The evolution of skill premia over the past 60 years: A global perspective

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Abstract

While the analysis of skill premia is central within labor and trade economics, current empirical studies tend to be limited in terms of country and/or time coverage due to the absence of internationally comparable wage data for a large number of countries over an extended time period. In this paper, we use a novel data set on annual wages for 162 occupations to estimate and analyze the evolution of skill premia for 188 countries in the period 1953-2008. We find that the average country skill premium declined by 23% between the 1950s and the 1980s and by 15% over the full period. Using a supply-demand framework, we find that increases in relative skill supplies were robustly associated with decreasing skill premia within countries, and the secular trend of increasing relative skill supplies appears to be the main reason for the overall compression of skill premia. A residual increase in high skilled wages, consistent with skill-biased technological change, has cushioned the skill-supply induced decline in skill premia in high income countries. Given that there are large cross-country differences in relative skill supplies that the supply-demand framework takes as given, we also introduce a modified Solow model of the proximate country determinants of relative skill supplies. Consistent with the model, we find that economic development and the effective share of output devoted to education are associated with higher relative skill supplies, and lower skill premia, whereas the opposite holds true for population growth. Finally, we also test the Heckscher-Ohlin prediction that trade openness reduces the elasticity of skill premia with respect to domestic relative skill supplies. We find evidence of a reduced elasticity in a sample of predominantly high income countries, but not in the pooled sample, suggesting that increasing openness has not generally reduced the relevance of domestic relative skill supplies, and its proximate determinants, for skill premia.

JEL: J31, O33, F16.

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1 Introduction

Skill premia have been at the centre of attention of labor and trade economists, yet internationally comparable data on the evolution of wages and skill premia since World War II remain scarce (cf. Ashenfelter 2012). This is true in particular for the period prior to the spread of household surveys in the 1980s, and for low and middle income countries. At the same time, the world has witnessed an unprecented surge in global investment in skills since the 1950s, and one wonders whether this has led to a massive compression of wage dispersion around the world. However, the famous metaphor by Tinbergen (1975) posits that skill premia are not determined by relative skill supplies alone, but by a "race between technology and education". In Tinbergen's view, technological change increases the relative demand for skill and hence skill premia, unless also the relative skill supply increases at a sufficient rate. If Tinbergen is right, who has been winning this race since the 1950s globally? Katz and Murphy (1992) and Goldin and Katz (2008) argue that for the US, fluctuations in the growth rate of the share of college graduates can account for much of the evolution of the US college wage premium throughout the 20th century. Since the US college wage premium has been declining between 1915-60 but increasing since the 1980s in spite of further increases in the relative supply of college graduates, education initially won the race before losing it in the USA. Jones and Romer (2010) propose as a "stylized fact" that also globally, the long-run increase in relative skill supplies has not been matched by a decline in skill premia. This view receives support from cross-country studies for the post 1980-period, such as Michaels et al. (2014), which however focus predominantly on high income countries.

At the same time, cross-country studies of Mincer returns to schooling who extend the time and country coverage paint a somewhat different picture: Montenegro and Patrinos (2014) use harmonized household surveys to estimate Mincer returns for 139 countries since 1970 and find a *declining* average return over time. This is in line with the synthesis of return estimates from the literature by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004), extending back to 1958. Hence, from a global perspective, education may have actually won the race since the 1950s.

The question how relevant domestic skill supplies are for skill premia has also been important for trade economists, as [1] the Heckscher-Ohlin model suggests that the expansion of world trade after

[1] A large number of studies have tested the predictions of the Stolper-Samuelson theorem that greater openness to trade increases skill premia in countries that are relatively well endowed with skilled labor, and reduce them in countries in which skilled labor is relatively scarce. For the US, studies have traditionally found a positive, but modest contribution of trade to increasing skill premia (Krugman, 2008), with more recent studies finding larger effects (Autor et al. 2013, Ebenstein et al. 2014). By contrast, the literature has documented instances of both decreasing and increasing skill premia in developing countries -where skilled labor tends to be relatively scarce- in response to trade (see Wood 1997, Goldberg and Pavcnik 2007). This has spurred the development of alternative theories about the distributive effects of trade that sometimes build on the Heckscher-Ohlin framework. For instance, Burstein and Vogel (2016) propose that

the 1950s did not only affect skill premia directly, but also interfered in the proverbial race between technology and education by weakening the impact of domestic relative skill supplies on skill premia. In the textbook example, factor prices - and hence skill premia - are even unaffected by changes in domestic relative skill supplies, as the composition of output changes in order to fully absorb any such changes (cf. Samuelson 1948, Samuelson 1949).[2] The literature on facor price equalization provides indirect support for the view that trade globalization has reduced the relevance of domestic relative skill supplies for skill premia (Trefler 1993,Freeman 1995), but direct empirical tests are scarce, as lamented by Leamer and Levinsohn (1995), Slaughter (1998) and Slaughter (1999). Case studies on the impact of large labor supply shocks on skill premia such as Card (1990) often fail to find large effects on skill premia (see Longhi et al. 2005 and Hatton 2014 for literature reviews), which may in part be due to adjustments of the composition of output. Indeed, Hanson and Slaughter (2002) find that among US states, changes in the output of traded goods absorb part of state-level changes in relative skill supplies, and hypothesize that this dampens region-specific wage adjustments. Rotunno and Wood (2016) find evidence that openness has decreased the elasiticity of skill premia in 40 mostly high income countries over the 1995-2009 period. These findings raise the question whether also more globally, the expansion of trade has reduced the relevance of domestic relative skill supplies for skill premia, and your wages are indeed increasingly "set in Beijing" (Freeman, 1995).

In this paper, we present and analyze an extended version of the “Occupational Wages around the World" (henceforth OWW) data file introduced by Freeman and Oostendorp (2001) to provide a global account of the evolution of skill premia for a period of almost 60 years, including the 1950s-1970s for which few alternative data sources exist. To be precise, our data set consists of male hourly wages for up to 162 narrowly defined occupations in 188 economies between 1953 and 2008. Our analysis makes the following four contributions to the literature.

First, we document that the average skill premium decreased by about 15% over the 1950s-2000s period, with a strong compression of skill premia up to the 1980s, and a period of generally increasing skill premia since. Hence, the view that the global increase in relative skill supplies has not been matched by a decline in skill premia is only adequate when considering the post 1980-period. Moreover, we show that the reduction of global skill premia has been accompanied by a strong convergence in premia across countries.

Second, using a simple supply-demand framework, we show that throughout the 60 year-period, and across high and lower income countries, there has been a robust association between within

trade allocates production to sectors with a comparative advantage, but at the same time towards more skill intensive firms within sectors, and may thus increase skill premia overall in all countries.

[2]This result depends on strong assumptions, such as the tradability of all goods, and the factor endowments of all countries being within the same "cone of specialization". See Dixit and Norman (1980) for a good textbook treatment.

country-changes in skill premia and the relative skill supply. Our estimates suggest that in the absence of global surge in relative skill supplies between the 1950s and the 2000s, the global average skill premium in the 2000s would have been 23% higher. Moreover, we find suggestive evidence of skill-biased technological change in high income countries, but not in other countries.

Third, we introduce a modified Solow model of the proximate determinants of relative skill supplies, extending the literature on cross-country patterns of skill premia which takes relative skill supplies as given. In line with the model predictions, the empirical analysis shows that economic development and a higher human capital savings rate are associated with higher relative skill supplies and lower skill premia, while economic development appears to influence skill premia solely by increasing relative skill supplies. We find that population growth has the opposite effect on skill premia, as high population growth means that the resources devoted to education are only sufficient to educate a smaller share of labor market entrants.

Finally, we contribute to a literature on the effect of trade openness on labor market adjustments to shocks to the domestic relative skill supply. We find evidence that openness has reduced the sensitivity of skill premia with respect to changes in domestic relative skill supplies in a sample of predominantly high income-countries, but do not find evidence of this effect in the global sample.

The remainder of this paper is organized as follows: In Section 2, we present the OWW data file, as well as a descriptive analysis of the evolution of skill premia and relative skill supplies. In Section 3, we use a simple supply-demand framework to estimate the effects of the increase in relative skill supplies and skill-biased technological change on skill premia around the world. Section 4 presents our model of the proximates determinants of relative skill supplies and confronts it with the data, and Section 5 investigates whether the increasing openness of countries has weakened the relationship between the domestic relative supply of skills and skill premia as suggested by standard trade theory. Section 6 concludes.

2 The evolution of skill premia and relative skill supplies

2.1 The evolution of skill premia

The extended “Occupational wages around the world" data file

Internationally comparable wage data are scarce, rendering cross-country comparisons of wages and skill premia difficult. The most extensive source of cross-national wage data is the “October Inquiry" of the International Labor Organization (ILO).[3] For this survey, first conducted in 1924 for 18

[3]There are a few popular alternative data sources for cross-country wage comparisons: The ILO Yearbook of Labor Statistics lists manufacturing wages, but does not differentiate occupations or skills. The collection of wages of

occupations, the ILO has asked national governments of all member states for annual reports of wages of an increasing number of occupations. From 1953 to 1982, 48 occupations were included, a number that increased to 161 between 1983 and 2008.[4] Importantly, 45 occupations were included in the inquiry throughout the full 56 year period. The occupations can be matched to the "International Standard Classification of Occupations" (ISCO-88 and -08) at the four digit-level, as well as the "International Standard Industrial Classification of All Economic Activities" (ISIC-68 and -88). Appendices D and E contain full lists of the industries and occupations covered.

Unfortunately, the October Inquiry did not collect data on occupational employment shares, but the ILO based the selection of occupations on economic relevance, next to the comparability of occupations across countries. If all governments obtained these reports from nationally representative surveys based on the ILO definitions, the October Inquiry would allow for a comparison of wages paid for occupations entailing quite narrowly defined tasks.[5] However, the use of the October Inquiry-date is complicated by the fact that countries have reported wages to the ILO in a number of different formats - for instance wage rates vs. earnings, mean vs. minimum, monthly vs. hourly, and male vs. female wages- and are hence not directly comparable across countries, occupations, or time. Moreover, the broad country and time coverage (see below) comes at the cost of varying capacities of the governments or statistical agencies that processed the requests, and hence varying data quality.

To alleviate the concern about data quality, Freeman and Oostendorp (2000) use a quality rating of the October Inquiry-sources conducted by the ILO to keep only observations from sources rated to be of "acceptable/good" or "excellent" quality. To convert wage reports into a comparable format, they exploit the fact that in many cases, countries have reported multiple pay concepts for the sameoccupation allowing them to estimate adjustment coefficients that reflect the systematic component of the relationships between the different pay concepts. They then use these adjustment coefficients, along

McDonald's employees around the world by Ashenfelter (2012) allows for a comparison of wages in narrowly defined occupations, but does not allow the analysis of skill premia. The "UBS Prices and Earnings Survey" conducted since 1970 reports wages for up to 15 professions in up 71 cities, but is confined to urban wages and includes few low income countries.

[4]The ILO listed 159 occupations on the questionnaire between 1983 and 2008, yet distinguished between government executives at the national, regional or provincial, and local level. Three occupations were included in the 1953-1982 period but omitted afterwards. Hence, in total 164 occupations appear in the October Inquiry for the relevant period. However, the wages of "Mixing- and blending-machine operators" and "Labourers" were included separately for the "Manufacture of industrial chemicals" and "Manufacture of other chemical products"-industries only between 1983 and 2008. To allow for a comparison of the wages of these two occupations across the entire period, we average wages over these two industries for the later period, reducing the total number of occupations appearing in the data file to 162. Reassuringly, reported wages for these occupations in both industries are very similar. In 2010, the "October Inquiry" was replaced by the ILOSTAT data base.

[5]For instance, the (abbreviated) description of the tasks of an accountant in a bank reads as follows: "Accountant. Plans and administers accounting services and examines, analyses, interprets and evaluates accounting records for the purpose of giving advice on accountancy problems or preparing statements and installing or advising systems of recording costs or other financial and budgetary data: ... keeps record of all taxes, fees, etc. to be paid by the bank ... conducts financial investigations on suspected fraud ... prepares and certifies financial statements for presentation to the board of directors, executives, shareholders ..."

with the reported hours of work, to estimate standardized wages for the period 1983-98.

Oostendorp (2005) and Oostendorp (2012) have refined the standardization methodology and extended the data file to include the 1983-2008 period.[6] The data base was further extended to the period 1953-2008 as described in Freeman et al. (2011), and here we use an improved version of this last extension. Wages are hourly rates for males and given in US dollars, converted at contemporaneous market exchange rates.

Table 1 provides an overview over the country coverage of this data file: In total, 188 countries, of which 166 sovereign states, are represented in the data set. As a result of the broad country coverage, low and middle income countries are well represented.[7] Table 1 also illustrates the imbalanced nature of the data set. In the "panel" sample of 45 occupations that were included in the October Inquiry throughout the entire period 1953-2008, countries reported wages for on average 21 of the 56 years. Conditional on reporting any wages, they reported wages for 33 of the 45 occupations on average. Appendix F contains a list of all countries included in the OWW data file.

Using the OWW data file to study skill premia

The ILO classifies October Inquiry occupations according to the level of schooling typically required for them, ranging from primary schooling (for instance for "underground helper/ loader" in the coalmining industry) to tertiary education (for instance, "chemistry technician" in the "manufacturing of industrial chemicals" industry) (see Appendix E). Hence, measures of wage dispersion can be considered as a proxy for the premium paid to higher relative to lower skilled labor in the OWW data file.

A common approach in the literature is to study the evolution of the premium for graduates from high school or college relative to non-graduates. Similarly, we could compare the wages of selected pairs of occupations with different skill requirements. However, this is complicated by the fact that the ILO assigns most of the occupations in the OWW data file, in particluar in the panel sample, to the secondary schooling-requirement (see Table 1). This category is, however, still highly heterogenous in terms of skill requirements containing occupations requiring basic literacy and numeracy skills obtained during the first stage of secondary education (or even earlier), as well as occupations requiring skills from the second stage of secondary education and sometimes additional specialized vocational education.[8] Also, reported wages of individual occupations are undoubtedly measured with some error,

[6] This data base is pubicly available from http://www.nber.org/oww/.

[7] We classify countries into income groups according to their 2016 World Bank-classification. We classify the dissolved Czechoslovakia and Yugoslavia as high and middle income respectively, in line with the classification of the (majority of) their successor states. We use the World Bank income thresholds to classify countries with a GNI per capita of $12,476 or more in 2016 as "high income", and countries with a GNI per capita below $4,036 as "low income".

[8] For instance, both "miners" in the coalmining industry and "bank tellers" in the banking industry are classified as secondary schooling occupations, although the latter occupation is likely to require more formal education.

Table 1: Overview of OWW data file

	Full sample	Panel sample
First year	1953	1953
Last year	2008	2008
Occupations	162	45
- primary	15	8
- secondary	112	35
- tertiary	35	2
Industries	49	18
All countries	188	187
- high income	73	73
- upper middle income	47	46
- low and lower middle income	68	68
- sovereign	166	165
Wage reports	198,502	112,866
No. of years with reports		
- average across countries	21.51	21.31
- standard deviation	14.77	14.71
No. of occupations per report		
- average	76.07	32.86
- standard deviation	44.20	9.38

and this is also the case for the standardized wages.[9] This makes it adviseable to consider all wage reports, and we will hence use the standard deviation of the natural logarithm of occupational wages as a proxy for the skill premium in the descriptive analysis of this section. Because countries do not report wages for all years, we calculate this measure for all (available) country-decade pairs, where the reported occupational wages are averaged within a given decade for a given country and occupation (at constant US$).

Before turning to the descriptive analysis, one may question whether this is indeed a good proxy for the skill premium. To validate, we can compare our proxy with estimated Mincer-returns to schooling from Montenegro and Patrinos (2014) and Psacharopoulos and Patrinos (2004). The estimates reported in these two studies cover mostly the post 1980-period, but include some estimates from the 1960s and 1970s as well. Analogous to our procedure for the wage data, we calculate the decade average if several estimates for a decade are reported. Montenegro and Patrinos (2014) estimate the average returns to schooling by regressing log earnings on the years of schooling and labor market experience, using samples of wage-earning employees from standardized household surveys included in the World Bank I2D2 data base. Psacharopoulos and Patrinos (2004) provide a literature review of estimated returns and the estimates are less standardized. If estimates from both sources are available for a country-decade cell, we use the one from Montenegro and Patrinos (2014). [10]

Conceptually, both proxies for the return to skill differ in a number of aspects. First, Mincer return estimates rely on functional form assumptions of the earnings function, and the evidence provided in Heckman et al. (2006) suggests that estimated skill premia can be sensitive to the choice of specification. By contrast, our proxy for the skill premium does not rely on functional form assumptions. Second, Montenegro and Patrinos (2014) find strong evidence of non-linear returns to schooling, with returns to tertiary schooling being highest. Hence, estimates of the average Mincer returns to schooling depend on the distribution of educational attainments in the population (and even sample if the Mincer regressions do not use sampling weights), whereas our proxy for the skill premium does not. [11] Finally, the ILO October occupations cover a subset of the entire distribution of skill requirements present in an economy, and the OWW includes estimates of male wages, whereas the Mincer returns are often for both sexes. Therefore, on conceptual grounds only, one cannot state that our proxy is clearly better or worse than the common Mincer return estimates as a proxy for skill premia.

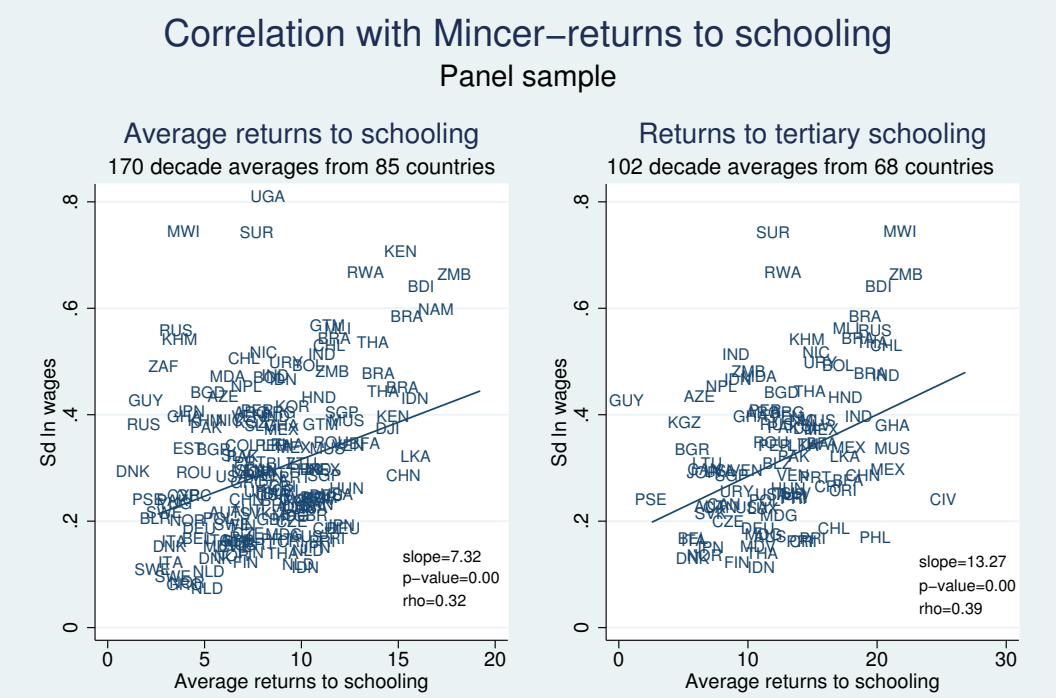
Figure 1 shows that in spite of the conceptual differences, the correlation between both skill premium

[9] Freeman et al. (2011) attempt to minimize this error in the standardization procedure, and show that the standardized wages are robust to choosing alternative weighting schemes.

