Occupational Choices, Human Capital, and Cross-Country Income Differences

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Abstract

We revisit the role of human capital in explaining the cross-country variation in GDP. We propose a general-equilibrium accounting model in which workers of different human-capital groups (education and experience) sort across broad occupational categories. The occupational assignment is determined by the comparative advantage of workers as well as occupational productivity, human-capital quality, and occupational distortions. We map the model to a unique harmonized micro dataset that allows to measure average wages by human capital and occupation for 50 countries that span the entire development spectrum. The calibration reveals that rich countries have particularly high productivity in more complex, white-collar occupations. They also have higher human-capital quality. The composition and quality of human capital explain half of the cross-country non-agricultural GDP per-worker gap relative to the US. For the poorest quintile of countries, a shift to US human capital would double non-agricultural GDP and the white-collar employment rate while decreasing the wage of white-collar relative to blue-collar workers by 30 percent. We also find that occupational distortions are more pronounced in poor countries. They depress white-collar employment and contribute to a high white-collar wage premium, yet have a modest quantitative effect on aggregate output.

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1 Introduction

How much does human capital contribute to the cross-country variation in GDP? To answer that question, the most straightforward "traditional" approach measures cross-country differences in the supply of skills by educational attainment and multiplies it by a common return to skill (Klenow and Rodríguez-Clare, 1997; Hall and Jones, 1999; Bils and Klenow, 2000; Caselli, 2005). Alternatively, the development accounting literature assumes some degree of complementarity between skilled and unskilled workers in the aggregate production function and uses country-specific returns to skill to infer skill-specific productivity terms. These can be interpreted as either embodied in human-capital (Jones, 2014, 2019) or disembodied as technology (Caselli and Coleman, 2006; Caselli and Ciccone, 2019). Depending on the interpretation, the contribution of human capital may be large or small. Various papers refine that approach by applying separate independent measures of human-capital quality to distinguish it from skill-specific technology (Hendricks and Schoellman, 2018, 2023; Rossi, 2022).

We go beyond that literature by quantifying a framework where the impact of human capital depends on the occupational tasks that various human-capital groups (by education and experience) perform within the economy. The value of human capital is therefore contingent on the economy's other fundamentals that jointly shape the required occupational needs: skilled workers can only shine if channeled toward activities in which they have sufficiently strong comparative advantage. We use the sorting patterns to disentangle human-capital quality from occupational productivity. As a result, we provide an arguably more precise measure of the contribution of human capital to GDP. We also answer anciliary questions, namely how human capital shapes occupational employment and relative wage patterns across countries. Along the way, we compare the importance of human capital to other (exogenous) country-specific parameters such as occupation-specific productivity occupational distortions, and the price of equipment.

The binding constraint is set be the data: we need observable measures of quantities and wages for each pair of human capital and occupation. For this, we turn to a cross-country dataset of harmonized labor force and household surveys. We operationalize it by constructing the required data moments for eight broad occupations and eight human-capital groups. The occupational categories cover the entire economy apart from the agricultural sector. The human-capital categories consist of four educational groups by two age groups. Altogether the data covers 50 countries and spans the entire development spectrum, including a large number of least-developed economies.

The first contribution of the paper is to document a number of empirical cross-country stylized facts about the distribution of employment and wages by human capital and occupation. First, as is well known, rich countries have more workers employed in white-collar occupations (clerks, technicians, professionals, and managers): 59 percent in the richest quintile of countries relative to 16 percent in the poorest quintile. Second, we show that conditioning on human capital, the white-collar employment rate is only slightly increasing in GDP. On average, the propensity to enter white-collar employment conditional on human capital is quite similar across the development spectrum.[1] Next, we turn to wages. We document that both the white-collar wage premium and the high-skilled (upper secondary and tertiary education) wage premium are decreasing in GDP. Again, these stylized facts are not new per se. What is new is that we can slice the wage data by conditioning jointly on the composition of human capital and occupational employment. In this case, both wage premia continue to be decreasing in GDP, albeit at a smaller rate. The upshot is that the wage premium patterns are not mere composition

[1]This replicates a stylized fact that has recently been uncovered by Engbom, Malmberg, Porzio, Rossi and Schoellman (2024).

effects, at least not in partial equilibrium.

The second contribution is the model. We build a simple static general-equilibrium model in the spirit of Hsieh, Hurst, Jones and Klenow (2019). Individuals belonging to distinct human-capital groups sort into occupations by comparative advantage. They do so based on idiosyncratic talent as well structural parameters that are specific to each human-capital group and occupation, namely (i) technology, (ii), human-capital quality, and (iii) wedges that distort occupational choices. Technology can further be decomposed into an exogenous occupation-specific productivity and an endogenous term as the economy adapts to the supply of human capital by directing technology to the relatively more abundant skill groups within each occupation. In addition, the production of occupational output combines labor with capital (equipment), with varying degrees of substitutability depending on the occupation. Consequently, cross-country differences in the relative price of equipment differentially affect occupational sorting and output.

The third contribution of the paper is the mapping of the cross-country data to the model in order to quantify the key structural parameters. As our least-skilled group group is quite fine (primary-school young workers), we assume that their human-capital quality is identical across countries. This anchor allows to measure the human-capital quality of all other skill groups without the need for external measures. It also allows to pin down occupational productivity. First, we find that the productivity gap between rich and poor countries is particularly pronounced in more complex, white-collar occupations. We deduce that development (i.e., productivity growth in the cross section) is biased toward white-collar workers. Second, we find that human-capital quality for all but the least-skilled workers is by and large higher in richer countries. This is true in almost all occupations and it is particularly strong for lower and upper secondary-school educated workers while less so for workers with completed college education. Also, the human-capital quality gap between rich and poor countries is particularly large for older, more experienced workers. Third, we find that occupational distortions are more prevalent in poor countries, and that they systematically discourage white-collar employment more strongly in lower-income countries. Finally, we also infer a clear pattern of endogenous technology. In all occupations, richer countries adopt technologies that benefit more highly educated and more experienced workers. For the lowest human-capital groups, rich countries operate technologies that are in absolute terms less productive than those of poor countries.

The final and main contribution of the paper is the evaluation of the general-equilibrium impact of human capital and various other exogenous endowments on aggregate outcomes. For this, we run counterfactuals on the model using the US as the benchmark economy. We find that for the poorest quintile of countries in our sample, the non-agricultural GDP gain from a shift to the US human-capital composition and quality is between 89 and 105 percent, depending on whether the base economy is the country itself or the US.[2] Most of that gain – about 80 percentage points – is associated with a shift in the educational composition of human capital, with the age composition accounting for a smaller portion. Altogether, we find that human capital on its own explains 46 percent of the non-agricultural GDP difference between the US and the poorest quantile in the sample. Human capital is therefore more important than productivity, which only accounts for roughly one-third of the non-agricultural GDP across countries. Interestingly, we find that occupational distortions play a modest role, explaining only about 2 percent of the GDP gap to the US in the poorest three quintiles. Also, human capital is a more important ingredient than the relative cost of equipment, which accounts for 8 percent of the GDP gap to the US in the poorest quintile and 25 percent for the fourth quintile.

Beyond GDP, we find that human capital in the poorest quintile of countries accounts for 34

[2] The first figure refers to endowing, say, Ethiopia with US human capital. The alternative is the GDP difference between the actual US economy and an economy like the US but with Ethiopia's human capital.

percent of the white-collar employment gap relative to the US. Across the sample of countries, the contribution is 31 percent. This stands in contrast to the partial-equilibrium regression analysis, which suggests that the gap is accounted for almost entirely by human capital. Here, occupational productivity is key. If poorer countries only increased human capital achievement without improving the productivity of white-collar occupations, the increase in white-collar employment is counteracted by a drop in the wage of white-collar workers. In general, we find that the human capital composition and occupational distortions sustain the higher white-collar wage premium gap to the US in poorer countries while productivity differences push in the opposite direction.

1.1 Related literature

This paper connects to a large literature researching the relationship between human capital and productivity across countries. In the first-generation development-accounting literature, human-capital groups are perfect substitutes and their efficiency units are measured using common Mincerian returns and cross-country differences in educational attainment (Klenow and Rodríguez-Clare, 1997; Hall and Jones, 1999; Bils and Klenow, 2000; Caselli, 2005). These papers generally find that human capital plays a comparatively minor role in explaining GDP differences. The subsequent second-generation literature allows low and high-skilled workers to be complementary in production and endowed with different skill-specific productivity. In such frameworks, productivity is found to be skill-biased because development entails a sizeable increase in educational attainment but only a slight drop in the wage skill premium. The required skill-biased productivity to match these facts is interpreted as disembodied technology by Caselli and Coleman (2006) and Caselli and Ciccone (2019). In contrast, Jones (2014) and Jones (2019) interpret it to reflect higher educational quality in richer countries. Rossi (2022) combines the same class of model with Mincerian returns of migrants to establish that the dominant force in the skill bias is technological as opposed to embodied in workers.

