s-2000s, most of our analysis focuses on the full sample of 162 occupations.[7]

Table 1 summarizes the coverage of the sample used in this paper. This differs from the full OWW dataset available online in that it excludes the data from 21 non-sovereign countries with current populations of less than one million inhabitants (such as Falkland Islands, Gibraltar etc.).[8] The dataset has far fewer observations than if each of the remaining 171 countries had reported every occupation in all years. The reason is that most countries responded to the Inquiry intermittently and reported pay for only some occupations. On average, countries reported wages for 22 years and for 78 occupations.[9] Even with the incomplete reporting by ILO member countries, the bottom rows of table 1 show that our sample contains 191,618 country-occupation-year data points on wages. Somewhat over half of the observations (107,978) are for the 45 occupations overlap sample.

We examine several related measures of skill differentials. As the broadest measure, we use the standard deviation of log wages of occupations. This measure covers the entire distribution of reported wages in the same log wage units as human capital analysis of earnings for individual workers. We calculate standard deviations for 5 year averages of the available wage reports to smooth out measurement error and reduce the imbalance of the sample.[10] The left panel of figure 1 displays the time paths of the mean of differentials for the 45 occupations that are included in the dataset before and after the expansion in all countries and in countries in the high income, medium income, and low income groups, as defined by the World Bank. The right panel presents the corresponding averages for all occupations in the dataset starting from 1980.[11]

Figure 1 summarizes the key pattern of change found in our data: a long-run decline of occupational skill premia, with a partial rebound starting in the 1980s. Further analyses showed that changes in the sample composition in the form of a disproportionate exiting of countries with high pay differentials decrease the sample averages in the first and last

[7] Of which 3 are only available between 1953 and 1982, and 114 are only available between 1983 and 2008. We note that the full OWW dataset described in Freeman and Oostendorp (2020) includes 164 instead of 162 (=3+45+114) occupations. This is because for this paper, we have collapsed the wage reports for the two occupations in the chemical industry that were reported at a more disaggregated industry level only since 1983, to make their reporting more consistent over the full 1953-2008 reporting period.

[8] Results are robust to including them (available upon request).

[9] Appendix C contains a full list of the occupations, industries and countries from OWW used in this paper.

[10] Except for the 1953-54 and the 2005-2008 period averages, which are based on up to 2 and 4 wage reports, respectively.

[11] The average standard deviation in the early 1980s is about 0.1 ln points larger in the right panel of figure 1. This is due to the larger number of occupations at the upper end of the wage distribution in this sample.

periods.[12] To probe the U-shaped pattern of skill premia in the data further, we examined decadal average wages for a balanced panel of countries, filling gaps in wage series of one decade by means of log-linear inter- and extrapolations as described in the note of appendix figure A.2.1. This balanced sample shows a U-shape relation similar to figure 1. From the 1950s to the 1980s the variance fell in 76 of the 91 countries (84%), whereas from the 1980s to the 2000s the variance increased in 68 of them (75%).[13] Each country grouping follows the same pattern.[14]

We further estimated pay differentials in particular parts of the wage/skill distribution, dividing occupations the ILO characterizes as more or less skilled in terms of the education "required" to do the work. We distinguish four skill groups: unskilled occupations that require at most primary schooling, lower medium skilled occupations that require lower secondary schooling, upper medium skilled occupations that use upper secondary education, and high skilled occupations that correspond to post-secondary education.[15] Table 1 reports the number of occupations per skill group. Using these categorizations, the U-shaped pattern in differentials occurs when we consider the top or top two skill groups as "skilled" (see the top two panels of appendix figure A.2.2). At the bottom of the skill distribution, however, the 16 unskilled occupations show a continuous narrowing in the gap compared to the 146 more skilled occupations (bottom panel of appendix figure A.2.2).[16]

Even though the different measures show some variation, the basic pattern is narrowing followed by a partial rebound among occupations higher in the skill distribution. What caused the substantial narrowing and partial rebound of differentials?

[12] Only 64 countries are represented in the first period, and 58 countries the last period.

[13] The other panels of figure A.1.2 show that the pattern is similar when we weight occupations by their estimated share of covered employment (see appendix B.2 for details), and when we weight each country by its population.

[14] 14 of 21 high income countries (67%), 40 of 45 middle income countries (89%), and 22 of 25 low income countries (88%) had declines in occupational differentials between the 1950s-80s, while 71% of high income countries, 76% of middle income countries, and 76 % of low income countries had increases between the 1980s-2000s.

[15] Since the ILO does not distinguish between occupations requiring lower and upper secondary education, the distinction between lower and upper medium skilled occupations is based on the typical ranking of relative wages: See appendix A.1 for details. Occupational wage ranks correlate highly over time (appendix figure A.1.1), implying that relative skill requirements of occupations are quite stable over the sample period. Note that while we base our assessment of the relative skill requirements of occupations on the ILO classification, there are large differences across countries in the extent to which workers with a specific education level actually work in the assigned occupations. Our supply variable takes such differences into account, see section 3.

[16] This pattern is reminiscent of the finding of declining average returns to schooling, driven by declining returns to primary and secondary schooling, but increased differentials for tertiary education, by Montenegro and Patrinos (2014) in a sample of 139 countries and mostly after 1990.

3 Educational Expansion and Occupational Labor Supply

The large increase in years of schooling in all countries post World War II offers a plausible explanation for the narrowing of occupational differentials. More education would increase the supply of workers to the higher-skill and higher-paid occupations where they presumably work, while decreasing the supply of workers in lower-skill and lower-paid occupations.

Figure 2 displays the upward trend in schooling worldwide in terms of the average years of schooling for workers above 15 years of age. Measured by absolute years, the mean years of schooling increased by 5.3 years for all countries, with a modestly larger increase for middle income countries and a smaller increase for low income countries of 4.3 years. Measured in percentage increases, however, the increase is biggest for the low income countries due to their extremely low level of education in the initial year, and decelerated over time.

Because workers in the same occupation – say teacher or carpenter or laborer – have higher levels of schooling in advanced countries, where most persons have at least a high school degree, than in low income countries, where many persons have at most elementary school education, increases in education have differential effects on occupational labor supplies across countries. To measure these differences requires country level information on the occupational distribution of workers by education. We obtained such data from the World Bank's I2D2 database, a collection of harmonized and nationally representative household surveys developed by Montenegro and Hirn (2009). I2D2 allows us to estimate the distribution of employees aged 15 to 64 in one-digit ISCO-88 occupations for four educational groups: no schooling, primary schooling, secondary schooling and post-secondary/tertiary schooling in countries with household surveys.[17] Absent education data for more detailed occupations, we develop our supply measures for occupations at the one digit level and apply those measures to the more detailed occupations in each one-digit group.

Even at the one digit occupation/four education groups level, the data show huge country differences in the distribution of workers with the same education level across occupations. In countries where few workers possess post-secondary education, many workers with secondary schooling are in professional and other high skill occupations. By contrast, in countries where many workers have post-secondary education, few secondary

[17] The I2D2 distinguishes between incomplete and completed primary and secondary education for a smaller sample. However, figures for more detailed occupations and education levels would be problematic in many countries due to the size of the surveys.

school workers obtain such jobs. For example, in Honduras in 1998, where only 5 percent of employees possessed any post-secondary education, 46 percent of secondary-educated employees worked as professionals or managers whereas in the USA in 2010, where 67 percent of employees had post-secondary education, only 16 percent of employees with secondary schooling worked in professional or managerial occupations.