[10] Montenegro and Patrinos (2014) contains return estimates disaggregated by gender and the level of schooling. From Psacharopoulos and Patrinos (2004), we take the comparable over time estimates of the average return to schooling in Table A4, which is not disaggregated by gender.

[11] Even if returns at all levels of schooling are identical across countries (and highest for tertiary schooling), estimates of the average Mincer returns obtained from a cross-section of employees will -all else equal- tend to be higher in a country in which most employees have completed either secondary or tertiary schooling, as compared to one in which most employees have attained either primary or secondary schooling.

Figure 1: Correlation with Mincer return estimates



Mincer returns from Psacharopoulos (2004) and Montenegro & Patrinos (2014).

measures is strong and highly significant. The left panel shows the correlation with the more widely available average returns to schooling, and the right panel shows the correlation with the estimates of tertiary returns from Montenegro and Patrinos (2014). Correlations with Mincer returns to tertiary schooling are highest, especially in the post 1980 sample where highly skilled occupations are better represented (see Figure 5 in Appendix A).[12] These reasonably strong correlations with the best available Mincer return estimates lend confidence that the OWW data file allows us to study the evolution of skill premia in a sample with a much wider country and coverage than the one for which Mincer return-estimates are available.

Skill premia over time

Comparing this proxy for the skill premium over time raises the issue that the OWW data set is imbalanced - since countries did not report for all occupations in all years, changes in the measured

[12]These Mincer returns are for both sexes. For tertiary schooling, Montenegro and Patrinos (2014) also report returns disaggregated by gender. The correlations increase slightly when using the male Mincer return estimates, to 0.43 for the panel sample (as expected given that the OWW data base includes male wages).

dispersion of wages may be driven by changes in the sample composition. The most direct way of ensuring comparability across time would be to restrict the data set to a set of countries and occupations for which data for all years is available. However, this approach would drastically reduce the representativeness of the sample along both the country and occupation dimension. We address this problem in two different ways. First, we have collapsed the data to decade average wages, correcting for US inflation.[13] This way, one report per decade is sufficient to fill a country-occupation-decade cell, which reduces the imbalancedness of the data set significantly. When several wage reports are available, we take the simple average of these reports, which has the additional benefit of reducing any measurement error. In addition, we also will report results for a sample that is balanced over time by keeping only country-occupation time series for which at most one consecutive occupation-decade cell is empty, and inter- or extrapolating these series using inverse distance weighting.[14] A total of 97 of the 187 countries represented in the panel sample of occupations reported in a sufficient number of decades to stay in this inter/extrapolated balanced sample. Figure 2 plots the evolution of country group-averages of this skill premium for high, middle and low income-countries for both the raw (decade average) wages and balanced sample of wages for the panel sample of occupations. It also depicts the standard deviation of this skill premium across countries for the balanced sample. A reduction of this dispersion indicates a convergence of skill premia across countries.

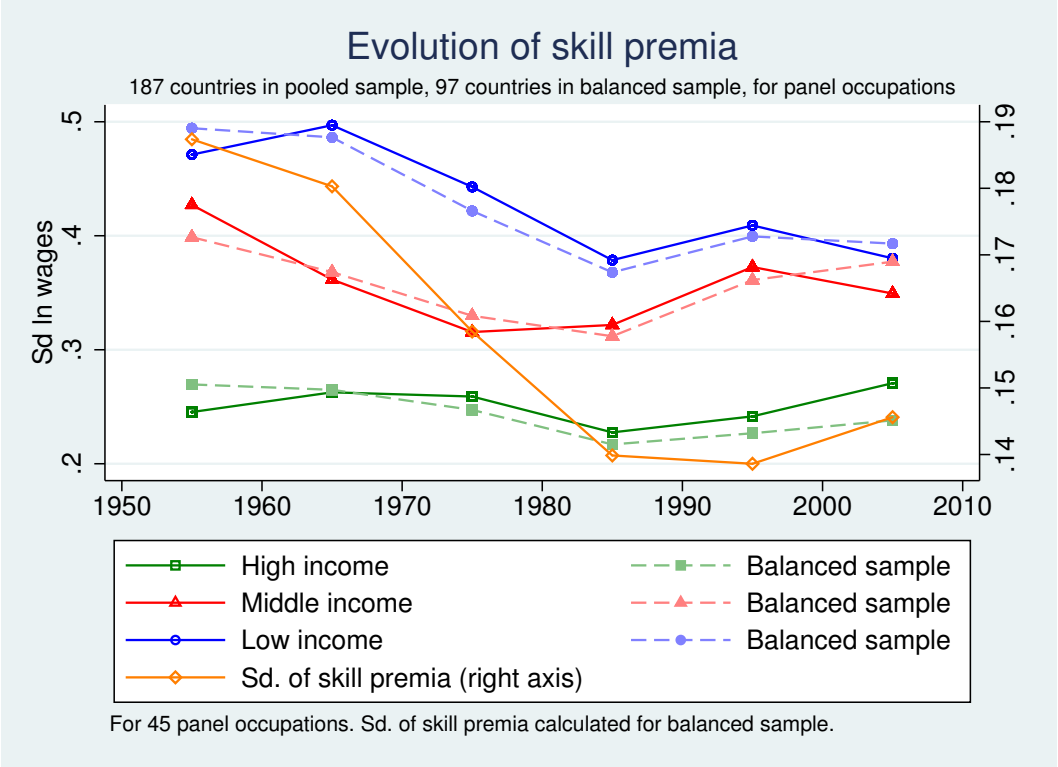
Figure 2 shows that skill premia have been higher in lower income-countries throughout the entire period. This is in line with the findings of an early literature comparing skill premia across countries (Reynolds and Taft 1956, Papola and Bharadwaj 1970). Between the 1950s and the 1980s, the average skill premium decreased in all income groups, and the cross country-average of the balanced sample decreased by 23%. Moreover, since the decrease in skill premia was relatively larger in lower income countries, there was a convergence across countries, cf. the decrease in its cross-country standard deviation. Since then, there has been an increase in skill premia in all country groups, of about 11% on average. Considering the full 1950s-2000s period, the average skill premium decreased by about 15%. Reassuringly, the interpolated series track the series using the raw data relatively closely.[15]

[13]This yields correct domestic annual real wages under the assumption that relative purchasing power parity holds within the decade.

[14]We use inverse distance weighting with the Stata default power of 2: This means that observations from neighboring decades receive a weight of 1, observations from two decades away receive a weight of 1/4, etc. Results are robust to increasing or decreasing the weight of neighboring observations. Note that this approach is conservative in the sense that it makes it harder to find a time trend in the data, as the 16% missing wage observations in the balanced sample are replaced by a weighted average of the available ones.

[15]Moreover, the country group averages are not driven by outliers, and reflect the developments in a substantial majority of countries in all groups. A comparison of the country group-averages relies on the assumption that there are no systematic differences across income groups in terms of which occupations are reported, since the standard deviations are calculated for a number of occupations that can vary across countries also in the balanced sample. We do not find evidence of such differences. Finally, skill premia also increase since the 1980s when including the additional occupations available from 1983 on.

Figure 2: The evolution of skill premia in the panel sample



For 45 panel occupations. Sd. of skill premia calculated for balanced sample.

2.2 Global increase and convergence of relative skill supplies

A prime candidate for explanining the global changes in skill premia are changes in the relative supply of skilled labor, considering a supply and demand-framework in the spirit of Tinbergen (1975). The Barro and Lee (2013) data set on educational attainment contains estimates of educational attainment for 146 countries between 1950 and 2010. Figure 3 plots the evolution of the share of the male population aged 15 and above with secondary and tertiary education.[16]

As the official skill requirement-classification of the October Inquiry-occupations is somewhat imprecise, we can most confidently distinguish between a group of occupations requiring at least skills commonly obtained in secondary education, and a group of occupations unlikely to require these skills. This holds especially true for the panel sample of 45 occupations (see the discussion in Section 2.1, and Table 1). Because of this, the most relevant measure of relative skill supplies is the share of the male population with *at least* some secondary education.[17]

Figure 3 shows first, and unsurprisingly, that relative skill supplies tend to be higher as countries become richer. But second, and importantly, educational attainment has increased dramatically between the 1950s and the 2000s in countries at all income levels. In percentage terms, the increase amounted to 157% in years of education between 1950 and 2010 for males, and even 181% for both sexes. And third, *relative* increases have been largest in low and middle income countries: For instance, the share of the Togolese population with at least secondary schooling increased from 1% in the 1950s to 42% in the 2000s. In the USA, a similar absolute increase over this time period (from 56 to 97% of the population) amounted to a much smaller relative increase. Consequently, there has been a sizeable decline in the cross-country standard deviation of the log attainment measures in Figure 3 over time. Put differently, the convergence of skill premia up to the 1980s documented in subsection 2.1 has been accompanied by a marked convergence of relative skill supplies. Since the 1990s, the picture is less clear, and there appears to have been some divergence of both skill premia and tertiary educational attainment.[18]

3 Skill premia and skill supply

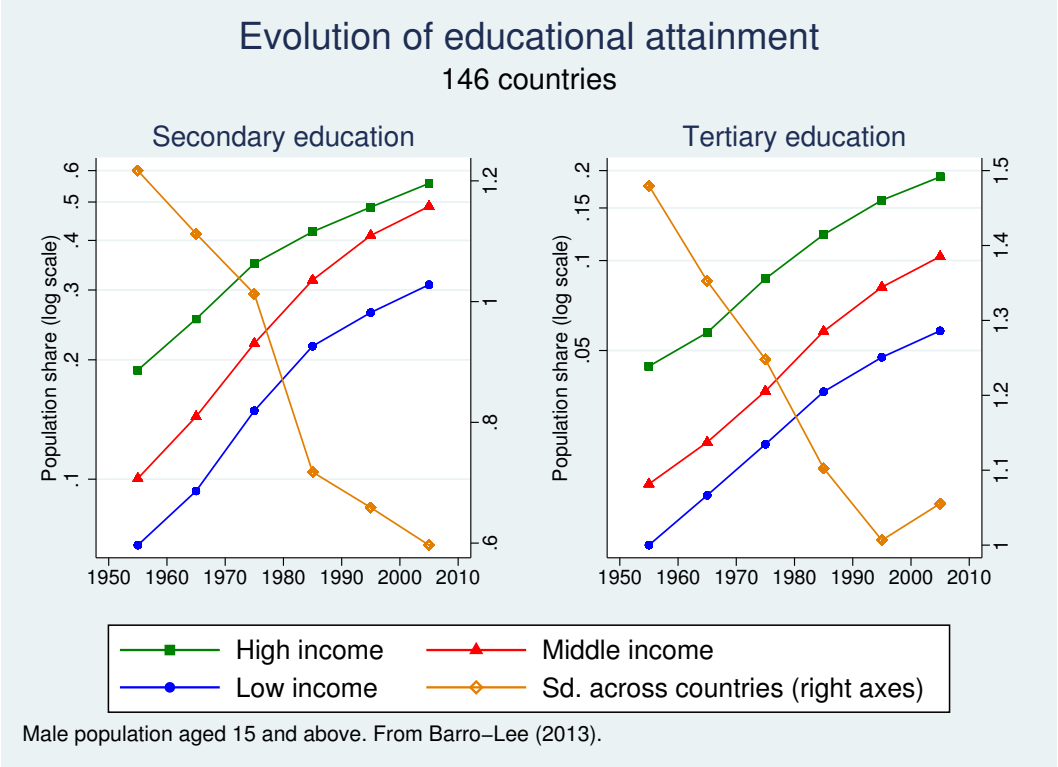
In this section, we will address the question to what extent the global surge and convergence in relative skill supplies can account for the global decline and compression of global skill premia. This is

[16] We report male educational attainment for comparability with our wage data. However, the figure looks very similar if we use the average educational attainment of the total population instead.

[17] With equal participation rates of women and men, and perfect substitutability of female and male labor, what matters for male skill premia is the *total* relative skill supply. However, these assumptions do not hold for many acountries and time periods in our data set, which is why we prefer to use the relative skill supplies of only men. However, all results presented in this paper reamin virtually unchanged when using the average educational attainment instead.

[18] 137 of the 146 countries in the Barro-Lee data base also appear in the OWW data file. The corresponding figures for this sample look very similar.

Figure 3: Educational attainment by decade



Male population aged 15 and above. From Barro–Lee (2013).

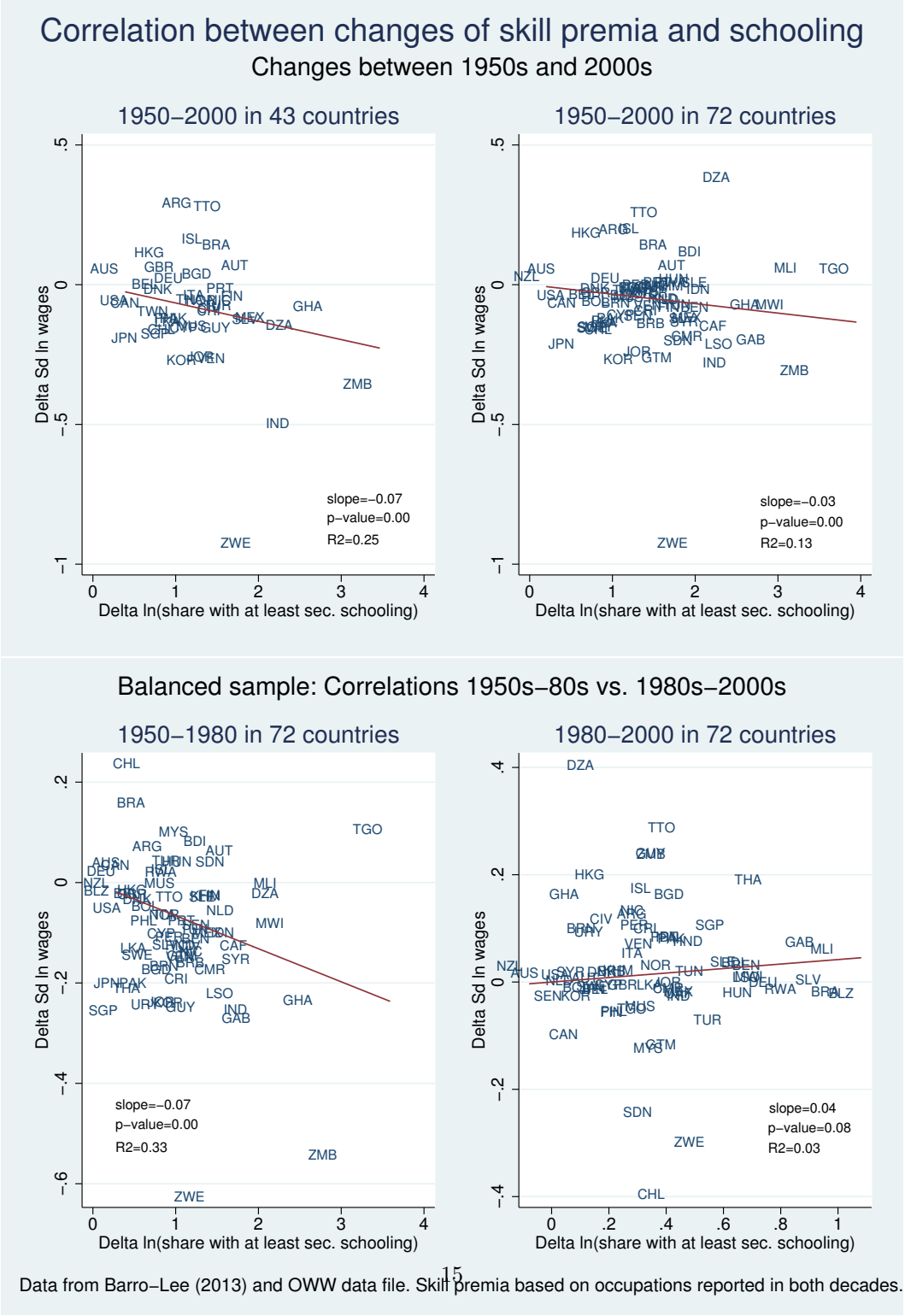
an important question as education is considered an important policy area for societies to influence not only productivity and thereby incomes, but also social equity through a reduction in skill premia. If skill premia are increasingly affected by other factors, such as technological change or the global integration of goods, capital and/or labor markets, then this may reduce the role of education policy in maintaining wage equity. We will first look at the prima facie (bivariate) evidence on the global link between skill supplies and premia across and within countries, followed by a broader supply-demand framework analysis that allows also for other factors (trade, labor market institutions, economic development).

The global link between skill supplies and premia: Prima facie evidence

The data show a strong and negative cross-sectional relationship between skill premia and relative skill supplies across all decades. Table 6 in Appendix B shows this correlation for the earliest and the latest available decade in the sample of panel occupations. However, this correlation is driven by the fact that lower income countries tend to have both higher skill premia and lower relative skill supplies, and the level of income may be correlated with other factors that influence skill premia. Considering time variation only by controling for time invariant country characteristics, Figure 4 plots *changes* in our proxy for the skill premium against *changes* in the log share of the male population with at least seconary schooling. The top left panel shows that among the 43 countries with wage reports in both the 1950s and the 2000s, there has been a significant negative association between changes in the skill premium and changes in the relative skill supply. The right panels plot the corresponding figures for a balanced sample of 72 countries, for which reports for the same occupations are available in all decades after using inter- and extrapolations as described in section 2.1. For this extended sample, the association over the full 60 year period is somewhat weaker, but still negative and significant. This balanced sample also allows us to compare the correlations for subperiods. The bottom panel reveals that increases in schooling correlated strongly and significantly with a reduction of skill premia between the 1950s and the 1980s, but that the correlation becomes *positive* (though only marginally significant) for the 1980s to 2000s period.