That literature has given rise to a debate on the long-run substitutability of skilled and unskilled labor, and how its size shapes the contribution of human capital to GDP accounting. We build on Okoye (2016), Hendricks and Schoellman (2023) and Bils, Kaymak and Wu (2024) who endogenize the substitutability of skill groups with directed technological choice. What distinguishes our approach is that we allow endogenous technological choice within occupations while identifying separate exogenous productivity terms for each occupation. Moreover, by having a sufficient number of skill groups we bypass the need to use migrant skill return data to disentangle productivity from human-capital quality. We find that productivity is not skill-biased *per se*. Instead, it is biased toward white-collar activities, which happen to be those in which skilled workers have a comparative advantage. Endogenous technology, on the other hand, is skill-biased because it is directed. Despite these differences, our results on the contribution of human capital to GDP are very much in line with those in Hendricks and Schoellman (2023).

There is ample evidence that the quality of human capital is low in poor countries. Most of the literature identifies it from the comparison of high versus low-skilled workers, either via the wages of migrants (Hendricks, 2002; Schoellman, 2012; Hendricks and Schoellman, 2018; Martellini, Schoellman and Sockin, forthcoming), from international-trade flows (Malmberg, 2022), or from wages of white-collar employees in multinational companies (Hjort, Malmberg and Schoellman, 2023). The literature also finds the quality of basic levels of education to be lower in developing countries (Hanushek and Woessmann, 2008; Hanushek and Woessman, 2012a,b). In addition, there is evidence that the quality of human capital associated with the experience (age) of workers is relatively low in poor countries (Lagakos, Moll, Porzio, Qian and Schoellman, 2018). Our alternative identification comes to a similar conclusion that human-capital quality associated with schooling and experience is low in developing countries. At the same time, we add to the literature by identifying that quality for different occupations.

We follow most of the above papers in treating the composition of human capital as exogenous. This contrasts with the strand of the literature that models human capital as an endogenous outcome and quantifies its importance in mediating cross-country differences in other fundamentals such as total factor productivity or education policies (Erosa, Koreshkova and Restuccia, 2010; Córdoba and Ripoll, 2013; Manuelli and Seshadri, 2014). Also, we restrict our attention to the non-agricultural sector. We therefore ignore any benefits accruing from the accumulation of human capital that are associated with shifting employment out of the agricultural sector (Porzio, Rossi and Santangelo, 2022).

This paper also relates to a growing literature that studies structural transformation in occupations. Duernecker and Herrendorf (2022), Bárány and Siegel (2018) and Bárány and Siegel (2021) investigate the impact of structural transformation in sectors on occupational employment across time, while our focus is on the cross section. This touches base with large literature studying how skill and automation shape the allocation of tasks and occupational employment over time (Acemoglu and Autor, 2011; Aum, Lee and Shin, 2018; Dvorkin and Monge-Naranjo, 2019). The closest papers to ours are those that investigate the interplay of skills and occupational choice in the cross-section of countries, which are Vizcaino (2021), Peña and Siegel (2024), Engbom, Malmberg, Porzio, Rossi and Schoellman (2024) and Bandiera, Kotia, Lindenlaub, Moser and Prat (2024). Our contribution relative to these is the measurement of relative wages by human capital and occupation which allows to infer productivities and distortions. In this, we follow Hsieh, Hurst, Jones and Klenow (2019) who study changes through time in occupational sorting as resulting from a drop in discrimination. Using a similar model structure, we also find that poorer countries feature stronger occupational distortions. These may well reflect institutional frictions that discourage delegation to managerial and professional workers (Grobovšek, 2020; Akcigit, Alp and Peters, 2021). However, in contrast to those papers, we do not find that the reduction of distortions generates a large impact on aggregate productivity.

In addition, our empirical measurements of wage premia complement a vast literature that measures cross-country differences in Mincerian returns.[3] The returns that we find are comparable in magnitude and pattern to those that the literature finds for education (Psacharopoulos and Patrinos, 2018) as well as experience (Jedwab, Romer, Islam and Samaniego, 2023). Our unique contribution is that we present returns to education and experience *conditional* on occupation for a wide range of countries.

Section 2 presents the main data and documents empirical stylized facts. Section 3 introduces the model. Section 4 quantifies the model and analyzes the pattern of inferred parameters. In Section 5 we measure counterfactual experiments. Section 6 concludes.

2 Data

2.1 Construction of the dataset

Our main database is the Harmonized World Labor Force Survey, an ongoing project to harmonize all publicly available household and labor force surveys across the world with a particular focus on least-developed countries. We restrict the dataset presented henceforth to those surveys for which we can harmonize individual-level hourly wages and hours worked in the main job, which are nationally representative (including self-employment), and for which we have information on demographic characteristics and the one-digit ISCO-08 occupational classification.

[3]See for example Flabbi and Gatti (2018) and Rossi (2020) for reviews of the various channels through which the literature measures the impact of human capital on growth.

Finally, we drop all agricultural workers to focus exclusively on non-agriculture.[4] More details are provided in Appendix 7.1.

Throughout the paper the analysis centers on eight occupations and eight human-capital groups. The occupations are "Elementary occupations," "Service workers," "Operators," "Craft and trade workers," "Clerical workers," "Technicians," "Professionals," and "Managers." The human capital groups are composed of four educational attainment categories by two age categories. The education bins are 0 to 8 years of schooling (labelled as "primary education"), 9 to 11 years ("lower secondary education"), 12 to 14 years ("upper secondary education'), and 15 years or more ("tertiary education").[5] The age bins are 16 to 40 ("young") and 41 or more ("old").

We then compute, for each country-year, the average wage and the employment share by human capital and occupation pair.[6] Splitting the data in $8 \times 8 = 64$ pairs implies that the raw moments sometimes do not exist or are imprecisely measured due to small samples. Instead, we use the micro data to estimate these moments using a multinomial logistic regression for occupational choice as well as wage regressions. These are precise in that the unconditional employment shares and average wages by occupation as well as the unconditional human-capital shares coincide exactly with the raw moments of the data. The procedure is laid out in Appendix 7.2.

Given that our focus is on the cross-section of countries, we only consider the most recent year for each country.[7] The final sample includes 50 countries and spans the entire development spectrum.[8]

2.2 Patterns in employment shares and relative wages

Table 1 summarizes the data on employment shares and relative wages by occupation and human capital. We group countries into quintiles ordered by non-agricultural GDP per worker, with "q1" indicating the lowest and "q5" the highest income group.

As countries develop, employment decreases in less complex occupations such as elementary work while it increases in more complex occupations such as managerial work. To see this more clearly, we group the first four occupations as blue-collar and the remaining four as white-collar. The share of white-collar work is 15% in the poorest quintile of countries and 58% in the richest

[4]We discard all workers whose main employment is in occupation "Skilled agricultural workers" and/or the agricultural sector (ISIC 4 code: A). Moreover, we drop all workers whose main occupation is "Armed forces."

[5]In a small number of countries, we redefine the cutoffs marginally to reflect more accurately the local degree structure.

[6]We use survey weights and hours worked in the main job to compute average wages and employment shares. Moreover, for employment shares, we also include the hours of the self-employed. This builds on the underlying assumption that wages are a good proxy for self-employed income (which we cannot measure) for each sub-group of workers.

[7]We stop at 2019 to discard the years of the Covid pandemic. In ongoing work, we are extending our results to the time-series dimension.

[8]Ordered by non-agricultural GDP per worker, the countries are: Ethiopia, 2013 (NLFS); Niger, 2014 (ECVMA); Senegal, 2018 (EHCVM), Sierra Leone, 2014 (SLLFS); Rwanda, 2016 (EICV); Ghana, 2017 (GLSS); Kenya, 2019 (KCHSP); Cambodia, 2019 (LFS); Zimbabwe, 2014 (LFCLS); Bolivia, 2018 (ECE); Zambia, 2017 (LFS); Peru, 2011 (ENAHO); Cote-d'Ivoire, 2018 (ERI-ESI); Pakistan 2018 (LFS); Philippines, 2018 (LFS); Yemen, 2013 (HLFS); India, 2019 (PLFS); Ecuador, 2018 (ENEMDU); Palestine, 2016 (HLFS); China, 2016 (CFPS); Brazil, 2015 (PNAD); Mongolia, 2019 (LFS); Namibia, 2016 (LFS); Sri Lanka, 2017 (LFS); Uruguay, 2017 (LFS); Argentina, 2019 (EPH); South Africa, 2019 (LMD); Mexico, 2014 (ENOE); Chile, 2017 (CASEN); Albania, 2010 (LFS); Egypt, 2011 (HLFS); Russia, 2017 (RLMS); Hungary, 2008 (SILC); Armenia, 2019 (LFS); Portugal, 2019 (SILC); Greece, 2019 (SILC); South Korea, 2007 (KLIPS); Japan, 2017 (ESS); Georgia, 2019 (LFS); United Kingdom, 2013 (SILC); Spain, 2012 (SILC); Germany, 2019 (SOEP); Canada, 2019 (LFS); Italy, 2019 (SILC); Belgium, 2005 (SILC); France, 2019 (LFS); Austria, 2018 (SILC); Switzerland, 2015 (SILC); United States, 2019 (CPS); Ireland, 2016 (SILC).