Figure 3 displays the general pattern across all countries. It shows that as the share of employees with post-secondary education increases, the share of professionals and managers among workers with secondary education decreases. Still, when we regressed the share of professionals among secondary education workers on the national share of workers with a secondary education, the regression explained only a modest proportion of the cross-country variation, indicating differences in the allocation of workers even among countries with a similar supply of post-secondary educated employees. This illustrates the importance of having country specific education-occupation matrices to link educational attainment to occupational labor supply by country.[18]

We estimate occupational labor supplies in a country by applying a single country-specific education-occupation matrix to the Barro-Lee estimates of the education distribution in the country. Let a_{io} be the share of workers in education category i in one digit occupation o in a country, and let E_{it} be the share of workers in education group i in a period. Then, our estimate of the change in the supply of an occupation's work force *relative to other occupations* in the country between two periods is:

$$\sum_i a_{io} \Delta E_i \tag{1}$$

With a_{io} fixed, shifts in the country's educational attainment distribution towards higher educated groups shift supply outward in occupations that employ relatively more educated workers, and shift supply inward in occupations that employ less educated workers. The shifts differ across countries due to different changes in the educational distribution and the different country-specific occupational employment distributions within education groups. By using a fixed education-occupation matrix to estimate the distribution of workers by education across occupations,[19] we focus our analysis on changes in supply resulting from changes in the distribution of national education as opposed to potentially endogenous changes of the a_{io} coefficients. We assign the change in labor supply

[18]Conversely, workers with post-secondary education have a slightly higher chance of ending up in jobs below professional and managerial occupation in countries in which many employees possess post-secondary education. However, this relationship is less robust, suggesting that as the supply of workers with post-secondary education increases, the demand for professional occupations and managers often expands at a sufficient pace to absorb them.

[19]When I2D2 had more than one survey for a country, we averaged education-occupation percentages across all available surveys. See appendix B.2 for a detailed description.

to the occupations in our dataset based on the one digit occupation group to which they belong. This produces measurement error in the change in supply, which is likely to bias downward the estimated supply coefficients.[20]

For about one-third of the countries in OWW, the I2D2 did not have household surveys from which to calculate education-occupation matrices. Rather than deleting these countries from our study, we imputed the employment distribution based on nine income-region specific averages as described in appendix B.2. We probed the robustness of our supply estimates by analyzing only countries with a non-imputed employment distribution in the sample and by using only income-region country group-specific averages and obtain results similar to those in the dataset with imputed education-occupation matrices.

Table 2 summarizes the resulting estimates of supply in the form of the average proportion of the work force that would be supplied to the specified major occupations *relative* to the total work force in a country.[21] Since each periods' labor supply is allocated to one of the main occupations, the labor supplies to the occupations sum to 100%. Despite our deriving the supply measures at the one digit occupational level and imputing the education-occupation matrices for some countries, our technique produces considerable variation in the estimated shifts of labor supply to occupations over time and across countries in different income groups.

Taking the all country panel first, the row for the early period (1950-55) shows that the educational distribution would have put an average of 36.3% of workers into elementary occupations, compared to 9% in the three highest skill occupations– professionals, associate professionals and managers. As average schooling increased over time, the supply in elementary occupations fell to 24.4% of the work force in 2005-2010, while the supply in the three highly skilled occupations increased from 4.1 to 9% for associate professionals, from 2.9 to 7.8% for professionals, and from 2 to 3.4% for managers. The global story is clear: the expansion of educational attainments reduced supply to less skilled occupations and increased supply to more skilled occupations across countries of all income levels.

Figure 4 shows that the estimated supply to skilled occupations exceeds the proportion with post-secondary school education, whereas the initial supply to elementary occupations is below the proportion of workers without schooling. This reflects the fact that in many countries, even workers without post-secondary education work in skilled occupations, while not all who are unschooled work in elementary occupations.

Do the estimated shifts in occupational supply reduce occupational wages in the more

[20]Appendix figure B.3.1 shows that around 60-69% of the wage variation between the detailed OWW occupations is related to the 9 major groups, suggesting that occupational labor supply shifts at this level will have some explanatory power.

[21]Since the Barro-Lee dataset contains educational attainments every 5 years starting in 1950, we take the average of two subsequent reports as our estimate for the respective 5 year-period between both years.

skilled occupations and increase wages in the less skilled occupations, as they should if they indeed measure the shift in supply?

4 Estimating the Determinants of Occupational Wages

To answer this question, we estimate an occupational wage equation that links OWW country-occupation wages to our estimated country-occupation labor supply, GDP per worker, the trade orientation of an economy reflected in merchandise export plus imports relative to GDP[22]) and to union density. Wages and GDP per worker are deflated to constant national prices using the Penn World Table GDP deflator. We use a log-log form for wages, supply and GDP per worker, so that parameters estimate elasticities:

$$\begin{aligned} log(w_{cot}) = \alpha + \beta_1 log(supply_{cot}) + \beta_2 log(GDP/w_{ct}) \\ + \beta_3 union_{ct} + \beta_4((X+M)/GDP)_{ct} + D_{co} + D_{ot} + \varepsilon_{cot} \end{aligned} \tag{2}$$

Including dummy variables for country-occupation (D_{co}) and for period-skill group (D_{ot}) in equation 2 eliminates any country-occupation or global skill group-period factors. Thus, we identify the β parameters from variation of wages within country-occupations over time.[23]

As noted, to deal with the fact that data on GDP per worker, trade openness and union density are at the country-level, we estimate equation 2 separately for occupations in four skill level groups: unskilled elementary occupations, lower medium skill occupations, upper medium skill occupations, and high skill occupations. To the extent that changes in these variables are associated with differential changes in the demand for workers with differing skills, the skill group regressions will yield different estimated coefficients for the groups

[22]We focus on merchandise trade because of concerns about the consistency of total trade measures that include service trade (Lipsey, 2009).

[23]We derive the estimating equation from an aggregate production function that depends on capital and an aggregate labor measure of occupational labor inputs with occupation specific labor productivity captured by the parameter occ_o and with an elasticity of substitution between occupations of $\rho < 1$: $Y = AK^{\alpha}\left(\sum_o occ_o L_o^{\rho}\right)^{\beta/\rho}$. Assuming wages are proportionate to the marginal product of labor up to a wedge I_o, the log wage for occupation o is $log(w_o) = log(\beta) + log(Y/L) + log(occ_o) - (1-\rho)log(L_o/L) + I_o$, where $L = \left(\sum_o occ_o L_o^{\rho}\right)^{1/\rho}$is aggregate labor input. Occupational wages vary with average labor productivity Y/L and occupation-specific labor productivity occ_o. The $\rho < 1$ implies that the wage will fall as labor supply increases, and increases with occupational labor productivity. The country-occupation fixed effects pick up the time invariant part of the occupational labor productivities occ_o, and the period-skill group fixed effects control for global labor share changes as well as residual demand shifters for the four skill groups. Through the lens of this framework, trade openness can be thought of as affecting wages by affecting effective labor supplies through the factor content of trade or by influencing the production technology and hence occupational labor productivities occ_o, and union density as influencing the wedge between wages and the marginal product of labor.

that can help explain changes in differentials within countries.