This descriptive evidence suggests that from a global perspective, education may have won the "race" between the 1950s and the 1980s - a period of decreasing skill premia, and increasing relative skill supplies -, whereas it lost, globally, between the 1980s and the 2000s, a period of increasing skill premia in many countries in spite of further increases in relative skill supplies. However, it is unclear whether education did indeed lose to technology, or whether other factors, such as as increasing trade or changes in labor market institutions, can (also) account for the increased skill premia.

Figure 4: Correlation between changes in skill premia and educational attainment



Data from Barro–Lee (2013) and OWW data file. Skill premia based on occupations reported in both decades.

Explaining global skill premia in a supply-demand framework

In a spirit similar to the analysis of Goldin and Katz (2008) for the USA, we now use a simple supply-demand framework for the analysis of the evolution of skill premia. The framework contains two principal forces. First, the relative supply of skilled workers, still defined as the share of the population with at least secondary education. Second, the relative demand for skill, which may be changing over time because of skill-biased technological change. To assess the robustness of our results, in the empirical analysis we will also control for measures of general economic development, trade and labor market institutions as plausible alternative drivers of skill premia.

Assume an aggregate production function of the Cobb-Douglas form, which depends on the supplies of both skilled (S) and unskilled workers (U), a technology parameter (α), and total factor productivity (A). The technology parameter captures the relative importance of skilled labor in the production process, which may change over time. We use the term "total factor productivity" as a catch-all term that includes all factors that affect wages other than the relative skill supply, such as the availability of capital or natural resources, and the quality of institutions. Hence, the aggregate production function is given by:

$$Y_t = A_t S_t^{\alpha_t} U_t^{1-\alpha_t} \tag{1}$$

Using the condition that wages equal marginal productivities in a competitive equilibrium, the following expressions for skilled and unskilled wages, and the skill premium, follow:

$$ln(w_{S,t}) = ln\alpha_t + lnA_t - (1-\alpha_t) ln\left(\frac{S_t}{U_t}\right) \tag{2}$$

$$ln(w_{U,t}) = ln(1-\alpha_t) + lnA_t + \alpha_t ln\left(\frac{S_t}{U_t}\right) \tag{3}$$

$$ln\left(\frac{w_{S,t}}{w_{U,t}}\right) = ln\left(\frac{\alpha_t}{1-\alpha_t}\right) - ln\left(\frac{S_t}{U_t}\right) \tag{4}$$

Due to the decreasing returns of each labor type and the assumed complementarity between skilled and unskilled labor, skilled and unskilled wages respond to increases in the relative supply of skilled labor with opposite signs, and the skill premium unambiguously decreases as a result. Moreover, the skill premium increases in the technology parameter α_t. One option would be to estimate Equation 4 directly, using as the dependent variable a proxy for the skill premium, such as the standard deviation of log wages. However, as outlined in section 2.1, the OWW data file does not contain generic “skilled" or “unskilled" wages. Instead, the skill requirement of an occupation should be considered a matter of degree, and every occupational wage is the compensation for labor of a skill level somewhere in the spectrum between the generic “skilled" and “unskilled" labor. Therefore, we base our empirical

analyses on Equations 2 and 3 instead, allowing for more than two skill categories and yielding direct estimates of the production function parameters.

An empirical skill classification of occupations

In order to estimate equations 2 and 3, a skill classification of the different occupations is needed. One option is to make use of the official skill requirements assigned by the ILO. However, as discussed in Section 2.1, this classification is imprecise, with a large variation of skill requirements within the "secondary schooling" category. An alternative, and preferred, option is to use the global ranking of occupations in terms of their average wage as a proxy for their skill requirement.[19]

Specifically, we estimate the relative skill requirements of the occupations by means of the ranking of occupation fixed effects D_o in the following wage decomposition:

$$ln(w_{c,o,t}) = D_c + D_o + D_t + \varepsilon_{c,o,t} \tag{5}$$

Since we include country fixed effects, the coefficients of the occupation-dummies can be interpreted as the average deviation of an occupational wage from the average wage reported by countries.[20]

Our skill classification raises two stability issues that need to be addressed, across countries and time respectively. First, for a global skill classification to yield a reasonable proxy for the relative skill requirements of occupations in all countries, the relative skill requirements of occupations should be similar across countries. The ILO has tried to ensure this comparability by means of providing national statistical agencies with a detailed description of the tasks typically performed by workers in each occupations. If this procedure was successful in harmonizing relative skill requirements of the occupations across countries, the *ranking* of occupations in terms of their wage should be similar across countries, even if skill premia differ. Still, differences in technology (Acemoglu and Autor, 2011) and consumer preferences (Caron et al., 2014) may affect the relative skill requirement of occupations, and are likely correlated with income. Hence, Figure 7 in Appendix B compares the rankings of occupation fixed effects obtained from estimating Equation 5 on the sub-samples of low and and high income countries, labelling each occupation with its October Inquiry code. The Figure shows that in low income countries, "Stenographer-typists" and "Stock records clerks" tended to be relatively better paid, whereas "Miners" tended to have a lower rank in the occupational wage distribution as compared to high income-countries. However, the overall rank correlation is 0.88 (0.83 in the panel sample), indicating that most occupations occupy a similar position in the occupational wage distributions of

[19] In the model by Mincer (1958), for instance, wage premia are the compensation for foregone earnings during the time spent on acquiring the skills required to perform the more demanding tasks.

[20] We include period-dummies in Equation 5 to account of the fact that 114 occupations are included in the data set only from the 1980-period onwards. With a general wage growth trend, the ranking of occupations may otherwise be biased, with the occupations for which also earlier wages are available receiving lower ranks than appropriate.

low and high income countries.[21]

The second issue is that in our analyses we use the evolution of relative occupational wages as a proxy for the evolution of skill premia. For this to be a good proxy, the relative *skill requirements* of occupations should be relatively stable across time, even as observed relative *wages* changed.[22] Again, we would expect the *ranking* of occupations in terms of wages to be similar across time in the absence of strong changes in the relative skill requirements of occupations. Figure 8 in Appendix B compares the occupational wage ranking obtained from estimating Equation 5 for the 1950s with the one from the 2000s, using the balanced (interpolated) sample: Some occupations such as "Loom fixers, tuners" lost ground, whereas others such as "Miners" tended to move up in the occupational wage ranking. However, the strong correlation (rho=0.87) shows that overall, the ranking of occupations in terms of wage is relatively stable over the entire 60 year-period. This suggests that at least when compared to the level of skill requirement-differences between occupations, the changes in these differences have been modest.[23]

In summary, the stability of the occupational ranking across income groups and time supports our interpretation of the ranking of occupation fixed effects as a good proxy for relative skill requirements. Hence, we use this empirical skill requirement classification for most analyses. Specifically, we assign each of the 162 occupations to one of three skill requirement tertiles (each comprising 54 occupations), which we refer to as "high skill", "medium skill", and "low skill" tertile (occupations). [24]

[21] What matters more for the adequancy of our empirical approach are the correlations of the income group-specific rankings of occupations with the global one, which is an average of the country group-specific rankings. These correlations are 0.96 for the sample of all 162 occupations, and 0.94 for the 45 occupations in the long run sample.

[22] Otherwise, the dispersion of wages may for instance have decreased overall not because of declining skill premia, but because of an increasing relative skill requirement of the low-skilled occupations. For instance, the literature on *routine*-biased technological change, initiated by Autor et al. (2003), argues that relative skill requirements of occupations have responded to the spread of ICT as many formerly routine-intensive jobs either disappeared or become more skill-intensive. Note that this particular trend would have an ambiguous effect on our proxy for the skill premium.

[23] In the balanced sample, the correlations of the decade-specific wage rankings of occupations with the global one are 0.96 and 0.94 respectively for the 1950s and the 2000s.

[24] By assigning the occupations to these skill requirement tertiles rather than using the ranks directly, we are agnostic about the relative skill requirements of occupations within each tertile. Comparing this empirical skill requirement-classification with the ILO classification in AppendixF , occupations in the bottom skill tertile tend to require primary or secondary schooling (most likely from the first stage of secondary schooling, although the ILO classification does not distinguish between both stages), occupations in the medium skill tertile tend to require secondary schooling (most likely from the second stage of secondary schooling), and occupations in the high skill tertile tend to require tertiary schooling. Reassuringly, there is a close match between the ILO's and our empirical skill classification: Only two of the 15 occupations classified as requiring primary schooling by the ILO is not in our low skill-tertile, and only 3 of the 35 occupations classified as requiring tertiary education are not in our top skill tertile. There are no cases of potential extreme misclassification, i.e. an occupation that would be high skilled according to the empirical, but low skilled according to the theoretical classification, or vice versa. Of the 45 occupations in the panel sample, 20 occupations belong to the low skill tertile, 18 occupations to the medium skill tertile, and only 7 occupations to the high skill tertile, reflecting the fact that high-skilled occupations are somewhat underrepresented in the long run sample, as is also apparent from the ILO skill classification in Table 1.

Estimating the supply-demand framework

Having thus classified the occupations, we can estimate a generalization of Equations 2 and 3 to test whether increases in the relative skill supplies of a country tended to decrease skill premia, after controlling for a trend in the relative demand for skilled labor. [25] Concretely, we estimate variants of the following equation:

$$ln(w_{c,o,t}) = c + \beta_1 ln(A_{c,t}) + \beta_2 ln(school_{c,t}) + \sum_i \beta_2^i D^i ln(school_{c,t}) \\ + \{D_c\} + \{D_o\} + \{D_t\} + \sum_i \beta_3^i D^i t + X_{c,t}\gamma + \sum_i D^i X_{c,t}\gamma + \varepsilon_{c,o,t} \tag{6}$$

for $i = \{medium, high\}$. The subscripts c, o, t indicate country, occupation and year respectively. $A_{c,t}$ is a (broad concept of) total factor productivity, $school_{c,t}$ stands for relative skill supplies, D^i denotes a dummy taking the value of one if occupation o belongs to the respective skill group, and $\{D_c\}$, $\{D_o\}$, and $\{D_t\}$ denote a set of country, occupation and time period fixed effects respectively. We include country fixed effects to control for time-invariant unobserved characteristics, occupation fixed effects to control for the direct association between skill requirement and wages, and period fixed effects to absorb residual factors, such as changes in the labor share. $X_{c,t}$ is a vector of variables controlling for other factors that may influence skill premia.

Our main coefficients of interest are the coefficients β_2^i, indicating whether the relative wages of higher skilled occupations tended to decrease following increases in the relative skill supply of a country, as well as the coefficients β_3^i, indicating whether there has been a linear residual wage growth trend among the higher skilled occupations. We would expect to find such a trend in the presence of skill-biased technological change (with positive coefficients β_3^i), although it may also capture other trends favoring skilled relative to unskilled labor such as the weakening of labor market institutions. Equation 3 suggests that coefficient β_2, which estimates the effect of increasing relative skill supplies on the wages in the omitted low-skilled category, is positive, reflecting an increasing scarcity of unskilled labor.

As in Section 2.2, our proxy for the relative skill supply is the share of the male population aged 15 and above with at some least secondary education from Barro-Lee, available in five year-intervals for 137 of the countries in the OWW data file. To match the frequency of the Barro-Lee data and reduce measurement error in the wage data, we collapse our wage data to five year averages. To ensure the comparability of wages across countries and over time, we convert the OWW data set into real wages using the price levels from the Penn World Table 9.0 by Feenstra et al. (2015), which reduces

[25] The assumption for treating relative skill supplies as endowments in an aggregate production function is that relative skill supplies are predetermined, and hence inelastic in the short run (cf. Goldin and Katz, 2009). If increases in skilled (unskilled) wages instead increase (decrease) the contemporaneous relative skill supply, our estimates would underestimate the effect of relative skill supplies on skill premia.

the number of countries to 129, accounting for 76% of the observations in the OWW data file.[26] As a proxy for $A_{c,t}$, we use real GDP per capita from the Penn World Table to reflect the fact that $A_{c,t}$ conceptually includes all factors that influence wages other than relative skill supplies in our framework.[27] We cluster standard errors at the country level to account for serial correlation.

Results

Table 2 presents estimates of Equation 6 for the pooled sample without control variables. According to the benchmark specification in column (1), the interaction terms β_2^i are negative and significant: Relative to low skilled wages, a 10% increase in relative skill supply (*school*) is associated with a 0.6% decrease in medium skilled wage, and a 1.9% decrease in high skilled wages.[28] Second, there has been a residual increase in high-skilled relative wages by on average 4.0% per decade, possibly in part due to skill-biased technological change.

Somewhat surprisingly, the main effect estimate indicates that also unskilled wages, the omitted category, are negatively associated with increases in $ln(school)$. There are at least two possible explanations: First, Karabarbounis and Neiman (2014) document a decline in the labor share since the early 1980s in a large number of the countries in their sample. This suggests a decreasing trend in wages even after controlling for the development of real GDP per capita, that may not be fully picked up by the global period dummies. However, in column (2) of Table 8 in Appendix B, the coefficient estimate on $ln(school)$ is not significantly different once we control for the labor share for the sub-sample for which the Penn World Table provides estimates of the labor share. Second, it may be that some of the occupations classified as "low skilled" actually do require secondary education, as suggested by the official ILO-classification in Table 1. In column (3) of Table 8, we use the share of the male population aged 15 and above with tertiary education as a more narrow proxy for the relative supply of skilled labor. The point estimate of the effect of schooling on low skilled wages becomes close to zero and is insignificant, suggesting that this may be part of the explanation. [29]

In column (2), we estimate Equation 6 on a fully balanced panel of decade averages for 66 countries, to assess the robustness of our estimates when accounting for the fact that our sample is imbalanced,

[26] In Section 2, we use US-inflation to correct for price level changes within a decade, which allows us to keep a larger number of countries. Because we now focus on a 60 year-period, the assumption that US inflation is adequate to control for price level changes becomes too restrictive, and we prefer to use the price level-estimates from the Penn World Table.

[27] Using GDP per capita or price level estimates from the World Development Indicators instead yields very similar results.

[28] 100*(exp(-0.067*ln 1.1)-1)=-0.6 and 100*(exp(-0.198*ln 1.1)-1)=-1.9. This is in the ballpark of cross country-results by Rotunno and Wood (2016) for a sample of 40 countries between 1995 and 2009. They distinguish between two skill types, workers with and without college degree, and find that a 10% increase in relative skill supplies is associated with a 2.7% lower skilled wage-premium.

[29] Moreover, the coefficient on GDP per capita is significantly below one, unlike suggested by Equations 2 and 3. Possibly, this is because of measurement error in GDP per capita. An alternative explanation would be that the October Inquiry wage reports tend to be from employees in the formal labor market who enjoy rents that increase less than proportionatelly with GDP per capita.

Table 2: Skill premia and skill supply

Dependent variable: ln real wage

			Measurement error		
	(1) Benchmark	(2) Balanced	(3) Schooling	(4) Wages	(5) Skill req.
ln A	0.682**	0.641**	0.657**	0.819**	0.682**
	(0.070)	(0.081)	(0.104)	(0.128)	(0.070)
ln school	-0.194^{+}	-0.113	-0.316	-0.509^{+}	-0.098
	(0.104)	(0.087)	(0.252)	(0.306)	(0.103)
x *medium skilled*	-0.067**	-0.091**	-0.043**	-0.012	-0.183**
	(0.016)	(0.025)	(0.016)	(0.019)	(0.016)
x *high skilled*	-0.198**	-0.210**	-0.173**	-0.174**	-0.268**
	(0.033)	(0.036)	(0.041)	(0.056)	(0.050)
trend med. skilled	0.000	-0.001	-0.016	-0.006	0.017*
	(0.007)	(0.009)	(0.010)	(0.012)	(0.009)
trend high skilled	0.039*	0.026	0.021	0.033	0.036
	(0.017)	(0.017)	(0.023)	(0.029)	(0.028)
Constant	-6.646**	-4.600**	-1.711	-8.409**	-8.147**
	(1.389)	(1.327)	(2.177)	(2.413)	(1.848)
Observations	53692	11574	24820	22431	53692
R^2	0.783	0.791	0.796	0.810	0.783
Countries	129	66	84	93	129
Intervals	5 year	10 year	10 year	5 year	5 year
Country FE	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓

Trend variables are divided by 10. Column (3) instruments BL schooling with CSL schooling. Column (4) excludes wage observations that were standardized using global adjustment coefficients. Column (5) uses only the 12 occupations requiring primary schooling according to the ILO as omitted category, and classifies only the 45 occupations requiring tertiary schooling as high skilled. Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

and the sample composition therefore changes over time.[30] The results are quite similar although less precise, presumably because of the smaller sample size.

Columns (3)-(5) probe the robustness of our results with respect to measurement error, which is likely to be present in all of our variables. First, the construction of data sets on educational attainment requires combining information from censuses and enrollment rates and hence judgment calls on the part of the authors, for instance due to classification changes over time. Cohen and Soto (2007) and Cohen and Leker (2014) (henceforth CSL) present a data set on average years of schooling in the population above age 15 by decade that they claim to be superior to the Barro and Lee (2013) data. We instrument our Barro-Lee skill supply-proxy with the CSL one for the 84 countries in our sample which are also present in their data base, which takes care of the part of measurement error that is uncorrelated across both data sets (cf. (Krueger and Lindahl, 2001)). Reassuringly, the IV-estimates in column (3) are not significantly different from the OLS estimates for the full sample.

Second, measurement error may also stem from the standardization process used in the OWW. To minimize this measurement error, Freeman et al. (2011) convert reported wages into mean hourly male wages using country-specific adjustment coefficients, whenever the October Inquiry data allows for their estimation. Only if this is not possible, they use the estimated adjustment factors from the pooled sample of all countries, for instance to transform wages for both sexes into male wages for countries that did not report wages disaggregated by gender. In column (4), we present estimates for the sub-sample for which wages were either directly reported by the country in the standard format (i.e., as average male hourly wages), or where the more reliable country-specific adjustment coefficients could be estimated. For this sub-sample, we cannot reject the hypothesis that low and medium-skilled wages were equally affected by schooling increases, but the coefficient on the interaction term for high skilled wages is not significantly different from the one for the pooled sample.

Finally, column (5) presents the results of using the “theoretical" skill requirement classification provided by the ILO, using only the 15 occupations classified as requiring primary schooling as the omitted category, the 112 occupations classified as requiring some level of secondary schooling as medium skilled, and the 35 occupations classified as requiring tertiary education as high skilled (cf. Table 1). The results remain very similar with increasing skill supplies tending to reduce skill premia.[31]

[30] For instance, the trend estimate may be picking up differences in skill premia between countries who drop out and enter the sample from one period to another. In the balanced sample, 17% of wages have been inter- or extrapolated, following the same procedure as in procedure as in the previous section. As compared to the sample used in Figure 4, we lose 6 countries not included in the Penn World Table for which we could not construct real wages. The income group-composition of this balanced sample is very similar to the pooled sample: 39% of observations are from high income-countries (vs. 43% for the pooled sample), 22% from upper middle income-countries (vs. 23%) and 40% from low income countries (vs. 33%).