Table 1: Employment shares and wages

	Employment shares					Relative wages				
All occupations	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Elementary	17	16	15	8	7	1.00	1.00	1.00	1.00	1.00
Services	38	29	24	19	16	0.89	0.99	1.00	1.10	1.05
Operators	8	11	10	10	7	1.30	1.32	1.33	1.34	1.17
Craft	21	17	17	15	11	1.22	1.27	1.26	1.32	1.24
Clerks	2	4	6	9	9	2.07	1.74	1.31	1.42	1.25
Technicians	4	7	10	14	19	2.41	1.94	1.83	1.53	1.47
Professionals	7	9	12	18	22	2.73	2.55	2.70	2.04	1.87
Managers	3	7	6	6	9	3.48	2.58	2.69	2.30	2.01
Main occupations	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Blue-collar	84	73	66	52	41	1.00	1.00	1.00	1.00	1.00
White-collar	16	27	34	48	59	2.50	1.99	1.95	1.51	1.51
All human-capital groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Primary & young	39	21	9	2	1	1.00	1.00	1.00	1.00	1.00
Primary & old	21	16	13	6	3	1.22	1.25	1.14	1.05	1.21
Lower secondary & young	14	16	16	7	5	1.35	1.17	1.15	1.05	1.06
Lower secondary & old	6	9	10	11	11	1.87	1.56	1.43	1.14	1.39
Upper secondary & young	10	14	18	20	17	1.85	1.45	1.49	1.17	1.25
Upper secondary & old	4	6	14	20	22	2.62	2.06	1.92	1.34	1.65
Tertiary & young	4	11	11	17	18	3.33	2.37	2.57	1.63	1.68
Tertiary & old	3	7	8	18	22	4.90	3.56	3.31	2.03	2.26
Main human-capital groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Low-skilled	79	62	48	26	21	1.00	1.00	1.00	1.00	1.00
High-skilled	21	38	52	74	79	2.27	1.82	1.77	1.41	1.43

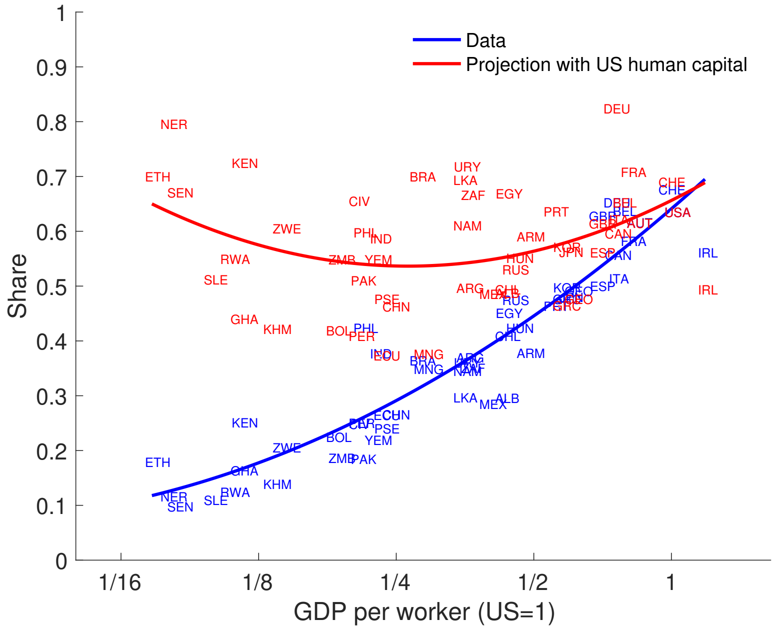
quintile. The upper right part Table 1 reveals that the wage differential between complex and simple occupations is substantially larger in poor than in rich countries. In particular, white-collar workers earn 151% more than blue-collar workers in the poorest quintile (2.51 relative to 1), while in the richest quintile the wage differential is 49% (1.49 relative to 1).

The lower left part of Table 1 shows that workers' educational attainment and age are increasing in development. To summarize the human capital groups, we define the first four groups as low-skilled (all ages, strictly less than 12 years of education) and the remainder as high-skilled. The share of the latter is 18% in the poorest quintile and 77% in the richest. Next, the lower right part of Table 1 indicates that the wage skill premium is larger in poor than in rich countries. High-skilled workers earn 134% more than low-skilled ones in the poorest quintile of countries, whereas in the richest quintile the wage differential is 46%.

In summary, the quantitative patterns in employment and wage premia are similar for occupations and human-capital groups. To dig deeper, we investigate the pattern for occupations conditional on human capital, and for human capital conditional on occupational employment. Appendix 7.4 reports the data analogously to Table 1. Here, we propose an alternative visualization of those results in Figures 1-2. The construction of these series is described in Appendix 7.3.

Figure 1 plots the white-collar employment share against non-agricultural GDP per worker (from here onward shortened always to "GDP per worker"). It is strongly increasing. Overlaid, in the left panel, is the projection of the white-collar employment share conditional on countries having the US composition of human capital. We construct it using each country's probability of white-collar employment conditional on one of the eight human-capital groups and then averaging by using US human capital weights. While still increasing in GDP, the relationship is substantially weaker than that of the observed share. It follows that conditional on human capital, the propensity to work in white-collar occupations is only slightly increasing in the

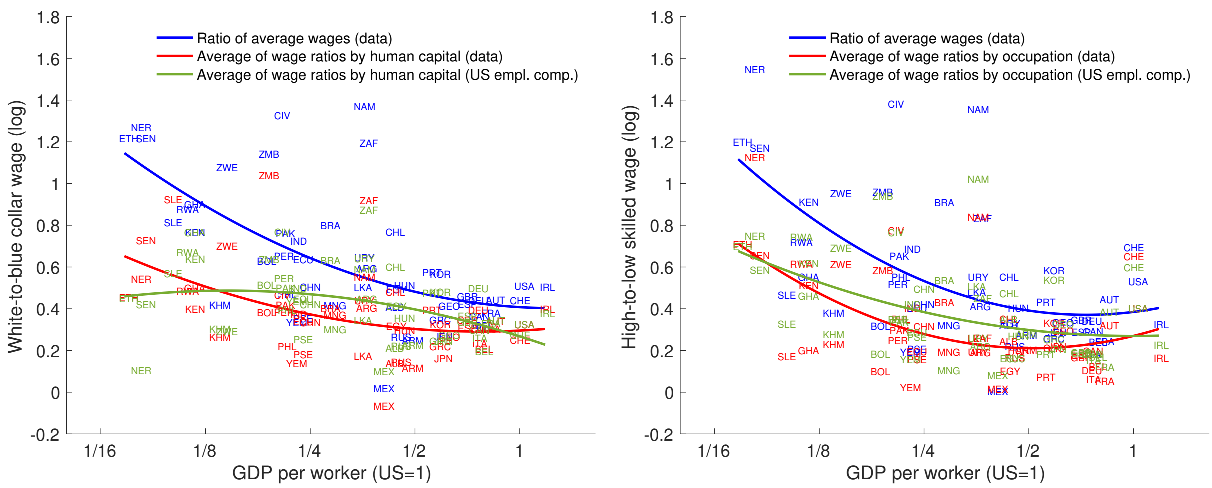
Figure 1: White-collar employment share



country's income level, something that has previously been documented by Engbom, Malmberg, Porzio, Rossi and Schoellman (2024).