Table 3 presents estimates of the impacts of the posited wage determinants on log real wages using five year-averages of all data, which gives us up to 12 time series data points for each country-occupation from the early 1950s through the late 2000s.[24] Columns (1) and (2) examine a sparse supply-demand model, which has only two independent non-dummy variables, the estimated supply of workers to the occupation from the analysis in section 3 and GDP per worker. Column (1) covers the 45 occupations available over the full period, while column (2) includes all 162 occupations in the OWW. The estimates in both columns show a substantial negative effect of supply on wages, with elasticities of response of wages to supplies of -0.41 and -0.32, respectively, and a large positive effect of GDP per worker on occupational wages.

We combine these elasticities with the table 2 estimates of changes in supply – an increase in supply in the high skilled occupations by 81 log points (= 100*log 20.2/9) and a decline in supply in the elementary occupations of 40 log points (=100*log 24.4/36.3) that yields a net increase in the relative supply of workers to highly skilled occupations versus the least skilled occupations of 121 log points – to assess the contribution of the change in relative supply on the change in relative wages. At the elasticity of wages of -0.32, the change in relative supply reduced the high skilled to elementary occupation premium worldwide by 39 log points. At the elasticity of wages of -0.41, the reduction in the occupation premium was 49 log points. The increased supply of education thus acted to depress skill premia over the half century in the countries in our dataset much as it did in Goldin and Katz (2008)'s analysis of educational differentials in the USA.

Columns (3) and (4) present estimates that include two additional factors that might have impacted occupational skill premia independent of the increase in education and growth of GDP per worker – the ratio of trade to GDP and the rate of union density. Column (3) estimates the model on a sample which includes all country-periods with data on both trade and union density.[25] The effect of supply is negative but smaller than in columns (1) and (2). Trade has an insignificant depressant effect on wages while union density has a substantial positive effect. Column (4) expands the sample by imputing values for 21 countries lacking schooling, trade/GDP or unionism data with the mean value of those variables in the dataset.[26] The estimated effect of labor supply increases, the coefficient of trade/GDP turns positive while the coefficient on unionization remains

[24] Appendix B.1 presents further information and summary statistics on the variables. The 1953-54 average is based on up to two wage reports, and the 2005-08 average is based on up to four wage reports.

[25] Low income countries are underrepresented in the augmented sample for a lack of union density data, as they only represent 3 of 48 countries in this sample (next to 24 high and 21 middle income countries). Among the 122 countries in the basic model, all income groups are well represented (29 high, 61 middle and 32 low income countries).

[26] We also include dummy variables for whether a variable has been imputed.

positive and substantial. Column (5) gives results for the balanced sample of 45 identical occupations. Here too, the estimates show that education-driven increases in supply reduce wages, whereas GDP per worker and union density increase wages, while the trade variable has a negligible effect. Conditional on GDP per worker, which presumably captures any positive effects of trade via improved productivity, there is no reason to expect trade to impact wages, which lends some support to the specification.

The evidence of a substantial negative effect of labor supply at the occupation level helps explain the downward pressure on skill premia in the 1960s and 1970s. But it cannot account for the rebound of differentials that began in the 1980s. To see if the country-level demand and institutional factors can explain the rebound, we replicate the equation 2 regressions for separate groups of occupations differing in skill requirements. Differences in the estimated coefficients between the higher and lower skilled occupations provide a way to differentiate the effect of the country-level factors on more or less skilled occupations. If, say, GDP per worker has a larger impact on the wages of highly skilled workers than on the wages of less skilled workers, increases in GDP per worker could counteract the depressant effect of supply changes on wages, at least to some extent in some time periods. Estimating the equations for different groups also allows for supply to have different effects on wages for different skill groups, which further increases the potential for explaining the observed pattern of change in the occupational differentials.

Table 4 presents the results of regressing log occupational wages on their posited determinants for the four skill groups in the ILO categorization: (1) the unskilled/elementary occupations; (2) lower medium skill occupations and (3) higher medium skill occupations; and (4) high skill professional, managerial, and technical occupations. The first four columns present estimates from a specification with only supply and GDP per worker as explanatory variables. The -0.42 estimated supply impact for the two lowest skill groups is substantially greater than the -0.10 estimated impact for the highest skill group, which suggests the value of analyzing occupations at the bottom of the education distribution as well as the more widely studied occupations of highly educated workers. By contrast, the estimated coefficient on log GDP/worker is larger for the high skilled workers than for the low skilled worker, indicating that greater growth of GDP widened skill differentials.

Columns (5)-(8) add the trade ratio and union density variables. The addition of the trade ratio complicates the demand side of the story. The coefficients on GDP per worker are greater for the unskilled occupations, as the trade ratio variable seems to pick up the bigger demand effect on the highly skilled with a positive 0.16 coefficient for the high skill occupations compared to a near 0 coefficient for upper middle skill occupations and negative coefficients for the low and lower-medium skilled occupations– all, however, have high standard errors. By contrast, the estimated coefficients on union density show a larger union impact on the wages of workers in the low and lower-medium skilled occupations and in the higher medium skill occupations than on workers in the higher skilled occupations.[27] Given that trade has increased over time and unionization has fallen, the implication is that these factors contributed to the widening of skill premia in the 1980s-2000s period.

5 Accounting for Occupational Skill Premium Changes

Taking the coefficients in table 4 as our best estimate of the impact of the factors influencing occupational wages, we assess the ability of our models to account for the changing pattern of skill premia over time. To obtain the longest possible period of change, we select the two five year periods that are furthest apart for each country which has data on at least one occupation in both periods. On average, the selected early period is 1960-64, and the selected late period is 1995-99. For occupations in the two periods, we compare the *observed* real wage change in log points to the change *predicted* from changes in log occupational labor supply and in log GDP per worker, and the period x skill group dummy coefficients.[28]

Figure 5 shows the results of this calculation in terms of the ability of the average predicted log wage change to explain the average observed log wage change, country by country. The model with labor supply and GDP per worker is relatively successful at predicting wage changes, with a regression coefficient of observed log changes on predicted log changes close to one and an R2 of 0.48.[29] Given this pattern, we assess next how well the model predicts changes in the wage premium for skilled occupations by country. To obtain country-level skill premia, we identify occupations in the top two skill groups as "skilled" and occupations in the bottom two skill groups as "unskilled", and calculate a skilled-unskilled premium as 100*(average log skilled wage-average log unskilled wage) for each country.[30] Since this procedure requires occupations from both skill groups in each

[27]The difference in the point estimates between the lowest and the highest skill group for trade to GDP and union density is statistically significant (p=0.05 for trade to GDP, and p=0.03 for union density). Appendix table A.3.1 shows similar results by skill group for the 45 occupation sample, except for the high skilled group for which we have only two occupations in this sample.

[28]We do this by calculating a predicted late period wage as the sum of the actual early period wage and the point estimates from table 4, multiplied by the changes in the respective variable between both periods. Our "predicted wage change" is the difference between this predicted late period wage and the actual early period wage. Put differently, our prediction is the answer to the question, from the perspective of the early period: "Given the changes in the explanatory variables between the early and the late period and our regression point estimates, how would we expect the early wages to change?"

[29]Giving more weight to more precisely estimated wage level changes by weighting the countries by the square root of the number of underlying wage reports increases the R2 slightly to 0.52.