[31] Since only 12 % of observations in the estimation sample are classfied and “unskilled" and 15% as “skilled" when using the official classification, we will use the empirical skill classification within the remaining analyses.

Controlling for heterogeneity and omitted factors

The pooled estimation results in Table 2 covering a large sample of countries and years may hide heterogeneity, such as between high income and other countries (for instance due to differences in the quality of schooling, as argued by Pritchett et al., 2013), and across time periods (for instance due to a changing pace of skill-biased technological change). Table 3 therefore presents estimates disaggregated by income group and time period.

Table 3: Skill premia and skill supply: Subsample analyses

Dependent variable: ln real wage

		By income		1953-79	1980-08	
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	High	Other	Panel	Panel	Pooled
ln A	0.682**	0.555**	0.567**	0.592**	0.626**	0.629**
	(0.070)	(0.071)	(0.096)	(0.123)	(0.117)	(0.111)
ln school	-0.194^{+}	0.156	-0.146	0.002	-0.429	-0.257
	(0.104)	(0.116)	(0.159)	(0.080)	(0.342)	(0.280)
x *medium skilled*	-0.067**	-0.016	-0.056*	-0.088**	-0.052*	-0.037
	(0.016)	(0.031)	(0.024)	(0.018)	(0.024)	(0.024)
x *high skilled*	-0.198**	-0.303**	-0.142**	-0.231**	-0.227**	-0.190**
	(0.033)	(0.074)	(0.044)	(0.030)	(0.041)	(0.046)
trend med. skilled	0.000	-0.000	-0.019	0.004	0.001	0.014
	(0.007)	(0.009)	(0.015)	(0.015)	(0.013)	(0.011)
trend high skilled	0.039*	0.076**	0.003	0.050*	0.081**	0.044
	(0.017)	(0.022)	(0.030)	(0.024)	(0.026)	(0.031)
Constant	-6.646**	-6.988**	-2.325	-4.810*	-6.803**	-7.916**
	(1.389)	(1.514)	(2.414)	(1.996)	(1.743)	(2.608)
Observations	53692	23234	30458	15321	13075	37439
R^2	0.783	0.838	0.610	0.771	0.840	0.824
Countries	129	48	81	106	121	122
Intervals	5 year	5 year	5 year	5 year	5 year	5 year
Country FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Trend variables are divided by 10. Panel sample consists of 45 occupations reported throughout. Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Columns (2) shows that for high income-countries, the effect of increases in relative skill supplies on relative wages conforms with the prediction of Equations 2 and 3: Unskilled wages increase (albeit insignificantly), whereas high skilled wages decrease. For other than high income-countries, column (3) shows that all schooling coefficients are negative, and the medium and high skill-interactions

are significant. This is consistent with the view that relative to the overall labor market (which includes informal (self-) employment), the October Inquiry-occupations are more highly skilled in low and middle income-countries, so that also wages in lower skilled-occupations decrease significantly in response to an increase in relative skill supplies. The strongest difference across the two income groups can be found with respect to the estimated time trends, however - showing that the positive trend-estimate for high skilled-occupations is entirely driven by high income countries, with a large 7.9% residual increase in high-skilled wages per decade in the latter. Possibly, this reflects a faster adoption of skill-biased technologies in high income countries relative to low income countries, as found by Berman and Machin (2000) and Meschi and Vivarelli (2009).

Columns (4) to (6) show that when splitting the time period into an early period (up to 1979) and a late period, the skill supply-coefficients are similar for the panel sample (and somewhat higher than for the sample that includes the additional occupations reported only between 1983 and 2008). Interestingly, the trend estimate for highly skilled wages is stronger in the later than early period (0.08 vs. 0.05, p-value= 0.11), consistent with the evidence of skill-biased technological change after the 1980s from a large number of countries in the literature (for instance, see Jaumotte et al. 2013, Michaels et al. 2014). [32] When including the additional 114 occupations only available from 1983 on (column 6), the high-skilled trend estimate becomes insignificant. Arguably, this is because these additional occupations include a higher share of occupations in service-sectors, which may have been less affected by skill-biased technological change. When adding only the observations from the 31 additional manufacturing occupations (results not reported), the trend estimate remains significant, and insignificantly different from the one in column (5).

Because skill premia may also reflect other factors, in Table 9 of Appendix B, we control for other plausible drivers of skill premia such as general economic development, trade, or labor market institutions. In column (2), we allow economic development to have a direct effect on skill premia, to address the concern that the (correlated) relative skill supply-variable is just picking up some other mechanisms through which economic development compresses skill premia. However, the skill group interaction terms of log GDP per capita are insignificant, and their inclusion does not significantly change the coefficients on the schooling interactions.

Considering trade, Heckscher-Ohlin theory predicts a positive effect on skill premia in high income, but a negative effect in low income-countries. Hence, in columns (3) and (4) we estimate models including interactions with the log of (trade/GDP) separately for high income and other countries.[33] For both high income and other countries, the point estimates for low skilled wages are negative, and for skilled

[32] In the balanced sample, this trend is of a similar order of magnitude, and only significant for the post 1979 period (not shown, results available upon request).

[33] We use the natural logarithm of the trade/GDP ratio since we deem it plausible that the same absolute change in the trade/GDP ratio has a larger effect on skill premia in relatively closed economies. Using the level of trade/GDP instead yields larger and more significant estimates, which are however sensitive to the exclusion of outliers with respect to the trade/GDP variable.

wages are positive, yet modest and jointly marginally insignificant .[34] This is not entirely surprising, as studies using aggregate data have tended to find positive, yet small increases in skill premia in high income countries, and the literature has documented instances of both increasing and decreasing skill premia in low income countries following trade liberalization, and proposed a range of theoretical mechanisms (see Wood 1997, Goldberg and Pavcnik 2007, and Burstein and Vogel 2016).[35]

In column (5), we control for union density from the ICTWSS data base by Jelle Visser (2016) for a sub-sample of 44 countries for which union density data is available. The estimates suggest a strong skill premia-reducing effect of union strength: An increase in union density by one standard deviation (21 percentage points) is associated with a 9.1% decrease in the high skilled-premium. The finding that strong labor market institutions tend to compress wage structures is in line with the country studies in Katz (1993), and the review by Freeman (1998).

Most importantly, the coefficient estimates on the interactions between relative skill supplies and skill group-dummies remain negative and significant across all specifications, and do not change significantly compared to the respective sub-sample when omitting the control variable. Also the residual skill-biased wage growth trends retain their sign and significance level. This is also true for column (6), where all controls are included jointly. In summary, the results in Table 9 in Appendix B lend support to our preferred interpretation of the results in Tables 2 and 3: The considerable increases in the relative supplies of skill over the past six decades have worked towards decreasing skill premia across countries and sub-periods.

The historical impact of changes in skill supply and technology on global skill premia

To get a sense of the order of magnitude of the global skill premia changes induced by the global changes in relative skill supplies and technology over the past 60 years, we compare the actual skill premia with counterfactual ones estimated using the coefficient estimates from Equation 6. Specifically, we calculate counterfactual wages by setting the value of the relative skill supply, or the time trend, equal to the respective value at some other point in time.[36] Comparing the skill premia of this wage distribution with the actual one provides us with an estimate of how different skill premia would have been if schooling, or the technology, had remained the same. Again, we use “technology" as a catch-all term for skill-biased technological change and other trending variables that increase skill premia.[37]

[34] The trade-variables are jointly only marginally insignificant for both high income (p-value=0.11) and other (p-value=0.16) countries.

[35] We do not find stronger effects of trade on skill premia when restricting the sample to occupations that are arguably most exposed to competition from trade.

[36] We use the coefficient estimates from estimating Equation 6 using the observations from the respective sub-period of interest.

[37] From the discussion in Section 3, the expansion of trade and the decline in union densities are likely to have contributed to the increase in skill premia.

Table 4: Skill premia simulations

Actual vs. counterfactual skill premia

		With 1950-values for:				With 1980-values for:			
	Actual	School	Δ(%)	Trend	Δ(%)	School	Δ(%)	Trend	Δ(%)
All countries:									
1950 Mean	0.38								
1980 Mean	0.29	0.35	19.01	0.30	0.86*				
2000 Mean	0.33	0.41	22.75	0.32	-3.83*				
2000 Mean	0.33					0.35	5.98	0.32	-5.09
1950 Sd	0.20								
1980 Sd	0.14	0.16	11.32	0.14	-1.81*				
2000 Sd	0.15	0.18	13.52	0.15	-2.68*				
2000 Sd	0.15					0.16	5.10	0.15	-1.12
High income-countries:									
1950 Mean	0.26								
1980 Mean	0.22	0.24	10.16	0.24	9.07				
2000 Mean	0.25	0.29	15.14	0.26	5.30*				
2000 Mean	0.25					0.27	6.70	0.23	-6.99
1950 Sd	0.12								
1980 Sd	0.11	0.11	6.10	0.10	-8.05				
2000 Sd	0.14	0.14	2.02	0.14	-2.39*				
2000 Sd	0.14					0.14	2.32	0.14	-1.03

* Trend-skill interactions insignificant at 10%.

Estimates for 66 countries/ 25 high income countries in balanced sample.

In order to be able to compare different sub-periods with each other, we do this exercise using the balanced sample of 66 countries. Column (3) in Table 2 shows that the coefficient estimates for this subsample are very similar to those for the pooled sample, and also its income group-composition is representative. We again use the standard deviation of log wages as our proxy for the skill premium.

The simulations in Table 4 for all countries suggest that if schooling had remained constant between the 1950s and the 2000s, skill premia in the 2000s would be 23% higher overall. This would more than offset the observed decrease in skill premia since the 1950s from Figure 2. Also the cross-country differences in skill premia would be larger, reflected in a 14% higher standard deviation of skill premia across countries. By contrast, the trend estimates suggest that on average, skill premia would be only 4% lower if technology had remained constant. Hence, this exercise suggests that over the long run and from a global perspective, the large increase in relative skill supplies have on average had a more substantial impact on skill premia than changes in technology, to the extent that these are picked up

by our trend estimate.

A comparison of the 1950s-1980s and 1980s-2000s subperiods reveals that in particular the large increases in the earlier period are estimated to have had a large effect on skill premia. For the 1980s-2000s period, the effects of skill supplies and technology are of a similar order of magnitude: Counterfactual skill premia are estimated to be about 6% higher without the schooling increases, and about 5% lower without technological change. Note that the trend growth of high-skilled wages is a global average. From Table 3, we know that this average pools high income countries -with a significant high-skilled trend estimate- and other countries, who for which we do not find evidence of such a trend. For the high income countries in the balanced sample, the counterfactual decrease in skill premia if technology had remained at its 1980s level is larger (7% vs. 5%), whereas the increase if schooling had stayed the same since the 1950s is not as large (15% vs. 23%).

This simulation suggests that for both groups of countries, the counterfactual skill premia in the 2000s would be approximately the same as the actual ones if both schooling and technology had remained at their 1980s level. Using Tinbergen's metaphor, the simulation implies a tied race between technology and education over that period, with relative skill supplies expanding at a rate roughly sufficient to offset the skill premia-increasing effect of skill-biased technological change. However, as shown in Figure 2, technology "won" during this period in countries of all income groups, as skill premia tended to increase.[38] Possibly, this is because country-level developments were too heterogeneous to be approximated well by a global trend. Nevertheless, the simulations suggest that the large increases in relative supplies during the 1950s-1980s period have played a key role in the reduction of skill premia around the world, and that the continued expansion of relative skill supplies between the 1980s and 2000s has dampened the increase in skill premia.

4 Skill premia and their proximate determinants

A model of relative skill supplies and skill premia

The evidence so far suggests that a substantial part of the changes in the observed cross-country differences in skill premia can be accounted for by the large cross-country differences in relative skill supplies documented in Section 2.2. However, the supply-demand framework guiding our analyses used takes relative skill supplies as given, and is hence unable to account for the large cross-country differences in skill supplies themselves. Also the previous literature linking cross-country returns to skill to relative skill supplies does not attempt to open the "black box" of relative skill supplies (for instance, Denny et al. (2002) and Montenegro and Patrinos (2014)). In this section, we propose a modified Solow model to explain how skill premia depend on a number of standard growth theory

[38] Reproducing Figure 2 for the countries and occupations in the balanced sample yields a similar pattern.

parameters, namely a human capital savings rate, technology parameters, and population growth. We then show that, empirically, these parameters are indeed predictive of relative skill supplies and skill premia.

As before in the supply-demand framework, we start from an aggregate production function given by Equation 1. We assume that countries devote a share s of output to invest in education, to transform unskilled labor U into skilled labor S, and denote the unit skill price in units of output by p.[39] Therefore a total investment of sY will increase S by sY/p, and reduce U by the same amount. Intuitively, we divide the total investment of output, sY, by the cost of transforming one unskilled worker into a skilled worker, given by p, to obtain the total number of unskilled workers who become skilled. We also assume that without investment, the relative supply of skilled workers decreases over time due to depreciation of knowledge, and the rate of skill depreciation is such that δS skilled workers become unskilled again in every period. Moreover, the population grows at rate n, and newly born workers are unskilled. We abstract from investment in physical capital in this model.

These assumptions imply that the time change in U_t and S_t are given by (ignoring the time index t):

$$\dot{S} = \frac{sY}{p} - \delta S \tag{7}$$

$$\dot{U} = n(U+S) - \frac{sY}{p} + \delta S \tag{8}$$

The model as represented by Equations 1, 7 and 8 corresponds to a variant of the Solow model where skilled labor instead of capital is accumulated, with the difference that investments in skilled labor reduce the availability of unskilled labor. For simplicity, we define $\tilde{s} \equiv \frac{s}{p}$, and refer to it as the "effective" savings rate, given that it reflects the unit skill cost in output terms.

In order to solve the model for the steady state relative skill supply, S/U, we divide Equation 7 by S and Equation 8 by U, and substitute for Y. Defining $l \equiv \frac{S}{U}$, rearranging yields:

$$\frac{\dot{S}}{S} = \tilde{s}Al^{-(1-\alpha)} - \delta \tag{9}$$

$$\frac{\dot{U}}{U} = n + nl - \tilde{s}Al^{\alpha} + \delta l \tag{10}$$

Consider the steady state where U and S are growing at some constant rate of γ_U and γ_S respectively. Then, it can be shown that $\gamma_U = \gamma_S = n$.[40] Moreover, in the steady state, 10 holds if and only if 9

[39] The unit skill price p reflects the technology of skill production (cf. Rosenzweig (2010)).

[40] Proof by contradiction: Given that $\frac{U}{U+S}\gamma_U + \frac{S}{U+S}\gamma_S = n$, then if $\exists i \in \{S,U\}$ such that $\gamma_i < n \Rightarrow \exists j \in \{S,U\}$ such that $\gamma_j > n$. For instance, assume that $\gamma_S > n$. Further assume that the economy is in the steady state from period $\bar{t}$

holds[41] and we can use Equation 10 to solve for the steady state relative skill supply:

$$l^* = \left(\frac{\tilde{s}A}{n+\delta}\right)^{1/(1-\alpha)} \tag{11}$$

Using Equations 2 and 3, the steady state wages are given by:

$$w_S^* = \alpha A(l^*)^{-(1-\alpha)} = \alpha\left(\frac{\tilde{s}}{n+\delta}\right)^{-1} \tag{12}$$

$$w_U^* = (1-\alpha)A\,(l^*)^{\alpha} = (1-\alpha)A^{1/(1-\alpha)}\left(\frac{\tilde{s}}{n+\delta}\right)^{\alpha/(1-\alpha)} \tag{13}$$

Rewriting these expressions in log form yields:

$$lnw_S^* = ln\alpha - ln\tilde{s} + ln(n+\delta) \tag{14}$$

$$lnw_U^* = ln(1-\alpha) + \frac{1}{1-\alpha}lnA + \frac{\alpha}{1-\alpha}ln\tilde{s} - \frac{\alpha}{1-\alpha}ln(n+\delta) \tag{15}$$

From Equations 14 and 15, the skill premium in the steady state is given by:

$$ln\left(\frac{w_S^*}{w_U^*}\right) = ln\left(\frac{\alpha}{1-\alpha}\right) - \frac{1}{1-\alpha}lnA - \frac{1}{1-\alpha}ln\tilde{s} + \frac{1}{1-\alpha}ln(n+\delta) \tag{16}$$

Hence, the skill premium decreases if the effective human capital savings rate ($\tilde{s}$) increases, and increases if the population grows more quickly (n increases), or skills depreciate at a faster rate (δ increases). Intuitively, a higher population growth implies that relatively fewer workers can become educated for any given investment $\tilde{s}Y$.[42] Interestingly, the skill premium also decreases in the total factor productivity, in line with the empirical finding that richer countries tend to have a lower skill premium than poorer countries. In our model, this reflects the fact that for a given $\tilde{s}$, economies with higher levels of productivity will save and therefore invest more in absolute terms, which increases the relative supply of skilled labor and drives down the skill premium.[43]

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onwards, and hence $X_t = X_{\bar{t}}e^{\gamma_X(t-\bar{t})}$, $X = S, U$. Then $1 > \frac{S}{S+U} = \frac{S_{\bar{t}}e^{\gamma_S(t-\bar{t})}}{(S_{\bar{t}}+U_{\bar{t}})e^{n(t-\bar{t})}} = \frac{S_{\bar{t}}}{S_{\bar{t}}+U_{\bar{t}}}e^{(\gamma_S-n)(t-\bar{t})}$, which will be violated as $e^{(\gamma_S-n)t} \to \infty$ when $t \to \infty$ given that $\gamma_S > n$. An analogous contradiction results if we assume that $\gamma_U > n$. Hence, it must be the case that $\gamma_S = \gamma_U = n$ in a steady state.

[41] This can be seen by noting that in the steady state $\frac{\dot{U}}{U} = \frac{\dot{S}}{S} = n$ and that $n = n + nl - \tilde{s}Al^{-(1-\alpha)} + \delta l \leftrightarrow \tilde{s}Al^{-(1-\alpha)} - \delta = n$.

[42] Unlike in Section 3, the effect of increases in α on skill premia is no longer unambigously positive since increases in α can have the indirect effect of increasing l^*.