Figure 2: Relative wages

(a) White-collar to blue-collar wages **(b)** High-skilled to low-skilled wages



Note: In panel (a), the relative average wage of white-collar to blue-collar workers is $\frac{\overline{w}_W}{\overline{w}_B}$ where $\overline{w}_W = \frac{\sum_{j \in W} \sum_s f_{sj} \overline{w}_{sj}}{\sum_{j \in W} \sum_s f_{sj}}$ and $\overline{w}_B = \frac{\sum_{j \in B} \sum_s f_{sj} \overline{w}_{sj}}{\sum_{j \in B} \sum_s f_{sj}}$. The average ratio of white-collar to blue-collar wages is $\frac{\overline{w}'_W}{\overline{w}'_B} = \sum_s f_s \frac{\overline{w}_{s,W}}{\overline{w}_{s,B}}$ where $\overline{w}_{s,W} = \frac{\sum_{j \in W} f_{sj} \overline{w}_{sj}}{\sum_{j \in W} f_{sj}}$ and $\overline{w}_{s,B} = \frac{\sum_{j \in B} f_{sj} \overline{w}_{sj}}{\sum_{j \in B} f_{sj}}$. The average ratio of white-collar to blue-collar wages using US weights is $\frac{\overline{w}''_W}{\overline{w}''_B}$ where the underlying employment shares are those of the US. In panel (b), the relative average wage of high-skilled to low-skilled workers is $\frac{\overline{w}_H}{\overline{w}_L}$ where $\overline{w}_H = \frac{\sum_j \sum_{s \in H} f_{sj} \overline{w}_{sj}}{\sum_j \sum_{s \in H} f_{sj}}$ and $\overline{w}_L = \frac{\sum_j \sum_{s \in L} f_{sj} \overline{w}_{sj}}{\sum_j \sum_{s \in L} f_{sj}}$. The average ratio of high-skilled to low-skilled wages is $\frac{\overline{w}'_H}{\overline{w}'_L} = \sum_j f_j \frac{\overline{w}_{H,j}}{\overline{w}_{L,j}}$ where $\overline{w}_{H,j} = \frac{\sum_{s \in H} f_{sj} \overline{w}_{sj}}{\sum_{s \in H} f_{sj}}$ and $\overline{w}_{L,j} = \frac{\sum_{s \in L} f_{sj} \overline{w}_{sj}}{\sum_{s \in L} f_{sj}}$. The average ratio of high-skilled to low-skilled wages using US weights is $\frac{\overline{w}''_H}{\overline{w}''_L}$ where the underlying employment shares are those of the US.

Panel (a) of Figure 2 plots the ratio of the average wages of white-collar to blue-collar workers against non-agricultural GDP per worker. The white-collar wage premium is clearly higher in poorer countries. This may either be due to white-collar workers earning a particularly high premium conditional on the human-capital group or due to high-skilled workers (who have a higher propensity to be employed in white-collar occupations) earning a particularly high premium. To further disentangle the two, we compute the ratio of white-collar to blue-collar workers for each human-capital group and then plot the average of these ratios weighted by each country's human-capital composition. The resulting red line in Figure 2 indicates that the white-collar wage premium is still decreasing in GDP per worker, albeit at a lower rate. Finally, the green line computes the using as weighting the US employment composition of human capital and occupational propensity. The relationship with GDP per worker is weaker still yet remains decreasing. We conclude that even after conditioning on the all countries having the same employment composition, the white-collar premium is somewhat higher in poorer countries.

Panel (b) of Figure 2 repeats the previous exercise for the wage premium of high relative to low-skilled workers. The blue line represents the average wage premium and follows a similar pattern to the white-collar wage premium discussed above. Next, the red line shows that even after conditioning on occupation, the skill premium remains higher in poorer countries. This is also true when all skill premia are weighted by the same (US) human-capital and occupational shares. The upshot is a slightly higher skill premium in poor countries even after applying the same composition of workers.

3 Model

Aggregate output, Y, is a composite of occupational tasks, Y_j, indexed by $j = \{1, 2, ..., J\}$

$$Y = \left(\sum_{j=1}^{J} Y_j^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

with the elasticity of substitution $\sigma > 0$. The production of occupational output combines capital, K, and efficiency units of labor, Q, according to

$$Y_j = \left(\alpha_j K_j^{\frac{\gamma_j-1}{\gamma_j}} + (1-\alpha_j)\, Q_j^{\frac{\gamma_j-1}{\gamma_j}} \right)^{\frac{\gamma_j}{\gamma_j-1}}$$

with elasticities of substitution $\gamma_j > 0$ and intensities $\alpha_j \in (0, 1)$. Occupations can thus differ in the degree to which capital and labor are substitutable. Within occupations, efficiency units of labor are assumed to follow

$$Q_j = \left(\sum_{s=1}^{S} (B_{sj} H_{sj})^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1}$$

with the elasticity of substitution $\varepsilon > 0$. The occupational labor aggregator is a composite of distinct technology-augmented human-capital groups where H_{sj} represents worker-specific efficiency units provided to occupation j by workers of human-capital group $s = \{1, 2, ..., S\}$.

The representative firm maximises profits

$$\max_{K_j, H_{sj}, B_{sj}} \left\{ Y - \sum_j \left(RK_j + \sum_s w_{sj} H_{sj} \right) \right\}$$

subject to the technological menu

$$\left(\sum_s B_{sj}^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}} \leq A_j, \tag{2}$$

with the parameter restriction $\nu > 0$ and $\nu(2 - \varepsilon) > 1$, where R is the rental rate of capital and w_{sj} is the wage rate of human-capital type s in occupation j.[9] Apart from the production factors, the firm hence also chooses the technology terms B_{sj} as in Caselli and Coleman (2006), Acemoglu (2007), Hendricks and Schoellman (2023) and Bils, Kaymak and Wu (2024). Here, the technological menu (2) is specific to each occupation and hence allows technologies B_{sj} to be directed to the relatively abundant and cheap human-capital group within each occupation. The productivity level for each occupation, A_j, in contrast, is assumed to be exogenous. Consider the example of managerial and elementary occupations. We posit that they are sufficiently different to be shaped by distinct exogenous forces, say due to technical or institutional constraints. Within each occupation, on the other hand, firms can mould technologies to make them suitable for their worker types. For instance, managerial tasks can be performed either by more or less experienced workers or, alternatively, by more or less educated workers. Depending on the task, the technology will adjust accordingly.

On the individual level, the economy is populated by a unit mass of workers partitioned into human-capital groups. The shares of human-capital groups are exogenous and given by L_s such that $\sum_s L_s = 1$. Each individual worker i of human capital s chooses to work in the occupation that maximizes her utility,

$$u_s(i) = \max_j \left\{ \frac{w_{sj} h_{sj} z_j(i)}{D_{sj}} \right\}_{j=1}^J .$$

The numerator represents the worker's labor income. Apart from the wage rate w_{sj}, the worker's choice is governed by two types of productivities. The first is common to all workers s, h_{sj}, and varies across occupations j. It measures worker-embodied quality of human-capital group s in occupation j relative to that of the lowest human-capital group, normalized as $h_{1j} = 1$, $\forall j$. The second type of productivity is idiosyncratic to each individual i, $z_j(i)$. It captures the fact that among, say, primary school-educated workers, there are *some* who are particularly talented in managerial tasks and therefore sort into that occupation. We assume that productivities z_j are drawn from the joint cumulative distribution function $G_s(z_1, ..., z_J) = \exp\left(- \left[\sum_{j=1}^J z_j^{-\frac{\theta_s}{1-\rho}} \right]^{1-\rho} \right)$. The draws follow a Fréchet distribution with shape parameter $\theta_s > 1$ and are correlated across occupations via a Gumbel copula. We allow the dispersion of productivities to vary by human-capital group, with higher θ indicating less dispersion. The dependence parameter ρ ranges from 0 (no correlation) to 1 (perfect positive correlation).

In addition, the worker's choice is affected by non-pecuniary wedges, D_{sj}. These can be viewed as institutional constraints, discrimination or as taste-shifters that equally affect all workers of a particular human-capital group. For example, licensing requirements can make

[9] The rental rate of capital is not indexed by j because capital is homogenous across occupations.

professional jobs inaccessible to workers with a low educational attainment, captured by a high D. Likewise, low-skilled workers may be discouraged from professional jobs because they are uncomfortable in that work environment due to a lack of peers or because their networks do not allow them to signal their qualification for such jobs. As the wedges are relative, they are normalized for any one particular occupation for each human-capital group, $D_{s1} = 1$, $\forall s$.

Let π_{sj} be the fraction of workers of type s who choose occupation j so that their labor supply is

$$L_{sj} = \pi_{sj} L_s \tag{3}$$

Their supply of human capital of type s to occupation j is hence

$$H_{sj} = h_{sj} \overline{z}_{sj} L_{sj}. \tag{4}$$

The second term, $\overline{z}_{sj}$, represents the average idiosyncratic productivity and captures the selection of individual workers of type s into occupation j. Finally, we assume that the relative price of capital, R, is exogenous. This means that the aggregate demand for capital, $\sum K_j = K$, is supplied completely elastically. We make this assumption so that we can interpret counterfactual changes as being sufficiently long-lasting for capital to adjust to a new steady state. In particular, note that R therefore not only represents the relative purchasing price of capital goods but also any factor that affects investment decisions such as discount rates, investment distortions or credit market frictions.