[30]We focus on the skilled-unskilled premium since it gives us greater leeway to take account of the differential effect of country-level variables in contributing to the pattern, based on the table 4 regression results. However, the pattern of narrowing followed by partially rebounding skill premia occurs in both the standard deviation of ln wages and the skilled-unskilled premium, cf. appendix figure A.2.2.

period, we exclude country-periods with very few occupations in either skill group.[31]

Panel A of table 5 summarizes the results. Columns (1) and (2) show that the model predicts a decline of 6 log points in the average skill premium, whereas the actual decline was 4.7 log points over the full period.[32] The correlation between the actual and predicted skill premium changes at the country-level is significant, though noisier than the correlation of changes in wages by occupation (see appendix figure A.3.1), as looking at changes in skill premia differences out common patterns of change shared by both skilled and unskilled occupations in a country. Columns (3)-(5) break down the predicted change into the contributions of changes in supply, skill group x period dummy coefficients, and GDP per worker. Over the full period, occupational labor supply changes pushed down the average skill premium by 11.3 log points, which the increase in log GDP per worker only partly offset, despite an increase of more than 100 log points.[33] The bottom row of panel A shows that the skill premium-reducing supply effect is both due to increased supplies in skilled occupations (+33.4 log points), and decreased supplies in unskilled occupations (-9.7 log points).

To account for the U-shape, our models must predict a turnaround in skill premia for the two post-1980 periods that are furthest apart for each country and that also have a sufficient number of skilled and unskilled wage reports in both periods. The average selected early period is 1985-89, and the average selected late period is 2000-2004. Panel B of table 5 shows that the average skill premium (scaled to a 25 year period) increased by 10.5 log points, of which the model predicts 6.7 log points. Columns (3)-(4) show that supply pushed down skill differentials by -6.6 log points in the post-1980 period. Working in the opposite direction, the coefficients of the period x skill group dummies increased for the skilled occupations to raise skill differentials by 9.9 log points. By contrast, increases in GDP per worker are associated with a decreasing skill premium, reflecting the stronger effect of GDP per worker on the lower skilled wages in the full model.

Columns (6) and (7) give calculations for our model which includes changes in trade to GDP and union density. The results suggest that these factors contributed to the post-1980

[31] We exclude the 20% of country-periods with the fewest wage reports by skill group. This reduces the number of countries and the average distance between the selected early and the late period slightly, while raising the correlation between actual and predicted skill premium changes. Including these observations gives similar results to those in the text (results available upon request).

[32] We scale the averages to a 55 year period, which corresponds to the approximate distance between the mid-points of the first and last sample period.

[33] We examined the robustness of the table 5 results to different weightings of observations: (1) weighting the skill premium changes by the geometric mean of the square roots of the number of wage observations that went into the cross country averages, on the notion that changes based on more occupations are more reliable; and (2) weighting occupations by their employment share in the average skilled and unskilled wages within countries, using employment weights per appendix section B.3. We obtained results similar to those in table 5 (available upon request).

U-turn in skill differentials. Trade to GDP increased on average by 25.8 percentage points, which translates into an estimated increase of skill premia by 6.3 log points, whereas union density declined by 21.7 percentage points, translating into an increase of skill differentials by 5.3 log points.

Figure 6 plots the observed skill premium changes on the vertical axis against four different sets of predicted skill premium changes on the horizontal axis, always for the same sample. In the top left panel, which predicts changes in the basic model, we find an insignificant association with the observed changes. In the next two panels, which include changes in trade/GDP or union density in the prediction, the association between actual and predicted skill premium changes strengthens to produce an R2 of 0.17-0.29. The association is strongest in the last panel where we include both trade to GDP and union density, giving an R2 of 0.42.[34] Thus, taken together, changes in trade to GDP and union density account for the entire observed net increase in the average skill premium after 1980, and are also strong predictors of skill premium changes at the level of the individual countries. As our estimated trade effect likely reflects the impact of unmeasured factors correlated with increasing trade openness[35], and our estimated union density effect likely reflects spill-overs of declining union density on the wages of non-unionized workers, we view these variables as "representative" of changes in the trade and institution domains that contributed to the increase of skill premia after 1980 that occurred in most countries.

6 The Case for a Better Measurement of Occupational Differentials Around the World, 2010s and Beyond

Did the U-shaped change in differentials found in the OWW persist after 2008 when the ILO terminated its October Inquiry of wages, or did occupational differentials move in a different direction in succeeding years? As no organization or statistical agency has gathered detailed occupational wage data for countries around the world, we answer this question by examining more aggregate occupational wage data from the ILO and from the Union Bank of Switzerland that come closest to the Inquiry data.

Calculating the change in skill differentials in the ILOSTAT and UBS data in a similar way as we calculated the OWW skilled-unskilled premium, we find that both sources show declining skill differentials in a slight majority of countries from 2008 to 2017.[36]

[34] Results for the post 1980-sample are similar if we count the upper medium skilled occupations as "unskilled" instead of as "skilled" (results available upon request).

[35] Replacing ln GDP per worker with ln capital per worker and ln TFP as potentially more fundamental indicators of the factors driving wages does not weaken the effects found for trade and union density (results available upon request).

[36] See appendix table A.2.1. This is mostly driven by middle and high income countries, which the

This pattern is consistent with what changes in our main drivers would predict for the period. Union density continued to decline after 2008 at an average rate of 3.2 percentage points per decade, pushing up the skill premium, while the ratio of merchandise trade to GDP declined at a rate of 5.6 percentage points per decade, pushing down the skill premium. Weighting these changes by the table 4 estimated effect of the two variables on wages suggests that differentials should have narrowed modestly even absent the continued expansion of education, which would further reduce skill differentials.[37] Thus the post-2008 reductions in occupational skill differentials weakened the U-turn that began in the 1980s but were neither as strong nor as wide-spread as to nullify it.

Finally, while modern forms of digital data have outmoded the survey design and statistical procedures by which the ILO obtained its October Inquiry data, we believe that there is a strong case for seeking a new source of data on more detailed occupations worldwide. Such data would contribute to understanding two of the biggest areas of concern in economics in recent years: the increase of inequality in individual incomes and the impact of technology on the future of work. On the inequality side, measures of pay in detailed occupations offer a lens into the underpinnings of the increased within country inequality in incomes – the extent to which this inequality reflects the divergence or polarization of income between skilled and unskilled work.[38] On the technology side, current analyses of the future of work focus almost exclusively on data on *employment* in occupations, classified by job tasks and the likelihood that machines will automate routine tasks.

Analytically, in both areas, absence of wage data for detailed occupations and the possibility of inferring "shadow wages" for particular tasks makes it difficult to disentangle the shifts in supply from shifts in demand that invariably show up in both the quantity (occupational employment) and price (occupational wages) side in the market.[39] Data on wages at a high level of occupational detail across countries, perhaps from internet

ILOSTAT and UBS surveys also cover most extensively.

[37]In the Cohen and Leker (2014) database, average schooling increases increased at an average rate of 0.85 years of schooling between 1960 and 2010, and at a rate of 0.94 years in the same countries between 2010 and 2020. The trend estimates for trade and union density come from a regression of all available data for the 2009-2017 period on country dummies and a trend. The trend point estimates for both variables are highly significant, with standard errors clustered at the country level. To translate the trade and union density point estimates for the four skill groups in table 4 into changes for the two coarse skill groups, we take the weighted average of point estimates, using the number of occupations per sub-group as weight.

[38]Acosta et al. (2019) find that there is a "close relationship between income inequality at the household level and the dispersion in wages, proxied by the wage gap between skilled and unskilled labor" (p. 5) in a large number of Latin American countries between 1991 and 2013.