[43] For the Cobb-Douglas production function, the direct and the indirect effect of productivity increases on skilled wages

Note that this is true because we assume that the price of skill, p, is independent of A.[44] While this is a strong assumption since, for instance, wage costs for teachers are likely to increase in A, our result goes through as long as the price of skill increases less than proportionately with A, which we would expect in the presence of fixed costs in the provision schooling (for instance, building schools), or tradable inputs in the production of skill.[45]

We can provide empirical support for this as follows. A testable corollary of the assumption that schooling prices increase less than proportionnaly in A is that variations in GDP per capita have a larger impact on proxies for the output of the education system than on expenditure measures relative to GDP.[46] One proxy for the output of an education system are enrollment rates. Figure 9 in Appendix C shows that there is indeed a much stronger correlation between log GDP per capita and secondary enrollment than between log GDP per capita and the share of GDP that is spent on education by the government, even when we control for the share of the population that is of secondary schooling age. The same pattern holds true for enrollment in tertiary education (not shown).[47]

Assuming that countries are in their steady state in each period, one can gauge the empirical validity of the model in a pooled regression without country fixed effects, exploiting variation in the variables across both countries and time. Equations 14 and 15 suggest the estimation of variants of the following equation:

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offset each other, so that skilled wages in the steady state do not depend on A (see Equation 12). More realistically, skilled wages will increase in A if we assume a CES production function. However, the key finding that the steady state skill premium decreases in A holds in the Cobb-Douglas case (as in the CES case).

[44] To see this, consider Equation 7, keeping in mind that $Y = AS^{\alpha}U^{1-\alpha}$: If p increased proportionately with A, increases in A would not affect the number of unskilled workers who become skilled in each period.

[45] In addition, it may be that the price of skill increases less than proportionately with A because economic development is associated with a general increase in the efficiency of public service provision, for instance due to reduced corruption (cf. Gundlach and Paldam 2009)

[46] Intuitively, compare the effect on educational spending of an increasein GDP per capita by 1% in a high and a low income country: If the skill price increases more slowly than GDP, the real increase in educational expenditures will be larger in the high income country.

[47] Econometrically, this implies that enrollment should be more responsive to spending relative to GDP at higher income levels. To test this prediction, we run regressions of the form $enroll_{c,t} = \alpha + \beta_1 spending_{c,t} + \beta_2 ln(income)_{c,t} + \beta_3 spending_{c,t} * ln(income)_{c,t} + \beta_4 enrollage_{c,t} + \varepsilon_{c,t}$ for secondary and tertiary education, using data from the UNESCO UIS data base and the Penn World Table 9.0. *enrollage* Is the share of the population of enrollment age, correlated with both income and enrollment rates. We use total spending on education since disaggregated data are less widely available. Estimates of β_3 are positive and significant for a sample of 160 countries between 1970 and 2015 (p-values of 0.04 and 0.00 respectively, with standard errors clustered at the country level). Hence, increases in spending on education relative to GDP do indeed translate into larger increases in the output of the education system in higher income countries, even after controlling for the share of population among which the spending is distributed. One caveat is that our data on public spending on education includes government subsidies to private schools, but no private expenditures on education. Since differences in the degree to which education is privatized are especially large across countries, country fixed effects may alleviate this concern. The introduction of country fixed effects renders $\hat{\beta}$ insignificant for secondary enrollment, whereas it remains highly significant for tertiary enrollment (p-value = 0.00). These results are available upon request.

$$ln(w_{c,o,t}) = c + \beta_1 ln(A_{c,t}) + \sum_i \beta_1^i D^i ln(A_{c,t}) + \beta_2 ln(\tilde{s}_{c,t}) + \sum_i \beta_2^i D^i ln(\tilde{s}_{c,t}) \quad (17)$$
$$+ \beta_3 ln(n_{c,t} + \delta) + \sum_i \beta_3^i D^i ln(n_{c,t} + \delta)$$
$$+ \{D_o\} + \{D_t\} + \sum_i \beta_3^i D^i t + \varepsilon_{c,o,t}$$

The model implies negative coefficients β_1^i and β_2^i, and positive coefficients β_3^i, with $i = \{medium, high\}$ and also the rest of the notation being the same as before. As before, we use real GDP per capita from the Penn World Table 9.0 as our proxy for A. To obtain a proxy for n, we use the average annual growth rate of the working age population from the World Development Indicators. For the human capital depreciation rate δ, we follow Mankiw et al. (1992) and set it equal to a plausible average depreciation rate for capital. We select 4.5%, as this is the global mean annual capital depreciation rate in the Penn World Table.[48]

To obtain a proxy for the real human capital savings rate, we start from Equation 7: $\dot{S} = \frac{sY}{p} - \delta S$. Solving for $\frac{s}{p} \equiv \tilde{s}$, we get:

$$\tilde{s} = \frac{(\frac{\dot{S}}{S} + \delta)S}{Y} \quad (18)$$

In the steady state -for which we have derived the wage Equations 14 and 15- , the growth rate of skilled (and unskilled) labor equals n. Hence, in steady state:

$$\tilde{s} = \frac{(n + \delta)S}{Y} \quad (19)$$

We construct our proxy for $\tilde{s}$ based on Equation 19, using the proxy for $(n + \delta)$ described above, real GDP from the PWT, and calculating the number of skilled people by multiplying the share of the male population with at least secondary education from Barro-Lee with the working age population. Intuitively, the change in the number of skilled people relative to GDP is a proxy for the output share devoted to education, after adjusting for differences in the skill price.[49]

[48] Conveniently, there are no negative values for the variable $n + \delta$ with this choice, which would otherwise result in a loss of the observations since the variables enters in log-form in the empirical specification.

[49] Conceptually, population growth and population should be "male only". However, gender disaggregated data are not available, and this should not matter much as the male numbers can be expected to be roughly proportional to the numbers for the total population. Second, note that input variables such as spending on education as a share of GDP would be an adequate alternative proxy for $\tilde{s}$ only if p were constant across countries and time, and included public as well as private expenditures on education. Empirically, there is more cross country-variation in our proxy for $\tilde{s}$ than in the available data on educational spending relative to GDP. Moreover, educational spending relative to GDP tends to be somewhat higher in high income countries, whereas $\tilde{s}$ is lower in high income countries, consistent with the view that p increases with income.

Results

Table 5 presents the results from estimating Equation 17. Since data on the working age-population are only available from 1960 on, we use the total population in column (1) for full comparability in terms of period coverage with column (1) in Table 2. For columns (2)-(6) we use the working age population, as described above. The high skilled and most medium skilled interaction terms are significant across all specifications, and have the expected sign: According to our main specification in column (2), a 10% increase in GDP per capita is associated with a 1.8% decrease in the high skill-premium.[50] Interestingly, the GDP per capita interactions are insignificant in specifications that include the relative skill supplies directly (see column (2) in Table 9 of Appendix C- the exclusion of country fixed effect in this specification does not change the insignificance of the GDP per capita interaction terms). This supports the assumption of the model that economic development affects skill premia primarily by altering relative skill supplies. Further, a 10% increase in the real human capital savings rate is estimated to decrease high skilled-premia by 2.4%, whereas a 10% increase in $(n + \delta)$ is associated with a 5.3% increase in high skilled-premia.[51] Effects tend to be somewhat larger and more precisely estimated in high income-countries as compared to other countries (cf. columns (3) vs. (4)), and for the 1953-1979 period as compared to the 1980-2008 period (cf. columns (5) and (6)).

Instead of exploiting the cross-sectional variation across countries and time, we can also assess whether within countries, *changes in* the hypothesized steady state-determinants correlate with *changes in* skill premia. Since it takes time for changes in total factor productivity, the human capital savings rate, or population growth to translate into relative skill supplies on the labor market, the question then becomes whether lagged values of the proximate determinants predict skill premia. For a model of transition to the steady state, it is more appropriate to construct our proxy for $\tilde{s}$ based on Equation 18 rather than its steady state equivalent 19.[52]

The choice of lag length is constrained by the lack of data before the 1950s. Columns (1)-(4) in Table 10 in Appendix C show the results from regressing relative skill supplies (5-year averages) on up to four lags of the proximate determinants.[53] The results indicate that the three variables jointly explain more than 90% of the within country-variation of relative skill supplies once all four lags are included, and that the longest lags tend to be most predictive of contemporaneous relative skill supplies. The latter is plausible as a four period lag corresponds to conditions 16-24 years ago. Therefore, we proceed by testing whether four period lags of the proximate determinants of relative skill supplies correlate with contemporaneous skill premia in the way that is predicted by the model.

[50] 100*(exp(-0.195*ln 1.1)-1)=-1.8

[51] 100*(exp(0.541*ln 1.1)-1)=5.3

[52] Since the share of skilled workers is only available in 5 year-intervals, we use the change from one interval to another, and thus cannot calculate a change for the 1950 period. In order not to lose two additional periods due to the lack of information on the share of working age population in the 1950s, we extrapolate the working age population for this decade using inverse distance weighting.

[53] Hence, relative skill supplies from 1970 on can be included in these estimations.

Table 5: Skill premia and their proximate determinants: Cross sectional evidence

Dependent variable: ln real wage

	By population		By income		Panel sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	W-age	High	Other	1953-79	1980-08
ln A	0.505**	0.528**	1.264**	0.312**	0.504**	0.505**
	(0.059)	(0.065)	(0.118)	(0.095)	(0.044)	(0.109)
x *medium skilled*	-0.066**	-0.058**	-0.045	-0.048+	-0.064**	-0.027
	(0.021)	(0.020)	(0.051)	(0.029)	(0.018)	(0.037)
x *high skilled*	-0.224**	-0.195**	-0.386**	-0.154*	-0.242**	-0.188**
	(0.039)	(0.040)	(0.084)	(0.059)	(0.031)	(0.050)
ln s	-0.164**	-0.188**	0.368**	-0.207**	-0.103	-0.217*
	(0.054)	(0.057)	(0.102)	(0.070)	(0.065)	(0.097)
x *medium skilled*	-0.089**	-0.084**	-0.004	-0.083**	-0.044*	-0.032
	(0.021)	(0.020)	(0.039)	(0.023)	(0.022)	(0.040)
x *high skilled*	-0.282**	-0.256**	-0.308**	-0.237**	-0.122**	-0.146*
	(0.051)	(0.052)	(0.077)	(0.063)	(0.034)	(0.058)
ln (n+delta)	-0.037	-0.229	-0.860**	0.134	-0.293	-0.298
	(0.138)	(0.163)	(0.309)	(0.177)	(0.196)	(0.192)
x *medium skilled*	0.130**	0.135**	0.148*	0.062	0.224**	0.039
	(0.049)	(0.044)	(0.064)	(0.065)	(0.059)	(0.061)
x *high skilled*	0.522**	0.541**	0.891**	0.300+	0.486**	0.277**
	(0.100)	(0.100)	(0.133)	(0.156)	(0.123)	(0.101)
trend med. skilled	0.004	0.003	0.010	-0.011	-0.048*	0.004
	(0.008)	(0.009)	(0.013)	(0.013)	(0.021)	(0.015)
trend high skilled	0.067**	0.055*	0.107**	0.036	-0.033	0.082**
	(0.019)	(0.022)	(0.022)	(0.035)	(0.032)	(0.027)
Constant	-5.322**	-5.900**	-17.481**	-1.440	1.826	-6.140*
	(1.349)	(1.596)	(2.419)	(2.483)	(2.480)	(2.387)
Observations	53552	49667	20859	28808	11631	13044
R^2	0.623	0.631	0.661	0.401	0.544	0.626
Countries	129	128	47	81	104	120
Intervals	5 year	5 year	5 year	5 year	5 year	5 year
Occupation FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Trend variables are divided by 10. Columns (2)-(6) for working age population..

Panel sample consists of 45 occupations reported throughout.

Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 6: Skill premia and their proximate determinants: Within country-dynamics

Dependent variable: ln real wage

		By income	
	(1)	(2)	(3)
	All	High	Other
ln A, t-4	0.471**	0.494**	0.097
	(0.127)	(0.167)	(0.353)
x *medium skilled*	-0.018	0.006	-0.077**
	(0.017)	(0.029)	(0.025)
x *high skilled*	-0.196**	-0.205*	-0.197**
	(0.029)	(0.076)	(0.047)
ln s, t-4	-0.004	0.034*	-0.147
	(0.041)	(0.016)	(0.178)
x *medium skilled*	-0.007	0.010	-0.035+
	(0.011)	(0.010)	(0.021)
x *high skilled*	-0.032	-0.047	-0.056
	(0.024)	(0.032)	(0.060)
ln (n+delta), t-4	-0.210	-0.346**	0.547
	(0.155)	(0.107)	(0.598)
x *medium skilled*	0.086	0.202*	0.086
	(0.052)	(0.091)	(0.153)
x *high skilled*	-0.016	0.449+	-0.563*
	(0.145)	(0.247)	(0.261)
trend med. skilled	-0.001	0.003	0.002
	(0.011)	(0.017)	(0.019)
trend high skilled	0.079**	0.098*	0.064
	(0.021)	(0.039)	(0.041)
Constant	-5.206**	-6.321*	0.450
	(1.702)	(2.427)	(4.702)
Observations	11721	6042	5679
R^2	0.873	0.822	0.682
Countries	90	36	54
Intervals	5 year	5 year	5 year
Country FE	✓	✓	✓
Occupation FE	✓	✓	✓
Period FE	✓	✓	✓

Trend variables are divided by 10.

Standard errors in parentheses, clustered at the country level.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Column (1) of Table 6 provides mixed support: The skill-interactions of the logs of GDP/capita and the effective human capital savings rate are negative as expected, albeit only the former one is significant. Unlike predicted by the model, the high skilled-interaction term with population growth is negative, albeit insignificant. Differentiating between high income and other countries reveals that the coefficient is positive and significant for high income countries -as expected and of a similar size as in the cross country specifications-, whereas it is significantly *negative* for other countries. However, column (6) of Table 10 in Appendix C shows that in the poorer countries, lagged population growth is associated with a decrease in relative skill supplies, in line with the model prediction. Hence, the negative association between lagged population growth and skill premia in poorer countries appears to be stem from some factor outside our model that is positively associated with lagged population growth, and negatively associated with skill premia.

We therefore conclude that the evidence from the pooled specification suggests that general economic development, the resources that governments devote to education, and population growth rates do indeed play an important role in the explanation of the large differences in relative skill supplies and skill premia. The time series evidence using within country-adjustments suggests that the model successfully can explain the evolution of relative skill supplies, and also supports the link between the evolution of the proximate determinants identified in the model and skill premia, but only for high income countries.

5 Trade, skill premia, and skill supply

In Section 3, we have considered trade as just another factor that may influence skill premia, and confound the estimation of the impact of changing relative skill supplies. From a trade theory-perspective, this approach misses an important way in which trade may affect the skill premia-skill supply relationship directly: In the textbook version of the Heckscher-Ohlin model, skill premia are not affected by changes in domestic relative skill supplies as long as the cross country-differences in relative endowments are not too large. Instead, the composition of output changes in order to absorb any change in domestic relative skill supplies. In our notation, $\frac{S_t}{U_t}$ in Equation 4 would be global rather than country-specific in such a world. Since changes in the domestic relative skill supply have a negligible effect on the global relative skill supply, their effect on domestic skill premia would also be negligible.

The literature provides some evidence of productivity-adjusted factor price equalization (FPE) (O'Rourke et al. 1996, Trefler 1993), which implies factor price insensitivity (FPI). However, as pointed out by Leamer (1995), the FPI theorem requires less stringent assumptions, and most accurately captures the intuition that trade creates a global labor market.[54] If FPI held true, we would not observe the inverse

[54]FPE requires the additional assumptions of identical technologies, no factor-intensity reversals, and/or sufficiently similar factor supply ratios (Leamer, 1995).

relationship between skill premia and the relative skill supply that we document in Section 3 for both the 1953-1979 period -during which economies tended to be relatively closed-, and for the 1980-2008 period, a period of rapidly increasing trade globalization.[55] The empirical failure of FPI in its strict form is not surprising, as it depends on very strong assumptions, most notably the tradability of all goods. As an empirically more relevant theorem, Leamer and Levinsohn (1995) propose a dynamic version of FPI which they label "Factor Price Adjustment" (FPA): *"The initial factor price response to an increase in a factor supply is reduced over time as the economy shifts its output mix towards sectors that employ this factor most intensively. The more open a country is to international commerce, the greater will be the opportunities for adjustment in the output mix and the less will be the factor price response at any point in time."*

Direct evidence on the role of openness in mediating shocks to the domestic relative supply of skills is scarce, as lamented by Leamer and Levinsohn (1995) and Slaughter (1999). In the past 20 years, a number of studies have adressed this question, though often only for the US, or indirectly: Slaughter (2001) tests whether international trade has been increasing the own-price elasticity of demand for US labor. He finds evidence of an increasing elasticity of demand for production labor in a majority of manufacturing industries over the 1961-1991 period, but cannot disentangle the potential impact of trade from a general time trend. Hanson and Slaughter (2002) combine state-level data on labor supply, industry employment and value added and find that among US states, changes in the output of traded goods absorb part of state-level changes in relative skill supplies. They hypothesize that this may contribute to explaining why the literature tends to find small impacts of immigration on US regional wages. Indeed, the literature on the wage effects of migration -which can be seen as a labor supply shock which often alters the regional or domestic relative skill supplies- tends to find only modest effects (see Longhi et al. 2005 and Hatton 2014 for reviews of the literature).

The most comprehensive study on FPA is Rotunno and Wood (2016): The authors present a generalized Heckscher Ohlin model in which the fact that most domestic suppliers enjoy some protection from international competition is captured by modelling the demand side of the economy using a CES utility function in which imported and home-produced varieties of each good are imperfect substitutes. This model retains a role for domestic skill supply conditions to influence skill premia even without invoking different "cones of diversification": If relative skill supplies change, the imperfect substitutability of home varieties of each good limits the restructuring of production across sectors, and relative factor prices need to adjust for a return to equilibrium. However, their model does retain the original Heckscher-Ohlin intuitions: As the exposure of an economy to international trade increases, domestic skill premia are expected to become less sensitive to changes in the domestic relative skill supply, as there is more scope for the composition of output to change in a way that absorbs such changes. The authors test their model using panel data on 40 countries over the

[55] According to the World Development Indicators, the ratio of world trade averaged 22% of world GDP over the 1960-1979 period, as compared to 36% over the 1980-2009 period.