3.1 Definition of the equilibrium

Given the price of capital R, productivity A_j, human-capital quality h_{sj}, distortions D_{sj} and the composition of human capital, L_s, the equilibrium consists a set of wage rates w_{sj}, capital allocations K_j, human capital allocations H_{sj}, technology choices B_{sj}, occupational probabilities π_{sj}, and average idiosyncratic efficiencies $\overline{z}_{sj}$, such that:

1. The representative firm chooses K_j, H_{sj} and B_{sj} to maximise profits subject to the technological menu constraint (2);
2. Individual workers choose their occupation to maximise utility;
3. The labor market clears, namely the occupational choices imply π_{sj} and $\overline{z}_{sj}$ such that (3) and (4) and hold.

3.2 Characterization of the equilibrium

The firm's optimality conditions with respect to the production factors are standard,

$$\alpha_j \left(\frac{Y}{Y_j}\right)^{\frac{1}{\sigma}} \left(\frac{Y_j}{K_j}\right)^{\frac{1}{\gamma_j}} = R$$

and

$$(1-\alpha_j) \left(\frac{Y}{Y_j}\right)^{\frac{1}{\sigma}} \left(\frac{Y_j}{Q_j}\right)^{\frac{1}{\gamma_j}} \left(\frac{H_j}{H_{sj}}\right)^{\frac{1}{\eta}} A_j = w_{sj}.$$

The optimality conditions with respect to B_{sj} imply the technological choice

$$B_{sj} = A_j H_{sj}^{\frac{\nu(\varepsilon-1)}{\nu-\varepsilon}} \left(\sum_{s'} H_{s'j}^{\frac{(\nu-1)(\varepsilon-1)}{\nu-\varepsilon}}\right)^{\frac{-\nu}{\nu-1}}. \tag{5}$$

Replacing the technologies from (5) in (1) allows to rewrite occupational labor efficiency as

$$Q_j = A_j H_j \tag{6}$$

where the human-capital aggregator is

$$H_j = \left(\sum_{s=1}^{S} H_{sj}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{7}$$

with the endogenous elasticity of substitution $\eta = \frac{\nu-\varepsilon}{\nu(2-\varepsilon)-1} > \varepsilon$. Notice that H_j is now recast as a pure aggregator of human capital that is independent of technology.

Now turn to the supply of human capital. The extreme-value distribution of idiosyncratic productivities implies that the probability of an individual of skill s choosing occupation j is

$$\pi_{sj} = \frac{\left(w_{sj} \frac{h_{sj}}{D_{sj}} \right)^{\frac{\theta_s}{1-\rho}}}{\sum_{i=1}^{J} \left(w_{si} \frac{h_{si}}{D_{si}} \right)^{\frac{\theta_s}{1-\rho}}}. \tag{8}$$

Moreover, the distributional assumption implies that

$$\overline{z}_{sj} = \Gamma_s \pi_{sj}^{-\frac{1-\rho}{\theta_s}}$$

where $\Gamma_s \equiv \Gamma\left(1 - \theta_s^{-1}\right)$ is the Gamma function. The term $\pi_{sj}^{-(1-\rho)/\theta_s}$ reflects that as more workers of type s flock into occupation j, their average productivity diminishes due to a drop in comparative advantage. The higher is the dependence parameter ρ, the smaller is that effect. Finally, since $L_{sj} = \pi_{sj} L_s$, the supply of human capital is

$$H_{sj} = \Gamma_s h_{sj} \pi_{sj}^{1-\frac{1-\rho}{\theta_s}} L_s. \tag{9}$$

3.3 Discussion

In the subsequent section we will combine the model with data to infer country-specific productivity A_j, human-capital quality $\overline{h}_{sj}$, and distortions D_{sj}. Our framework strikes a balance between the interpretation of efficiency as embodied in human-capital quality and that of efficiency as disembodied in technology. Within any given occupation, we follow the view held by Jones (2014) that relative wage across skills do not reflect differences in technological efficiencies. Instead, they only reflect differences in human-capital quality and occupational sorting. Let $\overline{w}_{sj} \equiv w_{sj}\overline{z}_{sj}$ be the observable average wage of workers s in occupation j. Given the normalization $h_{1j} = 1$, we can determine embodied human capital as

$$h_{sj} = \left(\frac{\overline{w}_{sj}}{\overline{w}_{1j}} \right) \frac{\Gamma_1}{\Gamma_s} \frac{\pi_{sj}^{\frac{\theta_s+(1-\rho)(\eta-1)}{\theta_s(\eta-1)}}}{\pi_{1j}^{\frac{\theta_1+(1-\rho)(\eta-1)}{\theta_1(\eta-1)}}} \left(\frac{\overline{w}_{sj} L_s}{\overline{w}_{1j} L_1} \right)^{\frac{1}{\eta-1}}. \tag{10}$$

When selection plays no role, $\theta_s \to \infty$, the model nests the Jones (2014) and Jones (2019) interpretation within any given occupation:

$$h_{sj} = \left(\frac{\overline{w}_{sj}}{\overline{w}_{1j}} \right)^{\frac{\eta}{\eta-1}} \left(\frac{\pi_{sj} L_s}{\pi_{1j} L_1} \right)^{\frac{1}{\eta-1}} = \left(\frac{\overline{w}_{sj}}{\overline{w}_{1j}} \right)^{\frac{\eta}{\eta-1}} \left(\frac{L_{sj}}{L_{1j}} \right)^{\frac{1}{\eta-1}}.$$

If the ratio $\frac{\overline{w}_{sj}}{\overline{w}_{1j}}$ does not vary strongly across across countries while $\frac{\overline{w}_{sj}}{\overline{w}_{1j}}$ does, a sufficiently low elasticity η would predict large cross-country differences in h_{sj}. Moreover, the model also nests the "traditional" accounting approach within any given occupation when human-capital groups are perfect substitutes, $\eta \to \infty$. In that case we have

$$h_{sj} = \left(\frac{\overline{w}_{sj}}{\overline{w}_{1j}}\right) \frac{\Gamma_1}{\Gamma_s} \left(\frac{\pi_{sj}^{\frac{1}{\theta_s}}}{\pi_{1j}^{\frac{1}{\theta_s}}}\right)^{1-\rho}.$$

Our strategy to identify human-capital quality h_{sj} rests on the assumption that within occupations, the long-run human-capital aggregator (7) and its components (4) do not depend directly on productivity A_j. We leverage the insight of Hendricks and Schoellman (2023) that the accompanying long-run elasticity of substitution η subsumes any endogenous technological choices resulting from changes in the supply of human capital. This reconciles the discussion between Caselli and Ciccone (2019) and Jones (2019) by arguing that within occupations, human-capital aggregators with either skill-neutral or skill-biased technology are plausible representations of the same data depending on the value of the elasticity of substitution between human-capital groups.

In addition, we go beyond that discussion by allowing technology, A_j, to be occupation-specific. Ultimately, technology is therefore not skill-neutral because human-capital groups differ in their occupational comparative advantage. We back out A_j as

$$A_j = \overline{w}_{sj} \frac{1}{h_{sj}} \frac{\pi_{sj}^{\frac{1-\rho}{\theta_s}}}{\Gamma_s} x_j^{\frac{1}{\sigma-1}} x_{sj}^{\frac{1}{\eta-1}} \left(\frac{1}{1-\alpha_j}\right)^{\frac{\gamma_j}{\gamma_j-1}} \left(\lambda_j^{\frac{\sigma-\gamma_j}{\gamma_j-1}} \lambda\right)^{\frac{1}{\sigma-1}} \tag{11}$$

where $x_j \equiv \frac{\sum_s \overline{w}_{sj} L_{sj}}{\sum_j \sum_s \overline{w}_{sj} L_{sj}}$ is the relative labor income share of occupation j, $x_{sj} \equiv \frac{\overline{w}_{sj} L_{sj}}{\sum_s \overline{w}_{sj} L_{sj}}$ is the relative labor income share of human-capital group s in occupation j, $\lambda_j \equiv \frac{\sum_s \overline{w}_{sj} L_{sj}}{\sum_s \overline{w}_{sj} L_{sj} + RK_j}$ is the labor share within occupation j, and $\lambda \equiv \frac{\sum_j \sum_s \overline{w}_{sj} L_{sj}}{Y}$ is the aggregate labor share. Using our data on averages wages and employments shares, normalizing $h_{1j} = 1$, and solving for the equilibrium value of λ_i obtains A_j. Notice that in the absence of capital, $\alpha_j = 0$, A_j could be simply pinned down by the data as

$$A_j \propto \overline{w}_{1j} \pi_{1j}^{\frac{1-\rho}{\theta_s}} x_j^{\frac{1}{\sigma-1}} x_{1j}^{\frac{1}{\eta-1}}.$$

First, technological efficiency in occupation j is increasing in the average wage of the bottom human-capital group of that occupation. Second, it is increasing in the selection of the bottom human-capital group toward that occupation: for a given average wage, a higher fraction of workers in that occupation implies a lower average idiosyncratic productivity and therefore a higher required technological level. Third, A_j is increasing in the income share of that occupation, x_j (for $\sigma > 1$). To the extent that more complex occupations comprise a large fraction of the wage mass in rich countries, this indicates a relatively high productivity in those occupations. This chimes with the intuition in Caselli and Ciccone (2013) and Caselli and Ciccone (2019), but at the level of occupations instead of human-capital groups. Finally, A_j is increasing in the income share of the lowest human-capital group in that occupation, x_{1j} (for $\eta > 1$). To the extent that it is relatively low across all occupations in rich countries, it attenuates the cross-country technological gap.