[39]For instance, see Kunst (2019), who combines occupational employment with OWW wage data to document a decline in the demand for skilled production worker tasks in manufacturing around the world since the 1950s due to automation.

surveys of firms and/or workers, with information on the job tasks and work activities in occupations in different countries, would improve our ability to infer from shifts in the value of tasks and work activities where technology has its bite. Analyses of labor markets would benefit greatly from a renewed effort to obtain such data updated to salient modern occupations.

References

Acosta, P., Cruces, G., Galiani, S., and Gasparini, L. (2019). Educational upgrading and returns to skills in Latin America: evidence from a supply–demand framework. *Latin American Economic Review*, 28(1):18.

Ashenfelter, O. (2012). Comparing real wage rates. *American Economic Review*, 102(2):617–642.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, 103(6):2121–68.

Autor, D. H. and Handel, M. J. (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of labor Economics*, 31(S1):S59–S96.

Barro, R. J. and Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, 104:184–198.

Bessen, J. (2015). *Learning by doing: the real connection between innovation, wages, and wealth*. Yale University Press.

Cohen, D. and Leker, L. (2014). Health and education: Another look with the proper data. mimeo.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105(10):3150–3182.

Freeman, R. B. (1998). War of the models: which labour market institutions for the 21st century? *Labour Economics*, 5(1):1–24.

Freeman, R. B. and Oostendorp, R. (2000). Wages around the world: Pay across countries and occupations. Technical report, NBER Working Paper 8058.

Freeman, R. B. and Oostendorp, R. (2020). The Occupational Wages around the World 1953-2008 Database. `https://data.nber.org/oww/`.

Goldberg, P. K. and Pavcnik, N. (2007). Distributional effects of globalization in developing countries. *Journal of Economic Literature*, 45(1):39–82.

Goldin, C. D. and Katz, L. F. (2008). *The race between education and technology*. Harvard University Press.

ILO (2019). ILOSTAT database. `https://ilostat.ilo.org/`. Retrieved on June 13, 2019.

Krugman, P. R. (2008). Trade and wages, reconsidered. *Brookings Papers on Economic Activity*, 2008:103–137.

Kunst, D. (2019). Deskilling among manufacturing production workers. Technical report, Tinbergen Institute Discussion Paper 19-050/VI.

Lipsey, R. E. (2009). Measuring international trade in services. In Reinsdorf, M. B. and Slaughter, M. J., editors, *International trade in services and intangibles in the era of globalization*. University of Chicago Press.

Montenegro, C. E. and Hirn, M. L. (2009). A new disaggregated set of labor market indicators using standardized household surveys from around the world. Technical report, World Bank, World Development Report Background Paper.

Montenegro, C. E. and Patrinos, H. A. (2014). Comparable estimates of returns to schooling around the world. *Policy Research Working Paper Series*.

Union Bank of Switzerland (2018). UBS prices and earnings survey 2018. `https://www.ubs.com/microsites/prices-earnings/en/`. Retrieved on June 10, 2019.

Visser, J. (2019). ICTWSS database. version 6.0. `http://uva-aias.net/en/ictwss`. Amsterdam: Amsterdam Institute for Advanced Labour Studies (AIAS), University of Amsterdam. June 2019.

Wood, A. (1995). How trade hurt unskilled workers. *Journal of Economic Perspectives*, 9(3):57–80.

World Bank (2019). World Development Indicators. `https://databank.worldbank.org/reports.aspx?source=world-development-indicators`. Data retrieved in March 2019.

Figures and Tables

Figure 1: Evolution of Occupational Skill Premia for the 45 Occupations available for the 1953-2008 Period, and the 159 Occupations available for the 1983-2008 Period

The figure plots the (unweighted) cross-country average standard deviation of ln wages, for the full sample and by income group. The standard deviations are calculated either for up to 45 occupations available throughout the full period (left panel) or for up to 159 occupations available from 1983 onwards (right panel). The number of different countries across which average standard deviations are calculated differs by period, depending on data availability in OWW. In the left panel, a total of 170 countries enter in at least one period (ranging between 58 and 119 countries per period). In the right panel, a total of 157 countries are represented (ranging between 58 and 109 countries per period). The income groups follow the World Bank's income group assignment in 1990. See appendix C for a list of countries represented in OWW by income group.

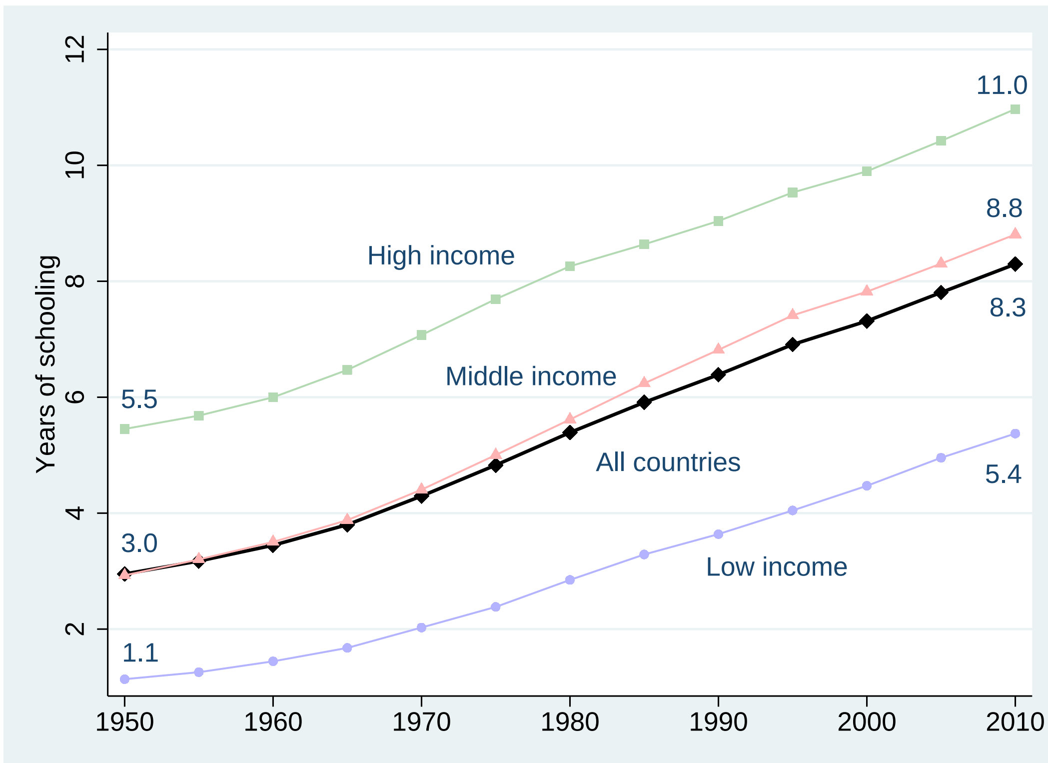

Figure 2: Evolution of Average Years of Schooling

Average years of schooling of the population above 15 years, taken from the Barro-Lee dataset. Averages are calculated for the 139 countries which are represented in both Barro-Lee and OWW.