1995-2009 period from the "World Input Output Database" by Timmer et al. (2015), and find time series-evidence of a reduced elasticity of skill premia with respect to skill supplies in more open countries: At the minimum level of openness in their sample, a 10% increase in relative skill supplies is associated with a 3.5% decrease in the skill premium, whereas they do not find a significant effect of increase in relative skill supplies in countries in the upper quartile of openness. Compared to WIOD, the OWW data base contains more countries, and a larger variation in trade/GDP ratios. Moreover, the OWW data base covers a much longer time period, allowing us to exploit the considerable time series variation in openness. [56]

Testing for a reduced sensitivity of skill premia

To test the Factor Price Adjustement hypothesis that the elasticity of skill premia with respect to relative skill supplies depends on the openness to trade, we augment Equation 6 by interactions with the logged ratio of trade/GDP:

$$\begin{aligned} ln(w_{c,o,t}) = c &+ \beta_1 ln(A_{c,t}) + \beta_2 ln(school_{c,t}) + \sum_i \beta_2^i D^i ln(school_{c,t}) \\ &+ \beta_3 ln(trade_{c,t}) + \sum_i \beta_3^i D^i ln(trade_{c,t}) \\ &+ \beta_4 ln(school_{c,t}) * ln(trade_{c,t}) + \sum_i \beta_4^i D^i ln(school_{c,t}) * ln(trade_{c,t}) \\ &+ \{D_c\} + \{D_o\} + \{D_t\} + \sum_i \beta_5^i D^i t + \varepsilon_{c,o,t} \end{aligned} \tag{20}$$

where $ln(trade)$ is the log of the trade/GDP ratio. In some specifications, we adjust $ln(trade)$ for the population size, as in Rotunno and Wood (2016).[57] If openness weakened the link between domestic skill supplies and skill premia, we would expect positive coefficients β_4^i (with $i = \{medium, high\}$), as the direct skill premia-reducing effect of increases in domestic skill supplies should be dampened at higher levels of openness.

[56] The WIOD allows Rotunno and Wood (2016) to use the trade/output ratio, which is conceptually preferable to the (more widely available and used) trade/GDP ratio since the latter divides a gross by a net-measure. However, their results are robust to using the trade/GDP ratio instead. Due to data availability, we hence base our main results on the trade/GDP ratio.

[57] Rotunno and Wood (2016) note that the 40 countries in their sample are atypically large. This makes these countries look relatively closed when considering the trade-to-GDP ratio, not due to higher trade barriers but because of a higher potential for realizing economies of scale internally and greater diversity of natural resources. Therefore, they use the residuals from a cross-section regression of the $ln(trade)$ on log population as a proxy for openness. We will use the residuals from a regression of the $ln(trade)$ on log population, both from WDI, including year fixed effects. Running this regression separately year-by-year leads to similar results.

Results

Table 7 presents the results from estimating Equation 20 for alternative sample and variable specifications. For a comparison with Rotunno and Wood (2016), in column (1) we restrict the sample to countries represented in the WIOD and to the years 1995-2008, and use their openness measure. 35 of the 40 WIOD countries are included in the OWW data file for this period, and trade data is available for 34 of them. In line with Rotunno and Wood (2016), we find that the response of the wage premium of highly skilled workers following increases in domestic skill supplies decreases in the openness of a country. The coefficient estimates imply that a 10% increase in relative skill supplies is associated with a 3.7% decline in the high skilled-premium in a country at the bottom quartile of openness in the sample (for instance for Turkey in 2005-09, which is approximately at the bottom quartile of openness in the sample, $ln(trade_{c,t}) = -0.04$)[58], as compared to a mere 1.1% decline in a country at the top quartile of openness (for instance, Romania in 2000-04, with $ln(trade_{c,t}) = 0.39$).

In columns (2) and (3), we assess the robustness of this result with respect to alternative openness proxies: First, we use the unadjusted logarithm of the trade/GDP ratio, which is a proxy for de facto-openness of the economy as opposed to policy-related barriers to trade. Second, we use the trade/GDP ratio in levels, as has been done in some other studies. The significantly positive interaction between relative skill supplies and openness for highly skilled wages is robust across these alternative proxies for openness (though the skill supply-interaction for high skilled wages becomes insignificant in column (2)).[59]

For columns (4)-(6), we retain the openness-definition used by Rotunno and Wood (2016), i.e. column (1), and extend upon their sample along both the time and the country dimension. In column (4), we include all available observations from WIOD countries since 1960, the first year for which trade data is available. For this extented sample, only the main effect β_4 is significant, implying that the estimated effect of increases in relative skill supplies on wages at all skill levels depends on the openness. For high skilled wages, the coefficients again imply a smaller elasticitiy in more open countries, albeit the estimated effect of openness is somewhat weaker.[60] For low skilled wages, the estimates from column (4) imply that following a 10% increase in relative skill supplies, wages increase by 0.9% at the bottom

[58] From Equation 20: $\frac{\partial ln(w_{c,o,t})}{\partial ln(school_{c,t})} = \beta_2 + \sum_i \beta_2^i D^i + \beta_4 ln(trade_{c,t}) + \sum_i \beta_4^i D^i ln(trade_{c,t})$. Hence, for high skilled wages in Turkey with the level of openness of the 2005-09 period, $\frac{\partial ln(w_{c,o,t})}{\partial ln(school_{c,t})} = 0.126 - 0.491 - 0.238 * (-0.04) + 0.885 * (-0.04) = -0.391$. Then, 100*(exp(-0.391*log 1.1)-1)=3.7%.

[59] While Rotunno and Wood (2016) use the adjusted openness measure, conceptually we prefer the unadjusted measures: What matters for the Heckscher-Ohlin mechanism is arguably the effective openness of an economy to trade, irrespective whether it is driven by policy or by factors related to the country size, such as less scope for the realization of economies of scale within the country.

[60] Again comparing the relatively closed Turkey in 2005-09 to the relatively open Romania in 2000-04, the coefficients imply that a 10% increase in the relative skill supply is associated with a 2.3% decline in skill premia in Turkey, whereas skill premia in Romania decline by only 0.2% and hence hardly change. Results are similar when restricting the estimation sample to WIOD countries in the 1960-1994 period.

Table 7: Trade, skill premia, and skill supply

Dependent variable: ln real wage

	WIOD, 1995-2008			Extensions		
	(1) Adj.	(2) Non-adj.	(3) Level	(4) Periods	(5) Countries	(6) Pooled
ln A	0.402^{+}	0.402^{+}	0.392^{+}	0.691**	0.573**	0.649**
	(0.228)	(0.222)	(0.216)	(0.106)	(0.094)	(0.078)
ln school	0.126	-0.059	0.501	0.108	0.343*	-0.180
	(0.301)	(0.390)	(0.316)	(0.176)	(0.163)	(0.112)
x *medium skilled*	-0.053	-0.024	-0.113	-0.013	-0.047	-0.067**
	(0.063)	(0.092)	(0.133)	(0.038)	(0.034)	(0.019)
x *high skilled*	-0.491**	0.134	-1.490**	-0.329**	-0.480**	-0.212**
	(0.140)	(0.207)	(0.223)	(0.079)	(0.108)	(0.042)
openness	0.134	0.145	0.105	-0.155	-0.121	-0.145
	(0.141)	(0.124)	(0.157)	(0.210)	(0.141)	(0.134)
x *medium skilled*	0.006	-0.004	0.018	-0.074^{+}	-0.027	0.028
	(0.047)	(0.039)	(0.059)	(0.039)	(0.048)	(0.037)
x *high skilled*	0.083	0.054	0.252^{+}	-0.075	-0.036	-0.022
	(0.114)	(0.091)	(0.141)	(0.073)	(0.069)	(0.069)
ln school x openness	-0.238	-0.208	-0.712	0.409*	0.055	0.012
	(0.222)	(0.158)	(0.733)	(0.190)	(0.086)	(0.053)
x *medium skilled*	0.086	0.035	0.112	-0.066	-0.076^{+}	-0.011
	(0.123)	(0.093)	(0.227)	(0.040)	(0.040)	(0.027)
x *high skilled*	0.885**	0.724**	2.099**	0.097	-0.132	-0.061
	(0.237)	(0.154)	(0.391)	(0.122)	(0.106)	(0.046)
trend med. skilled	0.038*	0.041*	0.039*	0.010	0.009	-0.000
	(0.017)	(0.015)	(0.016)	(0.011)	(0.010)	(0.009)
trend high skilled	0.104**	0.117**	0.097**	0.101**	0.105**	0.035
	(0.032)	(0.031)	(0.033)	(0.029)	(0.027)	(0.023)
Constant	-10.639**	-11.544**	-10.306**	-10.756**	-9.628**	-6.085**
	(3.599)	(3.399)	(3.275)	(2.138)	(1.943)	(1.810)
Observations	9652	9652	9652	18616	22175	47072
R^2	0.908	0.909	0.909	0.872	0.849	0.807
Countries	34	34	34	39	56	125
Intervals	5 year	5 year	5 year	5 year	5 year	5 year
Country FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Trend variables are divided by 10. Except for columns (2) and (3), openness is proxied as log trade/GDP ratio, adjusted for log population size. Standard errors in parentheses, clustered at the country level.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

quartile of openness, and by 2.6% at the top quartile of openness.[61] While our framework suggests a positive effect of increases in relative skill supplies on low-skilled wages (see Section 3), it is unclear why we are more likely to find such an effect at higher levels of openness in the sample of WIOD-countries. One possibility is that openness correlates positively with the average skill requirements of jobs in the economy. Then, October Inquiry-occupations would become less skilled relative to the rest of the labor market as openness increases, and would be more likely to include the lower part of the wage distribution that benefits from the increased scarcity of low-skilled labor (see the discussion in Section 3).

In column (5), we consider the 1995-2008 period, but include all available observations from in total 91 countries. In this sample, openness does not have a significant effect on the responsiveness of skill premia with respect to the relative skill supply. Also once we also include observations from 1960 on in column (6) using the maximum number of countries and years available in the OWW database, we do not find evidence for FPA.

In summary, we confirm the finding by Rotunno and Wood (2016) that increasing openness in the countries included in WIOD was associated with a decreasing sensitivity of skill premia with respect to domestic skill supplies in the 1995-2008 period. We still find evidence of a reduced schooling-elasticity of high skilled wages once we extend the time period by 35 years to 1960-2008 (and also if we look only at the pre-WIOD period 1960-94, not reported). However, we find no evidence of such an effect once we include countries not represented in the WIOD data base. The 40 WIOD countries currently account for about 85% of World GDP, and the additional countries we are able to include are correspondingly mostly low and middle income-countries. Possibly, non market factors play a more important role in wage determination in these countries compared to the WIOD countries[62], or there are higher barriers to reallocation of employment across sectors, both of which would make it harder to find Heckscher-Ohlin effects.

6 Conclusion

This paper presents a global account of the evolution of skill premia using a unique data set on internationally comparable wage rates for over 180 countries during a period of almost 60 years. We show that while relative skill supplies have increased throughout the six decades, the average skill premium decreased by about 23% up to the 1980s, with a rebound by 11% in the period 1980s-2000s. Using the metaphor of Tinbergen (1975), education won the race against technology during the first period, but lost it during the second (Figure 2).

[61] $\frac{\partial ln(w_{c,o,t})}{\partial ln(school_{c,t})} = 0.108 + 0.409 * (-0.04) = 0.268$. Then, 100*(exp(0.268*log 1.1)-1)=2.6%.

[62] Indeed, we find a lower responsiveness of skill premia with respect to skill supply in low and middle income countries, see Table 3.

We find strong evidence for the education part of Tinbergen's metaphor: Increases in relative skill supplies have been robustly associated with a decrease in skill premia, and consequently the observed global surge in relative skill supplies has been the prime factor in reducing skill premia around the world. As for the technology part of the metaphor, the results are consistent with the available evidence on skill-biased technological change in high income-countries, although our analysis is not able to clearly distinguish between skill-biased technological change and other factors that may have increased skill premia. For instance, we also find strong evidence that the decline in union density since the 1980s in a majority of countries has contributed to an increase in skill premia (cf. Table 9 in Appendix B). Moreover, the actual increase in skill premia since the 1980s has been larger than what our global trend estimate of relative skill demand growth can account for (cf. Figure 2 vs. Table 4).

Looking at the the determinants of skill premia within a modified growth theory framework, we find -not surprisingly- that higher effective human capital savings rates have been associated with lower skill premia. Less obviously, economic development appears to have compressed skill premia primarily via increasing relative skill supplies, as increasing resources devoted to education were met with less-than-proportional increases in the price of skill. At the same time, high population growth made the task more difficult for governments willing to influence skill premia by means of investments into education.

Finally, we find evidence for the claim that large increases in openness to trade have increasingly decoupled technology and education, leaving technology without a racing partner. However, we find this evidence only for a sample of predominantly high income-countries where increasing openness has indeed made skill premia considerably less elastic with respect to domestic skill supplies. This suggests that in these countries, domestic policies aimed at influencing skill premia by altering relative skill supplies -be it education policies, or restrictions in the inflow of less-educated migrants- may be less effective than they used to be. However, for the global sample, we do not find evidence of such an effect, suggesting that other effects are at work in lower and middle income countries. Uncovering these would be an interesting avenue for future research.

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Appendices:

A The evolution of skill premia and skill supplies

Figure 5: Correlation with Mincer return estimates in post 1980 sample

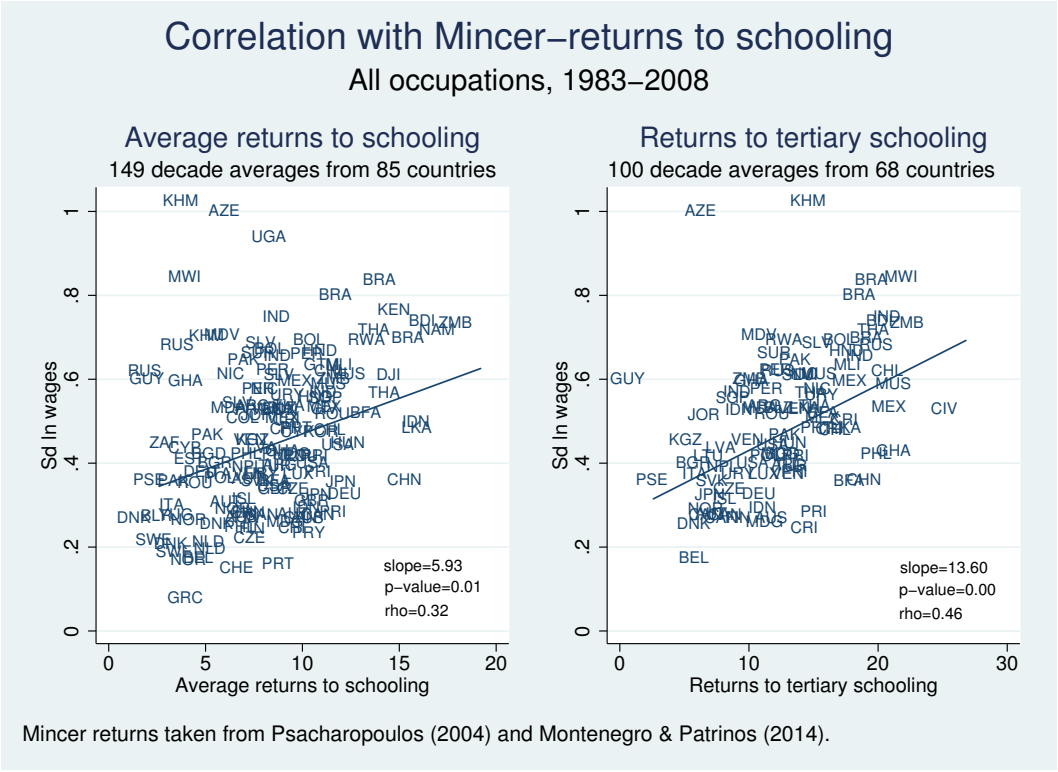
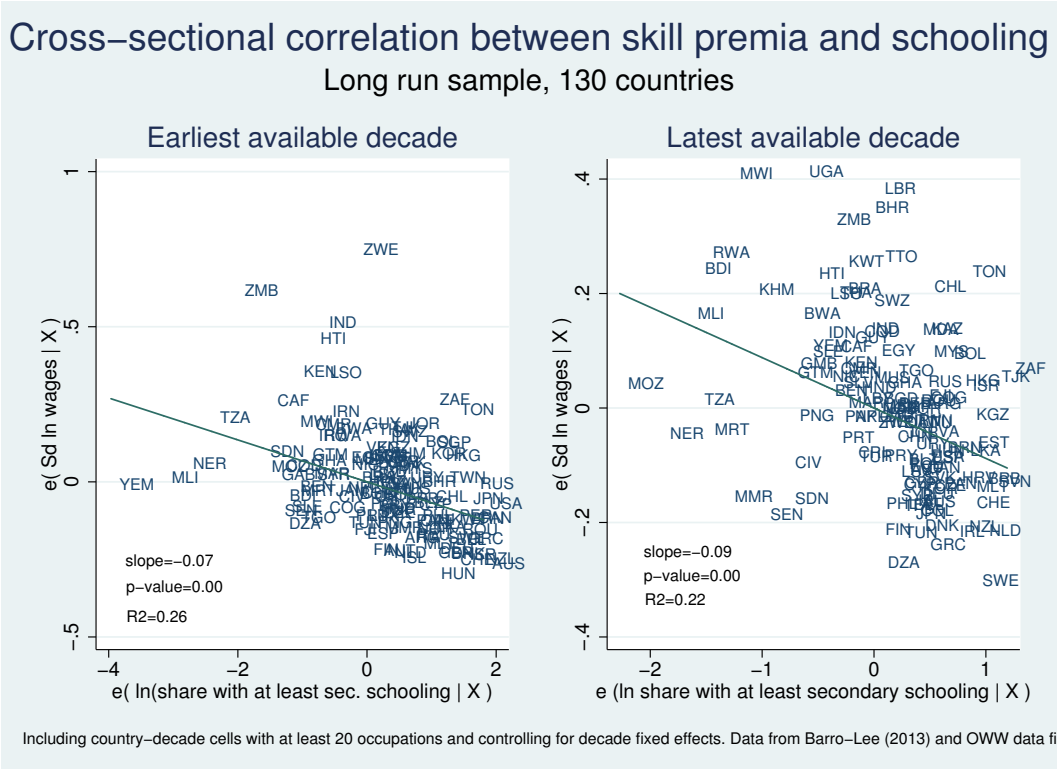
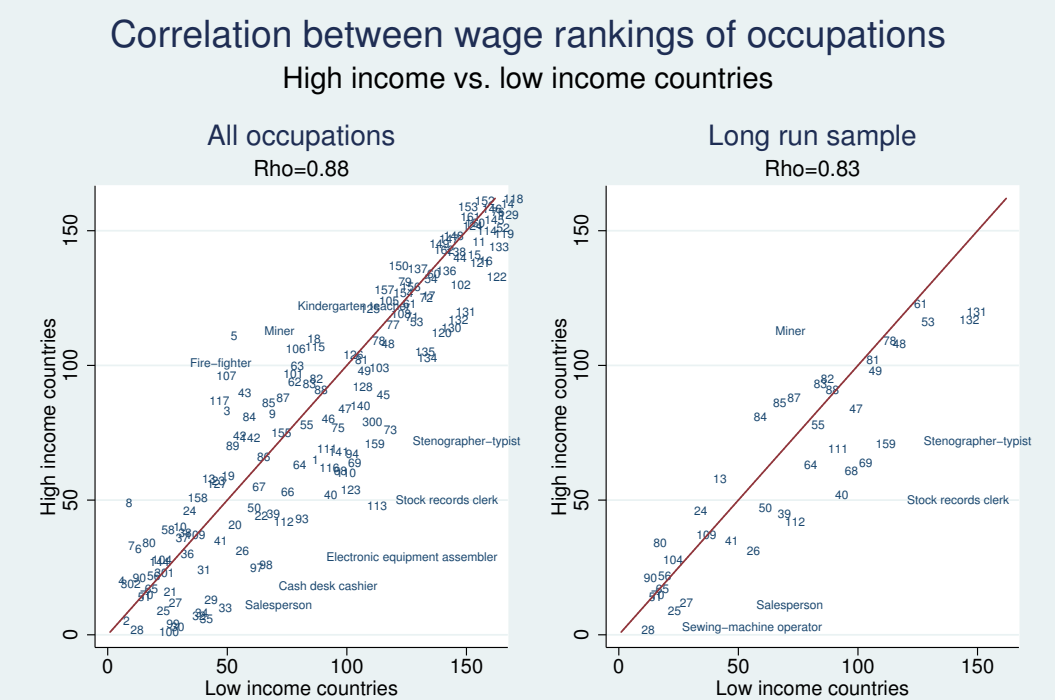