Finally, the assumption that idiosyncratic productivities are distributed Fréchet implies that

$$D_{sj} = \frac{\overline{w}_{sj}}{\overline{w}_{s1}} \tag{12}$$

where we used the normalization $D_{s1} = 1$ for the first occupation, $\forall s$. The wedges can therefore be read off directly from the average wages: if a human-capital group s has higher average wages in occupation j than occupation i, the model implies that its employment is distorted away from occupation j.

4 Model quantification

4.1 Calibration of common parameters

We follow the same classification of $S = 8$ human-capital groups and $J = 8$ occupations as in Section 2. This number of occupations allows to set several country-independent common parameters that have been estimated in the literature using models quantified on one-digit SOC occupations. The remaining parameters are calibrated, mostly to US moments.

Table 2: Calibrated parameters

Set parameters	Value	Source
ES between occupations, σ	1.81	Burstein, Morales & Vogel (2019)
ES elementary occ., γ_1	1.32	Caunedo, Jaume & Keller (2023)
ES service and sales, γ_2	1.38	Caunedo, Jaume & Keller (2023)
ES machine & plant operators, γ_3	1.41	Caunedo, Jaume & Keller (2023)
ES craft & related trade, γ_4	2.06	Caunedo, Jaume & Keller (2023)
ES clerks, γ_5	2.18	Caunedo, Jaume & Keller (2023)
ES technicians, γ_6	0.65	Caunedo, Jaume & Keller (2023)
ES professionals, γ_7	0.86	Caunedo, Jaume & Keller (2023)
ES managers, γ_8	0.93	Caunedo, Jaume & Keller (2023)
Calibrated parameters	**Value**	**Target**
ES between human-capital groups, η	6.97	Elasticity of subst.: 4.53
Gumbel dependence param, ρ	0.35	Spearman rank corr..: 0.50
Fréchet shape param. primary & young, θ_1	2.90	US var. of log wages, primary & young
Fréchet shape param. primary & old, θ_2	2.77	US var. of log wages, primary & old
Fréchet shape param. lower sec. & young, θ_3	2.67	US var. of log wages, lower sec. & young
Fréchet shape param. lower sec. & old, θ_4	2.47	US var. of log wages, lower sec. & old
Fréchet shape param. upper sec. & young, θ_5	2.68	US var. of log wages, upper sec. & young
Fréchet shape param. upper sec. & old, θ_6	2.58	US var. of log wages, upper sec. & old
Fréchet shape param. tertiary & young, θ_7	2.42	US var. of log wages, tertiary & young
Féchet shape param. tertiary & old, θ_8	2.33	US var. of log wages, tertiary & old
Capital intensity, α_j	–	US equipment income share: 0.193

Table 2 reports the parameters. The elasticity of substitution between occupational tasks, σ, is set to 1.81 following Burstein, Morales and Vogel (2019) who estimate it based on a similar model structure. We take the elasticity of substitution between equipment capital and efficiency units of labor from Caunedo, Jaume and Keller (2023). We focus only on equipment (as opposed to structures) because it varies substantially in its complementarity with labor across different occupations. As can be seen from Table 2, the elasticities are above 1 in blue-collar occupations, meaning that equipment and labor are gross substitutes. In contrast, white-collar occupations

Table 3: Variance of log wages, US

Human capital	Model	Data
Primary school & young	0.207	0.207
Primary school & old	0.226	0.226
Lower sec. school & young	0.245	0.245
Lower sec. school & old	0.289	0.289
Upper sec. school & young	0.252	0.252
Upper sec. school & old	0.287	0.287
Tertiary school & young	0.322	0.322
Tertiary school & old	0.356	0.356

Occupation	Model	Data
Elementary occupations	0.253	0.257
Service and sales	0.271	0.313
Machine & plant operators	0.249	0.240
Craft & related trade	0.263	0.254
Clerks	0.268	0.222
Technicians	0.304	0.344
Professionals	0.313	0.314
Managers	0.325	0.359

with the exception of clerks, feature gross complementarity between labor and capital.[10]

We set the dependence parameter ρ to 0.35 by targeting a Spearman rank correlation between the productivity draws z of 0.5. We choose that moment as it represents a moderate correlation of draws. It strikes a balance between the usual assumption of independent draws and evidence that skills are strongly correlated across occupations, for example between farming and non-agricultural entrepreneurship (Alvarez-Cuadrado, Amodio and Poschke, 2021). The Fréchet shape parameters, θ_s, are calibrated to match the variance of log wages for each human-capital group in the US in 2019. Note that in the model, wage variation within a human-capital group results both from variation in idiosyncratic productivity as well as sorting across occupations. More high-skilled workers draw from a more dispersed distribution (lower shape parameter θ) as they exhibit more variation in wages as reported in the upper part of Table 3. The lower part of the Table reports the model outcomes and data on the variance of log wages by occupation, which are not targeted. We see that the model can match the empirical fact that there is more wage variation within more complex occupations.

We calibrate the within-occupation elasticity of substitution between human-capital groups, η, to 6.97. The target is the long-run elasticity of substitution between low-skilled and high-skilled workers of 4.53 estimated by Hendricks and Schoellman (2023) across their sample of countries.[11] This elasticity is also in line with Bils, Kaymak and Wu (2024) who estimate a plausible lower bound of the long-run elasticity to be 4 based on the assumption that technology does not regress.

The final set of parameters is the capital equipment intensity parameters, α_j. We vary α_j

[10]The estimates in Caunedo, Jaume and Keller (2023) are based on the SOC classification while here we use ISCO. For most categories, the cross-walk is one-for-one. For the remaining categories, we choose the closes: "clerical support workers" corresponds to "administrative service workers," "elementary occupations" corresponds to "low-skilled service workers," and "craft related trades workers" corresponds to "precision occupations."

[11]To be most consistent with their estimate, we compute the elasticity of substitution for each country and target the average across countries. Most countries lie in a fairly close range around that mean value, ranging from 2.80 (Rwanda) to 6.29 (Canada). For the US, which has very few low-skilled workers (high-school dropouts), the value is 6.20.

in each occupation so that all occupational equipment capital shares are identical and equal to the US aggregate value of 0.193. See Appendix 7.5.3 for more details.

4.2 Inference of country-specific parameters

The remaining set of parameters are country-specific, indexed by c: productivities, A^c_j, human-capital quality h^c_{sj}, distortions, D^c_{sj}, and the relative price of capital, R^c. The key data moments are those described in Section 2, namely the worker shares by human capital and occupation, $L^c_{sj} = \pi^c_{sj} L^c_s$, and average wages, $\overline{w}^c_{sj}$, up to a normalizing constant since wages are reported in nominal units.

We fix the level by targeting non-agricultural output per worker, Y^c. We construct it using the GGDC Productivity Level Database (PLD) on real cross-country sectoral value added (Inklaar, Marapin and Gräler, 2023) as explained in Appendix 7.5.1. Finally, to determine the price of capital, R^c, we target real aggregate equipment, K^c, constructed from the detailed capital data auxiliary to the Penn World Table 10.01 (Feenstra, Inklaar and Timmer, 2015) as described in Appendix 7.5.2.

The inferred productivity and distortion parameters are depicted in the Appendix 7.6. Here, we investigate their pattern relative to non-agricultural GDP per worker. In addition, we also briefly analyze the pattern of the resulting endogenous technology choice, B^c_{sj}.