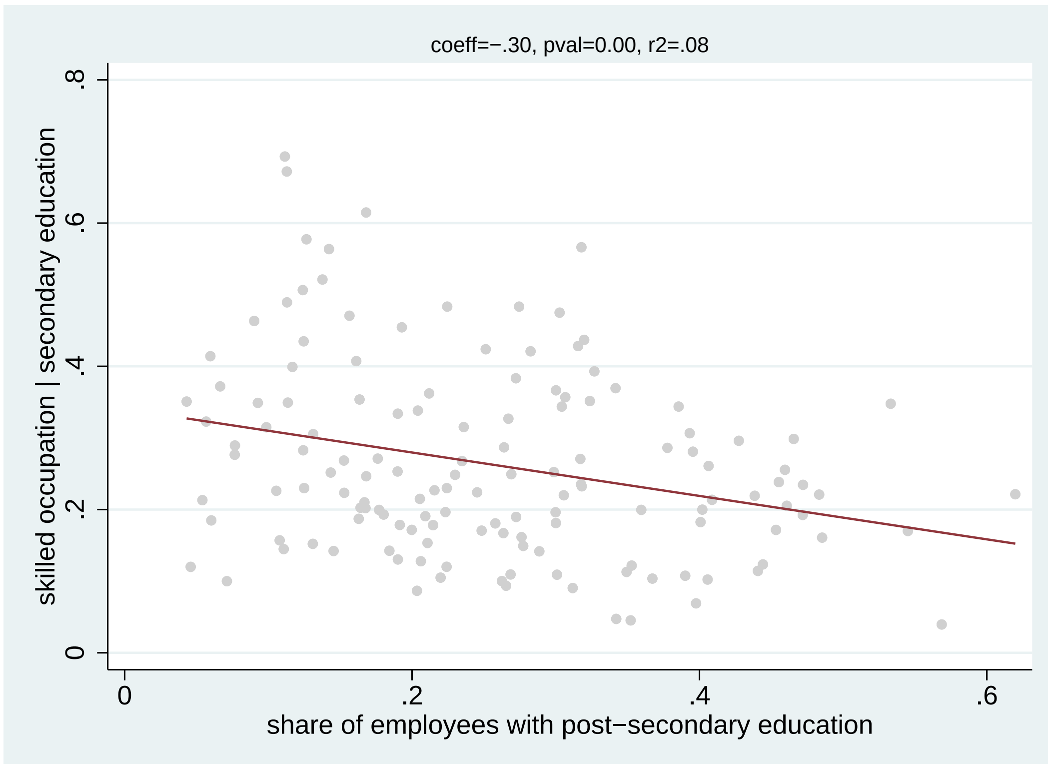

Figure 3: The Share of Secondary-educated in Skilled Occupations and the Supply of Post-secondary Educated Workers

Skilled occupations include major groups 1-3 (managers, professionals, and associate professionals). The figure shows averages across all I2D2 surveys of a country, using the square root of the number of observations with the respective education level as weight if several surveys are available. The red line shows the linear fit, and the title presents the associated coefficient, p-value and R-squared of the regression.

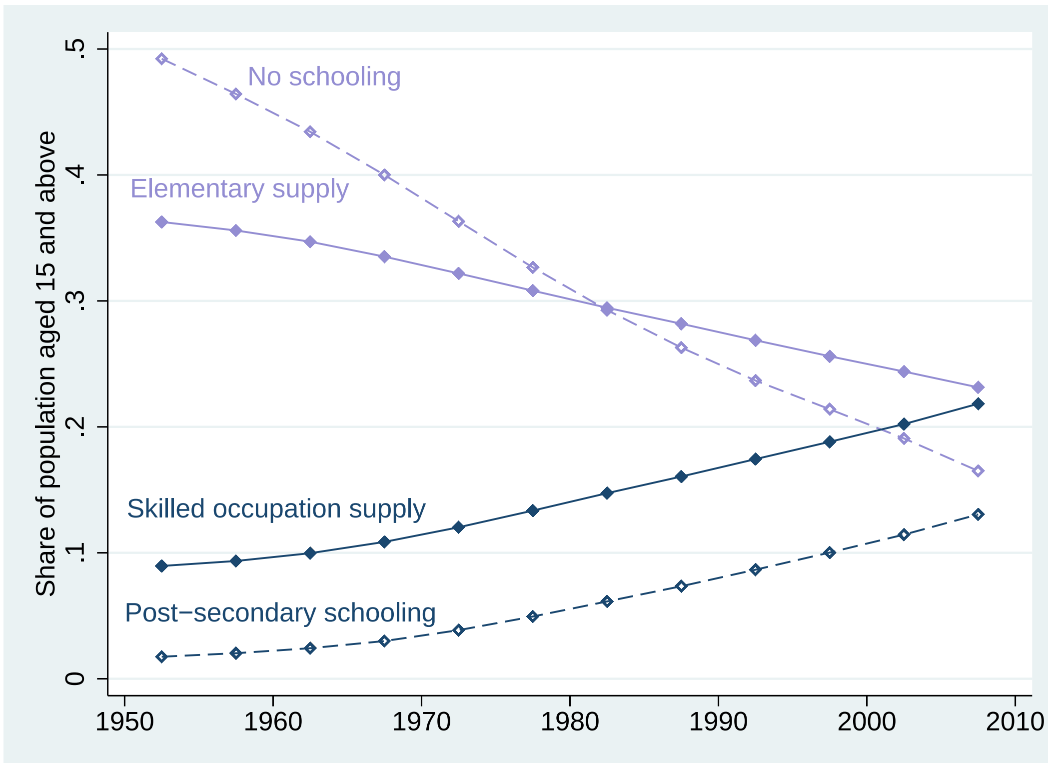

Figure 4: The Share of Workers without Schooling vs. the Estimated Supply to Elementary Occupations, and the Share of Workers with Post-secondary Schooling vs. the Estimated Supply to Skilled Occupations

Averages for the 139 countries represented in both Barro-Lee and OWW. Elementary occupations correspond to major group 9, skilled occupations to major groups 1-3. The education series are taken directly from Barro-Lee, and the occupational labor supplies are estimated based on the Barro-Lee educational attainments and the distribution of employees by level of education across major groups, as described in section 3.