Figure 6: Cross-sectional correlation between changes in skill premia and educational attainment



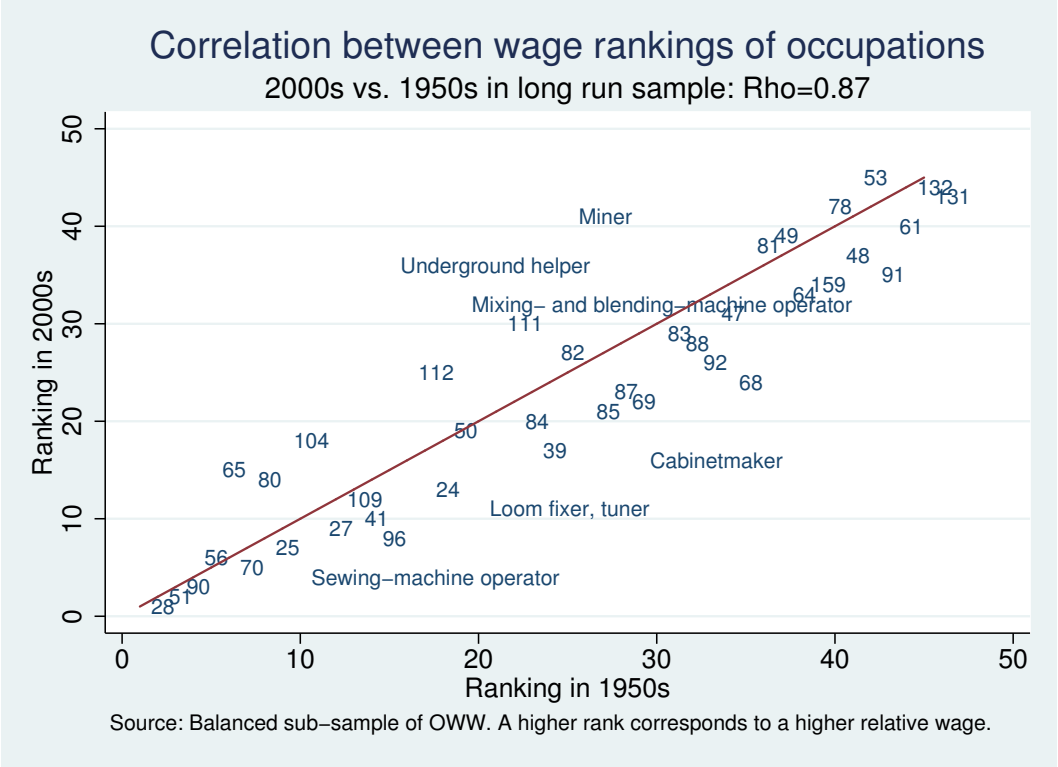
B Skill premia and skill supply

Figure 7: Correlation between occupation rankings across income groups



Source: OWW. A higher rank corresponds to a higher relative wage. Figures indicate name or occupation code.

Figure 8: Correlation between occupation rankings across time



Source: Balanced sub–sample of OWW. A higher rank corresponds to a higher relative wage.

Table 8: Robustness: Low skilled wages and skill supply

Dependent variable: ln real wage

	(1) Benchmark	(2) Labor share	(3) Tertiary
ln A	0.658**	0.670**	0.721**
	(0.073)	(0.074)	(0.072)
ln school	-0.108	-0.106	-0.002
	(0.109)	(0.111)	(0.073)
x *medium skilled*	-0.071**	-0.071**	-0.043**
	(0.017)	(0.017)	(0.011)
x *high skilled*	-0.243**	-0.241**	-0.122**
	(0.029)	(0.029)	(0.023)
trend med. skilled	0.004	0.004	-0.004
	(0.008)	(0.008)	(0.008)
trend high skilled	0.056**	0.055**	0.022
	(0.016)	(0.015)	(0.016)
labor share		0.935+	
		(0.559)	
Constant	-8.348**	-8.911**	-5.408**
	(1.320)	(1.381)	(1.353)
Observations	46202	46202	53692
R^2	0.792	0.793	0.780
Countries	107	107	129
Intervals	5 year	5 year	5 year
Country FE	✓	✓	✓
Occupation FE	✓	✓	✓
Period FE	✓	✓	✓

Trend variables are divided by 10.

Standard errors in parentheses, clustered at the country level.

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 9: Skill premia and skill supply: Controls

Dependent variable: ln real wage

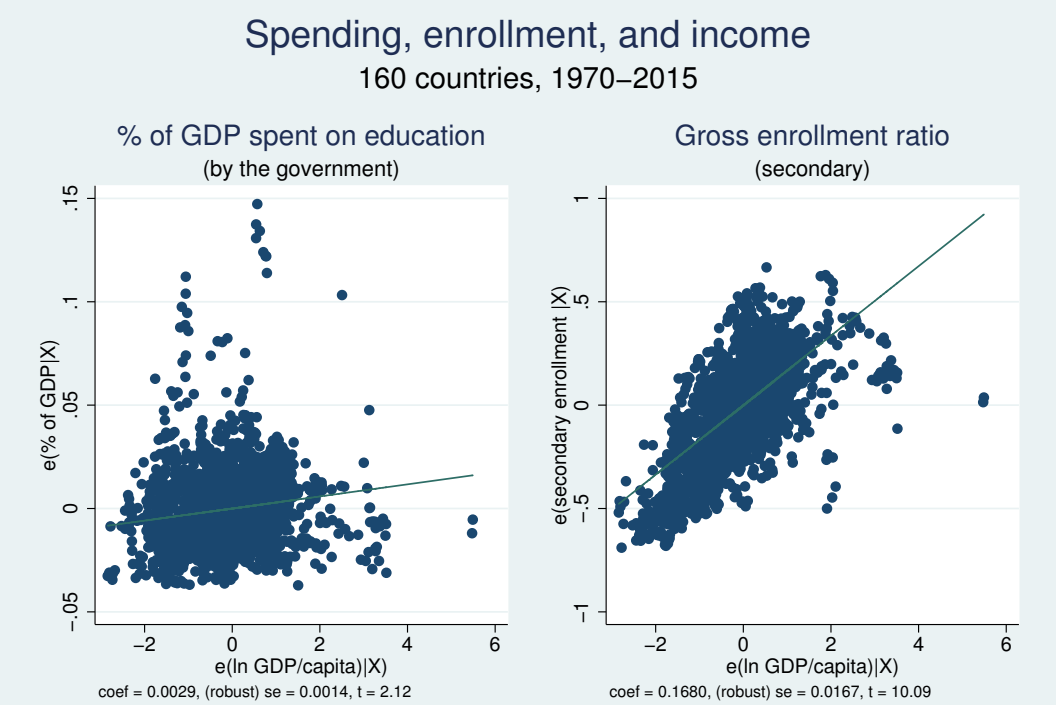
			Trade by income			
	(1) Benchmark	(2) GDP	(3) High	(4) Other	(5) Union d.	(6) Combined
ln A	0.682**	0.680**	0.574**	0.498**	0.712**	0.726**
	(0.070)	(0.072)	(0.096)	(0.106)	(0.110)	(0.108)
x *medium skilled*		0.008				-0.011
		(0.011)				(0.020)
x *high skilled*		-0.002				-0.060
		(0.027)				(0.047)
ln school	-0.194+	-0.192+	0.320*	-0.033	0.136	0.162
	(0.104)	(0.104)	(0.157)	(0.138)	(0.202)	(0.232)
x *medium skilled*	-0.067**	-0.075**	-0.029	-0.061*	-0.045	0.004
	(0.016)	(0.019)	(0.038)	(0.024)	(0.040)	(0.031)
x *high skilled*	-0.198**	-0.195**	-0.368**	-0.138**	-0.389**	-0.362**
	(0.033)	(0.039)	(0.092)	(0.052)	(0.087)	(0.092)
trend med. skilled	0.000	0.001	-0.002	-0.017	-0.002	-0.006
	(0.007)	(0.007)	(0.011)	(0.016)	(0.012)	(0.012)
trend high skilled	0.039*	0.038*	0.067*	-0.001	0.060*	0.061*
	(0.017)	(0.017)	(0.026)	(0.036)	(0.025)	(0.028)
ln (trade/GDP)			-0.142	-0.109		-0.212
			(0.112)	(0.135)		(0.183)
x *medium skilled*			0.025	0.055*		-0.004
			(0.027)	(0.024)		(0.020)
x *high skilled*			0.070	0.029		-0.016
			(0.046)	(0.066)		(0.062)
union density					0.124	0.275
					(0.253)	(0.298)
x *medium skilled*					-0.128**	-0.119*
					(0.046)	(0.047)
x *high skilled*					-0.455**	-0.450**
					(0.091)	(0.103)
Constant	-6.646**	-6.685**	-6.924**	-1.211	-8.382**	-8.463**
	(1.389)	(1.369)	(2.133)	(2.876)	(2.220)	(2.402)
Observations	53692	53692	19970	27102	19197	18632
R^2	0.783	0.783	0.830	0.651	0.850	0.852
Countries	129	129	47	78	50	50
Intervals	5 year	5 year	5 year	5 year	5 year	5 year
Country FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Trend variables are divided by 10. Varying sample coverage according to data availability.

Standard errors in parentheses, clustered at the country level. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

C Skill premia and their proximate determinants

Figure 9: Spending, enrollment, and income



Source: UNESCO UIS data base and Penn World Table 9.0. Partial regression plots, controlling for the population share of second. schooling age.

Table 10: Determinants of relative skill supply

Dependent variable: ln share of high-skilled population

	Separately			Jointly	Lag 4, by income	
	(1)	(2)	(3)	(4)	(5)	(6)
	A	s	n+d		All	Other
ln A	0.208*			0.219**		
	(0.093)			(0.043)		
t-1	0.055			0.171**		
	(0.100)			(0.044)		
t-2	-0.012			0.055		
	(0.084)			(0.045)		
t-3	0.079			0.075*		
	(0.067)			(0.037)		
t-4	0.290**			0.247**	0.478**	0.667**
	(0.106)			(0.043)	(0.056)	(0.099)
ln s		-0.102		0.124**		
		(0.072)		(0.019)		
t-1		0.058*		0.108**		
		(0.024)		(0.014)		
t-2		0.068		0.066**		
		(0.048)		(0.020)		
t-3		-0.015		0.036**		
		(0.033)		(0.010)		
t-4		0.066+		0.085**	0.133**	0.215**
		(0.036)		(0.022)	(0.039)	(0.056)
ln (n+delta)			-0.281	-0.227**		
			(0.219)	(0.079)		
t-1			-0.185	-0.125**		
			(0.127)	(0.042)		
t-2			-0.219	-0.163**		
			(0.173)	(0.041)		
t-3			-0.269*	-0.111**		
			(0.111)	(0.039)		
t-4			-0.731**	-0.221**	-0.392*	-0.814*
			(0.218)	(0.067)	(0.161)	(0.374)
Constant	-6.329**	-0.905**	-5.587*	-10.787**	-6.266**	-9.048**
	(0.613)	(0.181)	(2.235)	(0.680)	(0.617)	(1.115)
Observations	319	257	318	257	340	176
$R^2 within$	0.605	0.107	0.184	0.910	0.576	0.647
Countries	76	66	75	66	90	54
Country FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses, clustered at the country level.

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

D List of industries in OWW data file

Industry code	Industry name
AA	Agricultural production (field crops)
AB	Plantations
AC	Forestry
AD	Logging
AE	Deep-sea and coastal fishing
BA	Coalmining
BB	Crude petroleum and natural gas production
BC	Other mining and quarrying
CA	Slaughtering, preparing and preserving meat
CB	Manufacture of dairy products
CG	Grain mill products
CH	Manufacture of bakery products
DA	Spinning, weaving and finishing textiles
DB	Manufacture of wearing apparel (exc. footwear)
DC	Manufacture of Leather and Leather Products (exc. footwear)
DD	Manufacture of footwear
EA	Sawmills, planing and other wood mills
EB	Manufacture of wooden furniture and fixtures
FA	Manufacture of pulp, paper and paperboard
FB	Printing, publishing and allied industries
GA	Manufacture of industrial chemicals
GB	Manufacture of other chemical products
GC	Petroleum refineries
IA	Iron and steel basic industries
JA	Manufacture of metal products (exc. machinery and equipment)
JB	Manufacture of machinery (exc. electrical)
JC	Manufacture of electronic equipment, machinery and supplies
JD	Shipbuilding and repairing
KA	Electric light and power
LA	Construction
MA	Wholesale trade (grocery)
MB	Retail trade (grocery)

MC	Restaurants and hotels
NA	Railway transport
NB	Passenger transport by road
NC	Freight transport by road
ND	Maritime transport
NE	Supporting services to maritime transport
NF	Air transport
NG	Supporting services to air transport
NH	Communication
OA	Banks
OB	Insurance
OC	Engineering and architectural services
PA	Public administration
PB	Sanitary services
PC	Education services
PD	Medical and dental services
PF	Repair of motor vehicles

E List of occupations in OWW data file

Long run sample, included 1953-2008

	Occupation		Skill level*		Reports	
Industry	Code	Name	Own	ILO	Countries (total)	By year (avg.)
BA	12	Miner	2	2	84	18.5
BA	13	Underground helper, loader	1	1	84	17.2
CH	24	Baker (ovenman)	1	2	178	60.8
DA	25	Thread and yarn spinner	1	2	142	39.6
DA	26	Loom fixer, tuner	1	2	133	34.6
DA	27	Cloth weaver (machine)	1	2	144	40.4
DA	28	Labourer	1	1	150	42.2
DB	30	Sewing-machine operator	1	2	174	51.7
EB	39	Furniture upholsterer	1	2	173	51.5
EB	40	Cabinetmaker	2	2	175	59.3

EB	41	Wooden furniture finisher	1	2	168	49.2
FB	47	Hand compositor	2	2	175	62
FB	48	Machine compositor	3	2	174	59.6
FB	49	Printing pressman	2	2	176	61.5
FB	50	Bookbinder (machine)	1	2	173	56.9
FB	51	Labourer	1	1	174	54.5
GA	53	Chemistry technician	3	3	149	32.5
GA/GB	55	Mixing- and blending-machine operator	2	2	149	33.7
GA/GB	56	Labourer	1	1	147	38.8
IA	61	Occupational health nurse	3	3	123	23.4
IA	64	Metal melter	2	2	123	29.2
IA	65	Labourer	1	2	132	31.7
JB	68	Bench moulder (metal)	2	2	133	35.7
JB	69	Machine fitter-assembler	2	2	146	40.3
JB	70	Labourer	1	1	146	38.2
KA	78	Electric power lineman	3	2	178	59.1
KA	80	Labourer	1	1	174	56.4
LA	81	Building electrician	2	2	182	63.7
LA	82	Plumber	2	2	183	65
LA	83	Construction steel erector	2	2	179	53
LA	84	Building painter	2	2	184	66.8
LA	85	Bricklayer (construction)	2	2	183	64.9
LA	87	Cement finisher	2	2	173	55.4
LA	88	Construction carpenter	2	2	184	68.9
LA	90	Labourer	1	1	184	66.9
MA	91	Stenographer-typist	3	2	171	51.4
MA	92	Stock records clerk	2	2	177	52.4
MB	96	Salesperson	1	2	178	57.2
NA	104	Railway vehicle loader	1	1	124	30.8
NB	109	Bus conductor	1	2	160	44.3
NB	111	Motor bus driver	2	2	175	55.8
NC	112	Urban motor truck driver	1	2	174	50.3
OA	131	Bank teller	3	2	179	54.6
OA	132	Book-keeping machine operator	3	2	173	49.7
PF	159	Automobile mechanic	2	2	175	61.7

* From low skilled (1) to high skilled (3).