4.2.1 Productivity, A

We start by regressing the productivity A_j on non-agricultural GDP per worker:

$$\log A^c_j = \alpha + \beta^A_j \log Y^c + \varepsilon^c_j.$$

The estimated coefficients $\widehat{\beta}^A_j$ are reported in Table 4. Richer countries tend to more productive in all occupations except that of Service and Sales workers. Also, the elasticity is typically increasing in the complexity of the occupation (from left to right). These findings suggest that productivity growth is biased toward white-collar occupations.

Table 4: Elasticity of productivity, A, with respect to GDP per worker

Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
0.11	0.00	0.45	0.21	1.00	1.17	0.60	1.16

Next, we investigate how the cross-country variation in the productivity terms is driven by various components that enter the inference. For this, we use (11) to decompose the inferred productivity terms as follows:

$$\log A^c_j = \underbrace{\xi_j}_{\text{Constant}} + \underbrace{\log \overline{w}^c_{1j}}_{\substack{\text{Observed}\\ \text{wages}}} + \underbrace{\frac{1-\rho}{\theta_s}\log \pi^c_{1j}}_{\substack{\text{Observed}\\ \text{selection effect}}} + \underbrace{\frac{1}{\sigma-1}\log x^c_j + \frac{1}{\eta-1}\log x^c_{1j}}_{\text{G.E. demand effect}}$$
$$+ \underbrace{\frac{1}{\sigma-1}\left(\frac{\sigma-\gamma_j}{\gamma_j-1}\log\lambda^c_j + \log\lambda^c\right)}_{\text{G.E. capital effect}}.$$

The elasticity of each component with respect to non-agricultural GDP per worker is presented in Table 5. The first line just reports again the values of Table 4. The next line reports the income elasticity of the average wage of the lowest human-capital group. We see that is somewhat higher for blue-collar than white-collar workers. Neither is the selection effect elasticity in the third row. Instead, we see that the fact that the elasticity of A with respect to GDP is increasing in occupational complexity owes much to the general-equilibrium effects. Especially the elasticity of the fixed effect of the GE occupational share is strongly related to the complexity, as seen in the third row. The intuition is as follows. Occupations here are substitutes ($\sigma > 1$) and richer countries specialize more heavily in white-collar work. It follows that they must have particularly high productivity in that occupation. A similar effect is at work for the GE labor income share effect in row 4. Here, the elasticity is particularly high for the white-collar occupations technicians, professionals, and managers. Workers and capital are gross complements in those occupations. Their labor share is relatively low in rich countries, despite the fact that capital is relatively cheap, which reveal a high productivity A.

Table 5: Elasticity of components of A with respect to GDP per worker

	Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
Productivity, A	0.11	0.00	0.45	0.21	1.00	1.17	0.60	1.16
Average wage	0.93	0.99	0.90	0.87	0.74	0.70	0.69	0.76
Selection	0.04	-0.07	0.07	0.00	0.19	0.17	0.00	0.19
G.E. demand	-0.74	-0.79	-0.43	-0.62	0.12	0.26	-0.05	0.23
G.E. capital	-0.13	-0.11	-0.09	-0.03	-0.04	0.04	-0.05	-0.01

4.2.2 Human-capital quality, h

Consider now the cross-country pattern of the human-capital quality terms, h_{sj}. For each human-capital group s and occupation j, we first regress h_{sj} on non-agricultural GDP per worker:

$$\log h_{sj}^c = \alpha + \beta_{sj}^h \log Y^c + \varepsilon_{sj}^c.$$

The elasticities $\widehat{\beta}_j^h$ are reported in Table 6. In the first line, all coefficients are zero by construction due to the normalization $h_{1j} = 1$. Most of the other elasticities are positive. This suggests that the quality of human capital is higher in richer countries. This is particularly true for occupations such as service and sales, craft and trade, and professionals. We also see that income gradient of human-capital quality is typically more pronounced for old than young workers (comparing the β_{sj}^h for old versus young workers for a given education level and occupation). This is in accordance with Lagakos, Moll, Porzio, Qian and Schoellman (2018) who find that workers in richer countries experience higher wage gains with experience. Comparing across education levels, the rich-country human-capital quality advantage is particularly pronounced among (lower and higher) secondary school workers. Finally, note that in certain categories, richer countries tend to exhibit lower levels of human-capital quality. This is true for tertiary education workers in occupations such as machine operators, clerks, and managers.

Next, we investigate how the cross-country variation in the human-capital quality terms is driven by various components that enter the inference. For this we use equation (10) to

Table 6: Elasticity of human-capital quality, h, with respect to GDP per worker

	Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
Primary, young	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Primary, old	0.17	0.07	0.05	0.01	-0.09	0.02	0.03	0.07
Lower second., young	0.04	0.11	0.07	0.20	0.18	0.11	0.08	0.08
Lower second., old	0.24	0.19	0.15	0.25	0.12	0.11	0.10	0.19
Upper second., young	0.06	0.21	0.08	0.35	0.15	0.19	0.25	0.08
Upper second., old	0.23	0.29	0.17	0.41	0.09	0.20	0.25	0.18
Tertiary, young	-0.04	0.11	-0.09	0.30	-0.18	0.05	0.33	-0.16
Tertiary, old	0.09	0.15	-0.02	0.35	-0.30	0.02	0.31	-0.12

decompose the inferred human-capital quality terms as follows:

$$\begin{aligned}\log h^c_{sj} = & \underbrace{\log \overline{w}^c_{sj} - \log \overline{w}^c_{1j}}_{\substack{\text{Observed}\\ \text{wages}}} + \underbrace{\log \Gamma_1 - \log \Gamma_s + \frac{1-\rho}{\theta_s}\left(\log \pi^c_{sj} - \log \pi^c_{1j}\right)}_{\substack{\text{Observed}\\ \text{selection effect}}} \\ & + \underbrace{\frac{1}{\eta - 1}\left[\log\left(\overline{w}^c_{sj} L^c_{sj}\right) - \log\left(\overline{w}^c_{1j} L^c_{1j}\right)\right]}_{\substack{\text{Observed}\\ \text{endowment effect}}}\end{aligned} \tag{13}$$

To summarize our results more succinctly, we separate each component into a human-capital and occupation component by running for each country c the fixed-effect regression

$$\log X^c_{sj} = \alpha^c + \mathrm{FE}^c_s + \mathrm{FE}^c_j + \varepsilon^c_{sj} \tag{14}$$

where the primary-school young and elementary workers are omitted. The left-hand side variable X is either human capital quality h, the wage component, the selection component, or the endowment component of equation (13). In the second stage, we regress the human-capital fixed-effect components F_s associated to each X on non-agricultural GDP per worker and report the results in Table 7.

Table 7: Elasticity of human-capital fixed effect, FE_s, with respect to GDP per worker

	Productivity, h	Average wage	Selection	Endowment
Primary & young	0.00	0.00	0.00	0.00
Primary & old	0.04	-0.07	-0.01	0.12
Lower secondary & young	0.11	-0.05	-0.05	0.20
Lower secondary & old	0.17	-0.11	-0.05	0.33
Upper secondary & young	0.17	-0.11	-0.06	0.34
Upper secondary & old	0.23	-0.17	-0.05	0.45
Tertiary & young	0.04	-0.25	-0.08	0.36
Tertiary & old	0.06	-0.31	-0.05	0.43

The first column of Table 7 shows that, by and large, human-capital quality if higher in richer countries. Again, this is particularly true for secondary education workers and is also more pronounced for old than young workers. The next columns report the various components. The pattern of the elasticities in the second column show lower elasticities (negative) for more highly skilled workers. This is because holding occupations constant, relative wages for high-skilled workers are higher in poorer countries. This is reinforced by the selection effect, as can be seen in the third column. In richer countries, workers tend to specialise across occupations in such a way that have higher average idiosyncratic productivity. Conditional on observed wages, this implies a lower inferred human-capital quality. Finally, the endowment effect in the fourth column works in the opposite direction. Rich countries have more skilled workers, which, lowers their marginal product. Conditional on observed wages and selection, this implies that they have higher human-capital quality.

4.2.3 Endogenous technology, B

With productivity (A_j) and human-capital quality (h_{sj}) in hand, we can reconstruct the supply of human capital, H_{sj}, and hence the endogenous technology choices from (5):

$$B_{sj} = A_j H_{sj}^{\frac{\nu(\varepsilon-1)}{\nu-\varepsilon}} \left(\sum_{s'} H_{s'j}^{\frac{(\nu-1)(\varepsilon-1)}{\nu-\varepsilon}} \right)^{\frac{-\nu}{\nu-1}}.$$

For this, we set the short-run elasticity of substitution between low-skilled and high-skilled workers to $\varepsilon = 1.49$, which implies the technological menu elasticity $\nu = 2.15$.[12] We then regress B_{sj} on non-agricultural GDP per worker:

$$\log B_{sj}^c = \alpha + \beta_{sj}^B \log Y^c + \varepsilon_{sj}^c.$$

The elasticities $\widehat{\beta}_j^B$ are reported in Table 8. There is a clear pattern. Rich countries have particularly high (endogenous) technology levels associated with higher skilled workers. Technology is therefore endogenously skill-biased: countries with a larger share of educated and older workers direct technologies to those groups. We also find that across all occupations, low-skilled workers (primary-school educated and lower secondary-school educated young) tend to operate less productive technologies in rich than in poor countries.