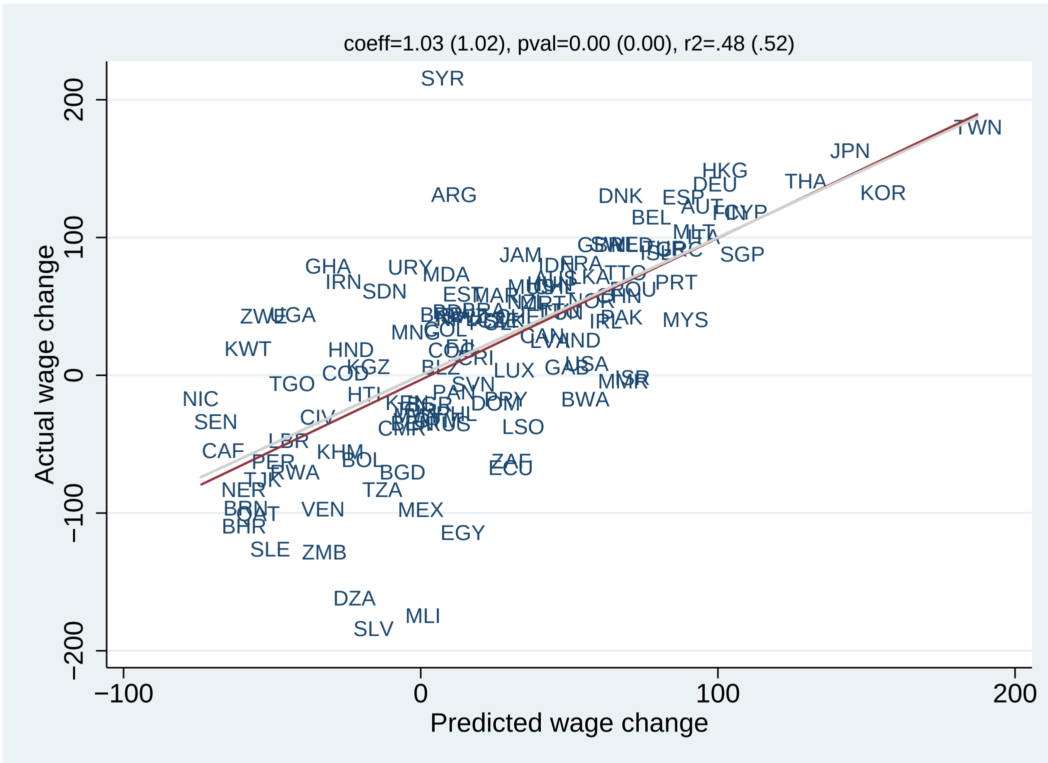

Figure 5: Comparing the Actual Wage Changes over the Full Sample Period to the Predicted Changes

For the 122 countries in column (2) of table 3, the figure compares the actual average real wage change between the first and the last period in the sample to the wage change that would be predicted based on the change in log occupational labor supply, the period x skill group dummy coefficients, and log GDP per worker. The average "early" period is 1960-64, and the average "late" period is 1995-99, so that the average period over which changes are calculated is around 35 years. The title presents the results from a regression of actual on predicted wage changes. In brackets are the results from the same regression in which we weight wage changes from each country with the square root of the number of occupations based on which the average wage change has been calculated, to give more weight to more precisely estimated wage level changes. The solid line plots the slope of the (unweighted) regression, and the shaded line is a 45 degree reference line. On average, changes are calculated based on 34 occupations.

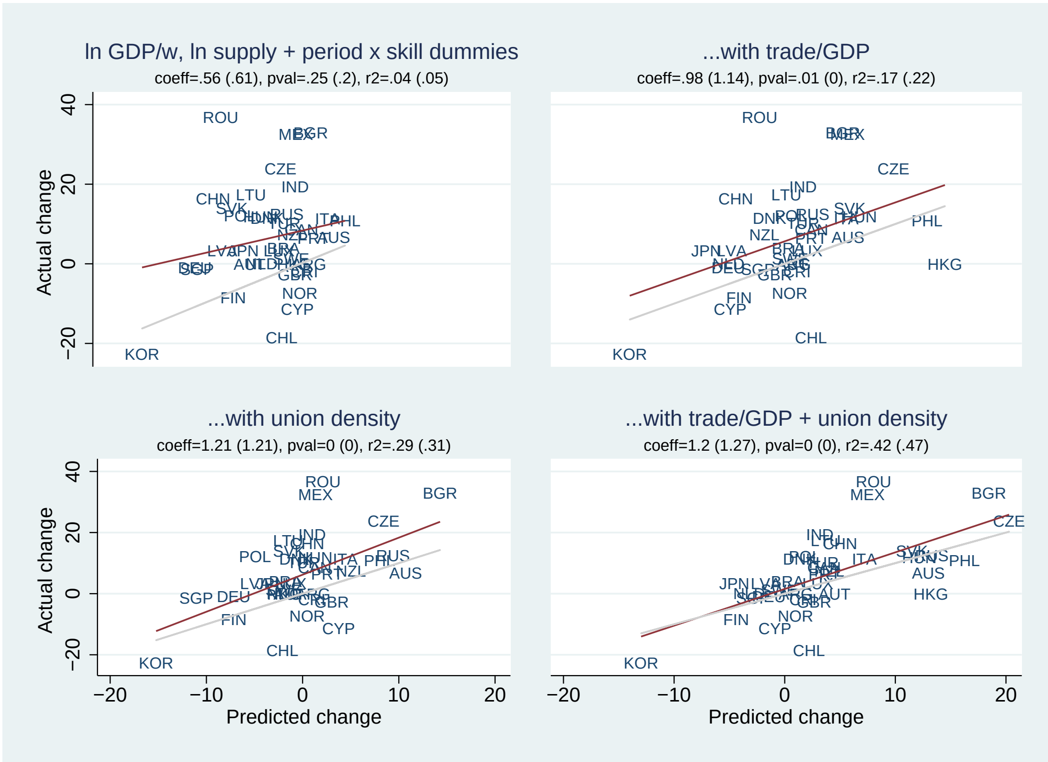

Figure 6: Comparing the Actual Changes of the Skilled-Unskilled Premium within 1980-2008 to the Changes Predicted by Factors

The figures plot the simulation results that are also summarized in panel B of table 5. The top left figure compares the actual skilled-unskilled wage premium change between both periods with the change that would be predicted from only taking into account variation in log supply, the skill group x period dummies, and ln GDP per worker. The further panels also take into account changes in trade/GDP, union density, and in both variables jointly for the prediction of wage premium changes. The title presents the results from a regression of actual on predicted wage premium changes. In brackets are the results from the same regression in which we give more weight to more precisely estimated wage premium changes, by weighting the wage premium changes from each country with the geometric mean of the square root of the number of skilled and unskilled occupations based on which it has been calculated. The solid line plots the slope of the (unweighted) regression, and the shaded line is a 45 degree reference line.

Table 1: The Occupational Wages around the World 1953-2008 Database

	Full Sample	Occupation available...	
		...throughout	...from 1983
First year	1953	1953	1983
Last year	2008	2008	2008
Occupations	162	45	159
- unskilled	16	8	14
- lower medium	74	25	73
- upper medium	37	10	37
- high skilled	35	2	35
Industries	39	16	39
All countries	171	170	153
- high income	30	30	28
- middle income	90	89	81
- low income	51	51	44
- sovereign	169	168	151
Wage reports	191,618	107,978	118,755
Years with reports by country			
- average	21.8	21.6	8.6
- standard deviation	15.4	15.3	7.7
Reported occupations			
- average	78.1	33.7	103.9
- standard deviation	44.2	9	36.8

The occupations can be matched to the "International Standard Classification of Occupations" (ISCO-88) at the four digit-level, and to the 'International Standard Industrial Classification of all Economic Activities' (ISIC-88) at the two to four digit level. 3 occupations were only included in the survey between 1953 and 1982, and 114 occupations only from 1983 onwards. The middle column presents data on the sample of 45 occupations for which we have data over the full 1953-2008 period, and the right column presents the sample from 1983 onwards. See appendix C for a detailed description of the occupation, industry and country coverage. The sample coverage in sections 4 and 5 differs according to the availability of covariates and price level estimates from the Penn World Table for the conversion to real wages. The full OWW database includes data from an additional 21 non-sovereign countries with current populations of less than one million, and two additional occupations since it distinguishes between the "industrial chemicals" and "other chemical products" industries for two occupations.