Included 1953-82

Industry	Occupation		Skill level		Reports	
	Code	Name	Own	ILO	Countries (total)	By year (avg.)
	300	Pattern makers (wood)	2	2	106	38.1
	301	Permanent way labourers	1	2	117	39.7
	302	Labourers (unskilled, public parks and gardens)	1	1	149	62.1

Included 1983-2008

Industry	Occupation		Skill level		Reports	
	Code	Name	Own	ILO	Countries (total)	By year (avg.)
AA	1	Farm supervisor	2	2	100	23.7
AA	2	Field crop farm worker	1	2	111	28.9
AB	3	Plantation supervisor	1	2	82	18.3
AB	4	Plantation worker	1	2	89	21.8
AC	5	Forest supervisor	2	2	96	20.7
AC	6	Forestry worker	1	2	99	24.1
AD	7	Logger	1	2	83	20.5
AD	8	Tree feller and bucker	1	2	74	15.6
AE	9	Deep-sea fisherman	2	2	60	11.9
AE	10	Inshore (coastal) maritime fisherman	1	2	66	10.9
BA	11	Coalmining engineer	3	3	49	12.9
BB	14	Petroleum and natural gas engineer	3	3	60	16
BB	15	Petroleum and natural gas extraction technician	3	3	64	15.6
BB	16	Supervisor or general foreman	3	2	65	17
BB	17	Derricksman	3	2	64	15.1
BC	18	Miner	2	2	82	21.6
BC	19	Quarryman	1	2	89	24.6
CA	20	Butcher	1	2	126	37.1
CA	21	Packer	1	1	112	32.1

CB	22	Dairy product processor	1	2	115	35.3
CG	23	Grain miller	1	2	105	31.4
DB	29	Garment cutter	1	2	131	37.8
DC	31	Tanner	1	2	93	25.6
DC	32	Leather goods maker	1	2	97	26.4
DD	33	Clicker cutter (machine)	1	2	103	28.7
DD	34	Laster	1	2	95	26.6
DD	35	Show sewer (machine)	1	2	106	30.6
EA	36	Sawmill sawyer	1	2	111	33.4
EA	37	Veneer cutter	1	2	94	25.8
EA	38	Plywood press operator	1	2	88	24.3
FA	42	Wood grinder	2	2	74	20.8
FA	43	Paper-making-machine operator (wet end)	2	2	82	24.8
FB	44	Journalist	3	3	125	35.1
FB	45	Stenographer-typist	2	2	128	33.8
FB	46	Office clerk	2	2	133	38.7
GA	52	Chemical engineer	3	3	101	27.3
GA	54	Supervisor or general foreman	3	2	106	27.8
GB	58	Packer	1	1	95	27.7
GC	60	Controlman	3	2	69	19.9
IA	62	Blast furnaceman (ore smelting)	2	2	70	22.4
IA	63	Hot-roller (steel)	2	2	65	21.2
JA	66	Metalworking machine setter	2	2	108	31.7
JA	67	Welder	2	2	122	39.3
JC	71	Electronics draughtsman	3	3	71	19.3
JC	72	Electronics engineering technician	3	3	91	24
JC	73	Electronics fitter	2	2	85	22
JC	74	Electronic equipment assembler	1	2	87	25.3
JD	75	Ship plater	2	2	65	19
KA	76	Power distribution and transmission engineer	3	3	129	34.4
KA	77	Office clerk	3	2	128	35.8
KA	79	Power-generating machinery operator	3	2	125	34.2
LA	86	Reinforced concreter	2	2	137	36.2
LA	89	Plasterer	2	2	132	35.6
MA	93	Salesperson	1	2	137	40.5

MB	94	Book-keeper	2	3	138	39
MB	95	Cash desk cashier	1	2	143	41.9
MC	97	Hotel receptionist	1	2	141	43.9
MC	98	Cook	1	2	146	48
MC	99	Waiter	1	2	146	46.4
MC	100	Room attendant or chambermaid	1	1	143	44.4
NA	101	Ticket seller (cash desk cashier)	2	2	79	23.2
NA	102	Railway services supervisor	3	2	82	20.4
NA	103	Railway passenger train guard	2	2	73	19.8
NA	105	Railway engine-driver	3	2	85	24.7
NA	106	Railway steam-engine fireman	2	2	51	11.8
NA	107	Railway signalman	2	2	76	20.7
NB	108	Road transport services supervisor	3	2	108	30.3
NB	110	Automobile mechanic	2	2	127	38.5
NC	113	Long-distance motor truck driver	2	2	106	29.6
ND	114	Ship's chief engineer	3	3	88	21.9
ND	115	Ship's steward (passenger)	2	2	73	16.9
ND	116	Able seaman	2	2	95	23.9
NE	117	Dockworker	2	1	99	25.4
NF	118	Air transport pilot	3	3	120	28.8
NF	119	Flight operations officer	3	2	110	25.3
NF	120	Airline ground receptionist	3	2	116	28.5
NF	121	Aircraft cabin attendant	3	2	112	28.3
NF	122	Aircraft engine mechanic	3	2	122	28.3
NF	123	Aircraft loader	2	1	115	27.1
NG	124	Air traffic controller	3	3	107	28.4
NG	125	Aircraft accident fire-fighter	3	2	93	21.8
NH	126	Post office counter clerk	2	2	126	34.7
NH	127	Postman	1	2	128	36.7
NH	128	Telephone switchboard operator	2	2	127	36.5
OA	129	Accountant	3	3	131	38.2
OA	130	Stenographer-typist	3	2	130	37.4
OB	133	Computer programmer	3	3	102	28.5
OB	134	Stenographer-typist	3	2	114	33.5
OB	135	Card- and tape-punching machine operator	3	2	95	24.1
OB	136	Insurance agent	3	3	111	29.7

OC	137	Clerks of work	3	3	98	23.3
PA	138	Computer programmer	3	3	106	28.7
PA	140	Stenograper-typist	2	2	117	31.8
PA	141	Card- and tape-punching machine operator	2	2	90	24
PA	142	Office clerk	2	2	123	35.5
PA	143	Fire-fighter	2	2	106	28.7
PA	160	Government executive official - central	3	3	105	27.4
PA	161	Government executive official - regional or provincial	3	3	77	16.5
PA	162	Government executive official - local authority	3	3	85	19.5
PB	144	Refuse collector	1	1	112	31.5
PC	145	Mathematics teacher (third level)	3	3	129	35.3
PC	146	Teacher in languages and literature (third level)	3	3	125	32.8
PC	147	Teacher in languages and literature (second level)	3	3	133	38.5
PC	148	Mathematics teacher (second level)	3	3	130	37.2
PC	149	Technical education teacher (second level)	3	3	126	36.2
PC	150	First-level education teacher	3	3	131	40
PC	151	Kindergarten-teacher	2	3	125	36.3
PD	152	General physician	3	3	134	40.6
PD	153	Dentist (general)	3	3	125	35
PD	154	Professional nurse (general)	3	3	136	44.8
PD	155	Auxiliary nurse	2	3	129	41
PD	156	Physiotherapist	3	3	120	34.4
PD	157	Medical X-ray technician	3	3	126	37.3
PD	158	Ambulance driver	1	2	125	36.4

F List of countries in OWW data file

High income countries

	Years with reports	Avg. reports by sample

	Occup.	Total	First	Last	Panel	1983-08
AIA - Anguilla	89	22	1964	2002	18.5	51.5
ANT - Netherlands Antilles	102	30	1953	1989	21.2	64.6
ATG - Antigua and Barbuda	129	19	1964	1996	23.4	64.9
AUS - Australia	156	49	1953	2006	42.1	129.7
AUT - Austria	152	50	1953	2002	43.5	133.9
BEL - Belgium	72	52	1953	2004	33.7	41.9
BHR - Bahrain	120	24	1978	2006	15.3	52.3
BHS - Bahamas	111	17	1965	2007	15.4	37.8
BMU - Bermuda	72	32	1964	2000	13.3	31.6
BRB - Barbados	118	39	1953	1995	28.3	75.0
BRN - Brunei Darussalam	38	14	1964	2002	18.4	17.3
CAN - Canada	131	41	1953	2008	24.7	86.4
CHE - Switzerland	28	32	1953	1984	25.3	24.5
CHL - Chile	145	20	1953	2007	37.7	88.8
CSK - Czechoslovakia	122	24	1960	1992	34.2	90.7
CYP - Cyprus	135	52	1953	2006	30.1	101.9
CZE - Czech Republic	136	16	1993	2008	36.8	109.8
DEU - Germany	160	56	1953	2008	42.1	153.0
DNK - Denmark	128	28	1953	2007	24.1	71.1
ESP - Spain	48	23	1953	1976	44.3	
EST - Estonia	139	5	1993	1997	30.4	103.4
FIN - Finland	143	54	1953	2007	34.4	107.2
FLK - Falkland Island	76	19	1964	1992	14.7	48.0
FRA - France	20	27	1955	2000	6.7	1.0
FRO - Faroe Islands	40	14	1966	1982	20.6	
GBR - United Kingdom	161	55	1953	2008	30.4	76.4
GIB - Gibraltar	77	29	1954	1991	17.3	37.8
GLP - Guadeloupe	100	21	1963	1991	24.1	27.5
GRC - Greece	48	32	1953	1984	41.4	41.0
GUF - French Guiana	80	22	1963	1991	17.8	45.8
GUM - Guam	95	17	1962	1989	16.4	28.5
HKG - Hong Kong	82	54	1953	2008	30.7	34.7
HRV - Croatia	117	1	1996	1996	32.0	117.0
HUN - Hungary	149	28	1968	2007	32.1	124.6
IMN - Isle of Man	121	8	1980	1990	23.4	79.6
IRL - Ireland	91	32	1953	1984	36.3	79.0

ISL - Iceland	68	54	1953	2008	19.5	15.4
ISR - Israel	54	27	1953	1984	29.7	21.0
ITA - Italy	154	53	1953	2008	40.4	138.7
JPN - Japan	69	45	1954	2008	21.4	37.5
KNA - Saint Kitts and Nevis	103	16	1964	2000	23.9	78.3
KOR - Korea, Republic of	159	37	1955	2006	34.6	133.4
KWT - Kuwait	138	8	1961	2004	32.6	126.0
LTU - Lithuania	139	4	1995	2006	27.0	90.3
LUX - Luxembourg	88	4	1977	2006	18.5	54.7
LVA - Latvia	146	10	1997	2006	35.5	118.5
MAC - Macao	20	18	1990	2008	6.7	9.5
MLT - Malta	35	20	1953	1985	23.6	7.0
MSR - Montserrat	34	12	1964	1980	20.1	
MTQ - Martinique	51	17	1963	1987	21.6	23.0
NCL - New Caledonia	105	21	1956	1983	29.2	65.0
NLD - Netherlands	107	38	1953	1990	36.9	76.5
NOR - Norway	79	54	1955	2008	10.3	30.0
NZL - New Zealand	153	39	1953	1991	41.5	122.2
POL - Poland	159	7	1996	2006	43.1	148.9
PRI - Puerto Rico	116	55	1953	2008	22.4	48.8
PRT - Portugal	145	48	1953	2007	24.9	72.4
PYF - French Polynesia	98	19	1957	1990	25.6	81.5
QAT - Qatar	35	7	1972	1981	30.1	
REU - Reunion	38	13	1963	1982	27.5	
SGP - Singapore	152	46	1953	2007	32.8	87.4
SHN - Saint Helena	89	20	1965	2007	15.0	51.8
SPM - Saint Pierre and Miquelon	74	23	1963	1991	13.0	48.3
SVK - Slovakia	155	13	1995	2007	39.7	126.8
SVN - Slovenia	102	4	1991	1997	29.3	73.8
SWE - Sweden	148	43	1953	1995	32.2	94.3
SYC - Seychelles	114	19	1965	1991	23.1	70.2
TTO - Trinidad and Tobago	138	35	1953	2000	26.7	98.2
TWN - Taiwan	102	21	1953	2004	37.4	77.7
URY - Uruguay	77	33	1954	1995	30.7	42.5
USA - United States of America	155	55	1953	2007	26.3	97.8
VGB - British Virgin Island	68	4	1974	1985	15.3	42.0
VIR - Virgin Islands (US)	93	14	1962	1990	24.6	62.0

Middle income countries

		Years with reports			Avg. reports by sample	
	Occup.	Total	First	Last	Panel	1983-08
AGO - Angola	161	7	1959	1999	36.1	131.0
ARG - Argentina	150	44	1953	2008	24.9	54.8
ASM - American Samoa	100	23	1962	1986	21.4	68.3
AZE - Azerbaijan	52	12	1996	2008	7.2	39.1
BGR - Bulgaria	143	2	1990	2002	38.0	116.5
BLR - Belarus	65	11	1995	2007	28.4	59.9
BLZ - Belize	112	36	1953	1995	26.7	90.5
BRA - Brazil	144	16	1958	2006	28.3	53.0
BWA - Botswana	84	8	1975	2007	17.4	37.8
CHN - China	131	14	1990	2006	26.1	69.4
COL - Colombia	143	7	1958	1990	27.9	73.3
CRI - Costa Rica	162	39	1958	2008	39.7	112.3
DMA - Dominica	31	11	1957	1984	14.3	7.0
DZA - Algeria	151	31	1953	2008	23.1	53.3
ECU - Ecuador	47	5	1958	1979	31.4	
FJI - Fiji	139	23	1953	1988	25.0	102.5
GAB - Gabon	113	23	1956	1995	21.0	45.8
GNQ - Equatorial Guinea	49	1	1985	1985	23.0	49.0
GRD - Grenada	108	22	1955	1995	22.7	86.3
GUY - Guyana	135	41	1954	2007	22.5	61.5
IRN - Iran	71	6	1959	1986	24.5	43.0
IRQ - Iraq	41	3	1959	1961	38.3	
JAM - Jamaica	45	18	1953	1979	20.4	
JOR - Jordan	155	32	1958	2006	30.3	105.9
KAZ - Kazakhstan	115	3	2002	2004	35.0	114.0
LBN - Lebanon	48	10	1955	1968	41.0	
LBY - Libya	34	2	1975	1979	21.0	
LCA - Saint Lucia	111	36	1955	1991	22.1	71.8
MDV - Maldives	18	2	2007	2008	2.0	18.0
MEX - Mexico	148	43	1955	2008	30.6	84.8
MUS - Mauritius	118	55	1954	2008	24.9	77.3

MYS - Malaysia	121	39	1953	1995	29.9	30.8
NAM - Namibia	36	3	1996	1998	5.0	17.0
PAN - Panama	47	9	1969	1979	28.9	
PER - Peru	152	38	1963	2008	31.6	72.7
PRY - Paraguay	47	13	1953	1982	37.7	
ROU - Romania	162	28	1973	2008	43.5	152.9
RUS - Russian Federation	125	12	1988	2007	22.5	56.7
SUR - Suriname	147	29	1960	1998	21.5	65.9
THA - Thailand	141	22	1954	2006	31.8	109.7
TUR - Turkey	153	10	1958	2006	26.8	59.2
VCT - St Vincent and Grenadines	99	21	1953	2003	24.9	78.5
VEN - Venezuela	156	28	1959	2001	35.3	100.8
YUG - Yugoslavia	157	8	1983	1990	34.0	144.8
ZAF - South Africa	38	13	1953	1994	26.3	7.0

Low income countries

		Years with reports			Avg. reports by sample	
	Occup.	Total	First	Last	Panel	1983-08
AFG - Afghanistan	22	2	1958	1981	12.0	
BDI - Burundi	97	24	1963	1992	32.3	64.1
BEN - Benin	139	21	1956	1991	20.7	65.9
BFA - Burkina Faso	121	26	1956	2000	24.5	61.4
BGD - Bangladesh	150	35	1953	2007	32.7	88.2
BOL - Bolivia	149	19	1953	1999	36.3	102.5
CAF - Central African Republic	123	25	1956	1997	26.9	78.3
CIV - Cote d'Ivoire	161	27	1956	2001	35.1	96.4
CMR - Cameroon	123	36	1956	1992	30.8	56.8
COD - Congo, DR	150	10	1953	1983	36.7	146.0
COG - Congo	46	12	1956	1979	30.5	
COM - Comoros	108	15	1978	1999	18.9	73.8
CPV - Cape Verde	83	5	1976	1986	20.8	79.5
DJI - Djibouti	72	4	1960	1996	22.3	49.0
EGY - Egypt	141	11	1987	2000	25.6	85.4
ERI - Eritrea	123	3	1993	2000	33.3	91.7
ETH - Ethiopia	70	10	1955	1997	26.7	23.5

GHA - Ghana	152	23	1954	2007	35.8	97.3
GIN - Guinea	46	4	1956	1961	28.5	
GMB - Gambia	30	2	1983	1984	19.0	19.0
GNB - Guinea-Bissau	37	3	1977	1981	23.0	
GTM - Guatemala	153	21	1953	1998	32.0	53.0
HND - Honduras	151	32	1955	1997	34.6	109.5
HTI - Haiti	61	22	1953	1988	24.3	35.5
IDN - Indonesia	133	18	1960	2006	17.1	41.8
IND - India	103	42	1953	2008	23.1	63.6
KEN - Kenya	101	11	1957	1985	27.5	77.0
KGZ - Kyrgyzstan	66	5	1994	2002	13.2	43.0
KHM - Cambodia	116	15	1962	2001	34.9	103.8
LBR - Liberia	68	7	1960	1986	21.8	26.5
LKA - Sri Lanka	64	40	1954	2000	13.2	24.1
LSO - Lesotho	122	5	1967	1990	28.0	97.0
MAR - Morocco	48	20	1953	1979	38.8	
MDA - Moldova	122	15	1994	2008	28.5	88.7
MDG - Madagascar	159	19	1956	2005	33.8	103.1
MLI - Mali	125	21	1956	1990	33.2	96.7
MMR - Myanmar	139	31	1970	2004	33.0	135.0
MNG - Mongolia	22	2	1994	1995		22.0
MOZ - Mozambique	145	3	1987	1989	32.7	115.7
MRT - Mauritania	36	9	1959	1971	18.3	
MWI - Malawi	138	18	1965	2002	20.2	59.3
NER - Niger	122	26	1956	1988	28.2	67.8
NGA - Nigeria	138	33	1953	1997	33.5	58.7
NIC - Nicaragua	112	20	1957	2002	24.7	61.9
NPL - Nepal	117	7	1975	1990	32.9	68.5
PAK - Pakistan	159	32	1953	2004	40.0	108.7
PHL - Philippines	139	35	1954	2008	23.0	38.9
PNG - Papua New Guinea	147	7	1979	1996	19.9	88.4
PSE - Palestine	6	2	2007	2008	2.0	5.0
RWA - Rwanda	131	12	1962	1991	33.1	123.9
SDN - Sudan	147	23	1953	1997	30.0	109.5
SEN - Senegal	91	21	1956	1992	32.2	49.3
SLB - Solomon Islands	46	2	1964	1986	11.5	42.0
SLE - Sierra Leone	114	32	1954	1996	26.2	98.1

SLV - El Salvador	149	25	1959	2008	36.3	123.8
SOM - Somalia	44	5	1960	1979	25.2	
SWZ - Swaziland	81	11	1975	1993	27.0	31.2
SYR - Syrian Arab Republic	47	23	1953	1995	33.0	8.0
TCD - Chad	109	17	1956	1999	22.2	68.0
TGO - Togo	83	24	1959	1998	27.2	40.8
TJK - Tajikistan	114	3	1993	1996	14.7	44.3
TON - Tonga	74	7	1964	1985	21.7	43.5
TUN - Tunisia	128	34	1954	1997	33.5	59.8
TZA - Tanzania	41	19	1953	1983	26.2	10.0
UGA - Uganda	148	4	1954	1993	32.8	143.0
UKR - Ukraine	74	3	1996	1999	13.7	49.7
WSM - Samoa	109	13	1968	2005	25.2	71.8
YEM - Yemen	148	6	1970	1996	28.3	146.0
ZMB - Zambia	152	34	1953	2006	30.4	98.3
ZWE - Zimbabwe	151	18	1954	2002	36.5	94.4