Table 2: Estimated Occupational Labor Supplies between the 1950s-2000s: All Countries and by Level of Income

	Elementary	Agricultural	Service & sales	Operators	Craftsmen	Clerks	Assoc. professionals	Professionals	Managers
All countries									
1950-55	36.3	9.9	13.1	10.6	16.6	4.5	4.1	2.9	2
2005-10	24.4	6.5	14.7	10.2	15.7	8.3	9	7.8	3.4
High income									
1950-55	29.4	2.2	15.7	14.6	16.5	8.4	6.9	3.4	2.8
2005-10	15.7	1.5	15.8	10.1	13.4	12.9	14.2	11.1	5.4
Middle income									
1950-55	37.5	8.9	12.6	10.7	18	3.9	3.8	2.9	1.6
2005-10	24.2	5.2	14.9	11.1	16.9	8.3	8.8	7.7	3
Low income									
1950-55	39.2	17.4	11.8	7.5	14.3	2.7	2.5	2.5	2.1
2005-10	31.2	12.7	13.3	8.8	15.1	4.8	5.5	5.7	2.7

The occupational labor supplies in each row sum to 100. They are calculated based on the share of the population with no schooling, primary, secondary and postsecondary schooling from Barro-Lee, and the distribution of wage employment by education level across occupations from the I2D2 data base, as described in section 3.

Table 3: Regression Estimates of the Determinants of Occupational Wages: Basic model and Augmented Model with Trade/GDP and Union density

Dependent variable: ln real wage

	(1)	(2)	(3)	(4)	(5)
ln supply	-0.41**	-0.32**	-0.17*	-0.22**	-0.21+
	(0.10)	(0.08)	(0.07)	(0.05)	(0.11)
ln GDP/worker	0.79**	0.76**	0.85**	0.75**	0.93**
	(0.07)	(0.07)	(0.13)	(0.07)	(0.13)
trade/GDP			-0.09	0.14	-0.27
			(0.13)	(0.09)	(0.16)
union density			0.36+	0.31+	0.39*
			(0.19)	(0.16)	(0.17)
Country-occup. FE	✓	✓	✓	✓	✓
Period x skill group FE	✓	✓	✓	✓	✓
Countries	121	122	48	143	48
Occupations	45	162	162	162	45
Industries	16	39	39	39	16
Intervals	5 year	5 year	5 year	5 year	5 year
R2 (within)	0.33	0.27	0.53	0.25	0.64
Observations	28103	51113	19787	57065	8755

Standard errors in parentheses, clustered at the country level. $^{+} p < 0.1$, $^{*} p < 0.05$, $^{**} p < 0.01$. Columns (1) and (2) present the results for the basic model, for the sample of 45 consistently reported and all occupations. Columns (3)-(5) present results for specifications that include merchandise trade/GDP and union density. In column (4), missing covariates have been set to the sample mean, and the regression includes a dummy variable for each covariate that takes a value of one for such observations (not shown). Trade data are available for 140 of the 143 countries, occupational labor supply data for 122, and union density for 53 countries. Occupational labor supplies are constructed as described in section 3 using data from Barro and Lee (2013) and Montenegro and Hirn (2009), merchandise trade/GDP is taken from the World Bank World Development Indicators, union density from Visser (2019), and all other variables (including the GDP deflator used for the conversion to real wages) are taken from the Penn World Table 9.0 (Feenstra et al., 2015). Column (5) includes only the 45 consistently reported occupations. Note that data on trade/GDP and union density are only available from 1960 onwards, so that the models in columns (3) and (5) do not include observations from the 1950s.

Table 4: Regression Estimates of the Determinants of Occupational Wages: Estimates by Occupation Skill Group

Dependent variable: ln real wage

	(1) low	(2) l. med.	(3) u. med.	(4) high	(5) low	(6) l. med.	(7) u. med.	(8) high
ln supply	-0.42*	-0.42**	-0.29**	-0.10	-0.22	-0.19+	-0.09	-0.18*
	(0.19)	(0.12)	(0.09)	(0.11)	(0.20)	(0.10)	(0.10)	(0.07)
ln GDP/worker	0.68**	0.76**	0.77**	0.81**	0.92**	0.89**	0.73**	0.81**
	(0.09)	(0.08)	(0.07)	(0.10)	(0.15)	(0.14)	(0.13)	(0.12)
trade/GDP					-0.13	-0.18	0.01	0.16
					(0.13)	(0.14)	(0.13)	(0.14)
union density					0.43*	0.45*	0.27	0.13
					(0.20)	(0.20)	(0.19)	(0.21)
Country-occ. FE	✓	✓	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓	✓	✓
Countries	121	122	121	114	47	48	48	44
Occupations	16	74	37	35	16	74	37	35
Industries	14	27	18	17	14	27	18	17
Intervals	5 year	5 year	5 year	5 year	5 year	5 year	5 year	5 year
R2 (within)	0.33	0.28	0.26	0.19	0.63	0.56	0.51	0.42
Observations	6625	25890	11317	7281	2187	9866	4429	3305

Standard errors in parentheses, clustered at the country level. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$. Columns (1)-(4) present results for the basic model separately by skill group, and columns (5)-(8) do the same disaggregation for the sample with trade and union density. The difference in the point estimates between the lowest and the highest skill group for trade to GDP and union density is statistically significant (p=0.05 for trade to GDP, and p=0.03 for union density).

Table 5: The Estimated Impact of Changes in Supply, Demand, and Union Density on Changes in Skilled-Unskilled Premia

Panel A: Narrowing of differentials, 1950s-2000s						
Changes from 1950s-2000s:		Contribution of change in factor to change of skilled-unskilled premium:				
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Actual	*From model*	*ln supply*	*Period x skill dummies*	*ln GDP/w*	*Trade/GDP*	*Union density*
-4.7	-6	-11.3	1.6	3.7	-	-
		Change of factors:				
		ln skilled supply	*ln unskilled supply*	*ln GDP/w*	*Trade/GDP*	*Union density*
		33.4	-9.7	106.5	-	-
Panel B: Widening of differentials, 1980s-2000s						
Changes from 1980s-2000s:		Contribution of change in factor to change of skilled-unskilled premium:				
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Actual	*From model*	*ln supply*	*Period x skill dummies*	*ln GDP/w*	*Trade/GDP*	*Union density*
10.5	6.7	-6.6	9.9	-8.1	6.3	5.3
		Change of factors:				
		ln skilled supply	*ln unskilled supply*	*ln GDP/w*	*Trade/GDP*	*Union density*
		20.9	-14.2	61.5	25.8	-21.7

The estimates in panel A are based on the specifications in columns (1)-(4) of table 4. The first row compares the actual and the predicted average change of the skilled-unskilled premium in the sample, scaled to a 55 year-period, as well as how changes in ln supply, the period x skill group dummies and ln GDP/worker contribute to the prediction. The second row shows the underlying changes in the average ln supply of the skilled occupations, the unskilled occupations, and ln GDP per worker. To ensure that the skilled and unskilled occupations for each country are at least somewhat representative, we exclude the bottom 20% of country-periods with smallest number of wage reports by skill group, which means that there are at least 6 occupations by skill group for each country (on average, 12 skilled and 26 unskilled occupations). With this restriction, the average change in panel A is calculated based on 118 countries, and the average selected period is 1960-1964 to 1990-1994. The estimates in panel B are based on the augmented models in columns (5)-(8) of table 4, and averages are scaled to a 25 year-period. Skilled-unskilled premia are based on at least 13 occupations by skill group for each country (on average, 36 skilled and 50 unskilled occupations), and the average selected period is 1985-1989 to 2000-2004. The average change is calculated based on 37 countries.