Table 8: Elasticity of endogenous technology B, with respect to GDP

	Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
Primary, young	-2.57	-3.62	-2.61	-3.31	-2.22	-2.59	-4.21	-2.20
Primary, old	-0.66	-2.29	-1.09	-2.04	-0.99	-1.44	-2.93	-0.94
Lower second., young	-0.35	-0.95	-0.42	-0.51	-0.09	-0.43	-2.47	-0.25
Lower second., old	1.66	0.47	1.19	0.87	1.11	0.70	-1.15	1.17
Upper second., young	1.10	0.86	1.05	1.35	1.22	1.20	-0.41	1.06
Upper second., old	2.76	2.01	2.41	2.51	2.13	2.08	0.51	2.22
Tertiary, young	1.39	1.34	1.12	1.79	0.76	1.21	0.71	0.87
Tertiary, old	2.53	2.00	2.05	2.59	1.14	1.60	1.25	1.54

4.2.4 Distortions, D

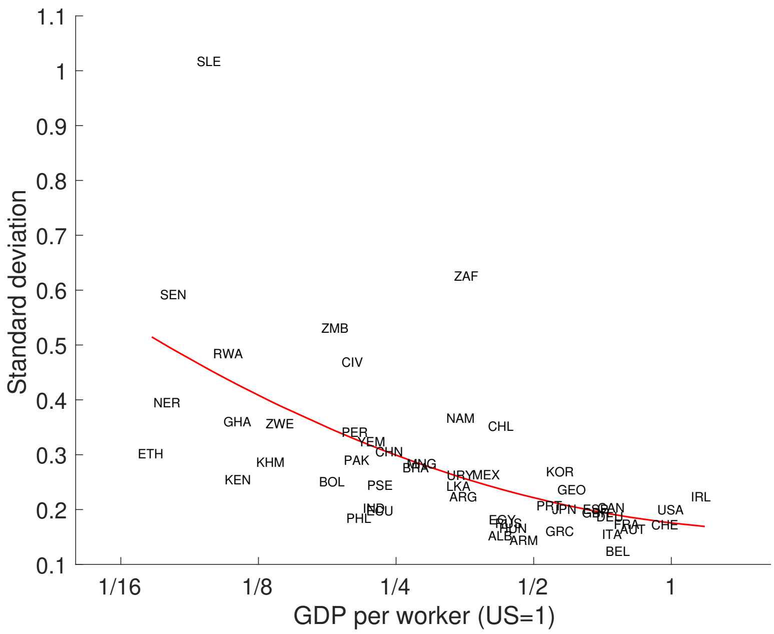
The second set of inferred parameters are the occupational distortions, D_{sj}. Figure 3 plots the standard deviation of $\log D_{sj}$ against non-agricultural GDP per worker.[13] It is clearly decreasing. Recall from (12) that we measure distortions directly from average wages, $D_{sj}^c = \frac{\overline{w}_{sj}^c}{\overline{w}_{s1}^c}$. It follows that *within* a given human-capital group, there is more wage dispersion across

[12] At $\varepsilon = 1.49$, the quantitative elasticity of substitution for the US is exactly 1.5 as estimated by Ciccone and Peri (2005). Recall that the endogenous long-run elasticity of substitution is $\eta = \frac{\nu-\varepsilon}{\nu(2-\varepsilon)-1}$ and calibrated as 6.97, which allows to infer ν.

[13] The standard deviation uses as weights the labor income shares of human-capital and occupation pairs, $\frac{\overline{w}_{sj}^c L_{sj}^c}{\lambda^c Y^c}$.

occupations in poorer countries. This, in turn, suggests greater occupational misallocation in these countries.

Figure 3: Dispersion of distortions



To analyze the cross-country pattern in the occupational distortions, turn to Table 9. It reports the elasticity of the wedge with respect to non-agricultural GDP per worker. Due to the normalization of the distortions for elementary occupation, $D^c_{1s} = 1$, the regression coefficients in the first line are zero by construction. Relative to that baseline occupation and conditional on human capital, the coefficient is typically more negative in more complex occupations (comparing across columns). What emerges is that distortions that discourage white-collar occupations are decreasing in non-agricultural GDP per worker. Given that $D^c_{sj} = \frac{\overline{w}^c_{sj}}{\overline{w}^c_{s1}}$, this reflects that conditional on human capital, the white-collar premium is typically higher in less-developed countries. This pattern is particularly pronounced for clerks, technicians, and professionals.

Table 9: Elasticity of distortions, D, with respect to GDP per worker

	Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
Primary, young	0.00	0.05	-0.04	-0.07	-0.19	-0.24	-0.24	-0.18
Primary, old	0.00	0.09	-0.09	-0.09	-0.35	-0.23	-0.25	-0.13
Lower second., young	0.00	0.03	0.00	-0.02	0.00	-0.15	-0.05	-0.06
Lower second., old	0.00	0.06	-0.03	-0.02	-0.10	-0.14	-0.05	-0.01
Upper second., young	0.00	0.03	0.00	0.05	-0.01	-0.11	-0.02	-0.05
Upper second., old	0.00	0.05	-0.03	0.04	-0.12	-0.11	-0.02	0.00
Tertiary, young	0.00	-0.02	-0.03	0.05	-0.11	-0.09	-0.03	-0.10
Tertiary, old	0.00	0.00	-0.06	0.04	-0.22	-0.09	-0.05	-0.07

5 Counterfactuals

In this section, we use the model to measure the general-equilibrium effect of the various country-specific parameters. We first focus on the impact of (i) human capital and (ii) distortions on

GDP, occupational employment, and relative wages. Subsequently, we compare the contribution of human capital and distortions to that of the remaining exogenous endowments, namely productivity and the relative price of equipment.

5.1 Human capital

We employ the US as the benchmark country and run two types of counterfactual measurements. In the first counterfactual, we endow countries with the US human-capital quality (h) and composition (L) and compare the resulting outcomes with their empirical counterparts. In the second counterfactual, we compute the difference between the US and counterfactual US economies that only differ in human-capital quality and composition. The two experiments are instructive in the sense that we expect an equivalent change in human capital to impact, say, Ethiopia differently than the US itself due to complementarities of human capital with other endowments.

Figure 4: GDP change after shift to US human capital quality and composition

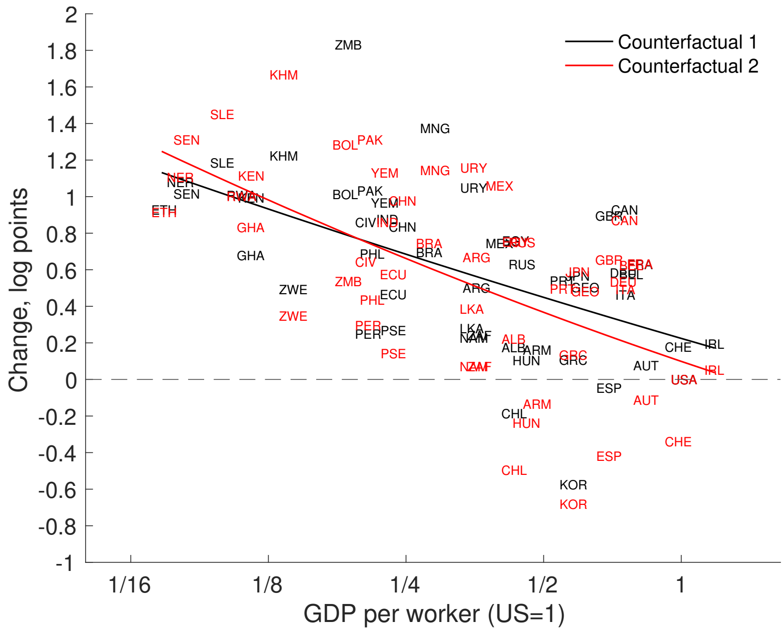


Figure 4 shows the resulting change in non-agricultural GDP per worker for each experiment. The group of least-developed countries is expected to experience an increase in GDP of 99%.[14] In the second counterfactual, the increase is similar, 105%. On average, the second counterfactual produces somewhat larger increases because the remaining US endowments (technology, distortions, the price of equipment) are typically more complementary with higher levels of human capital.

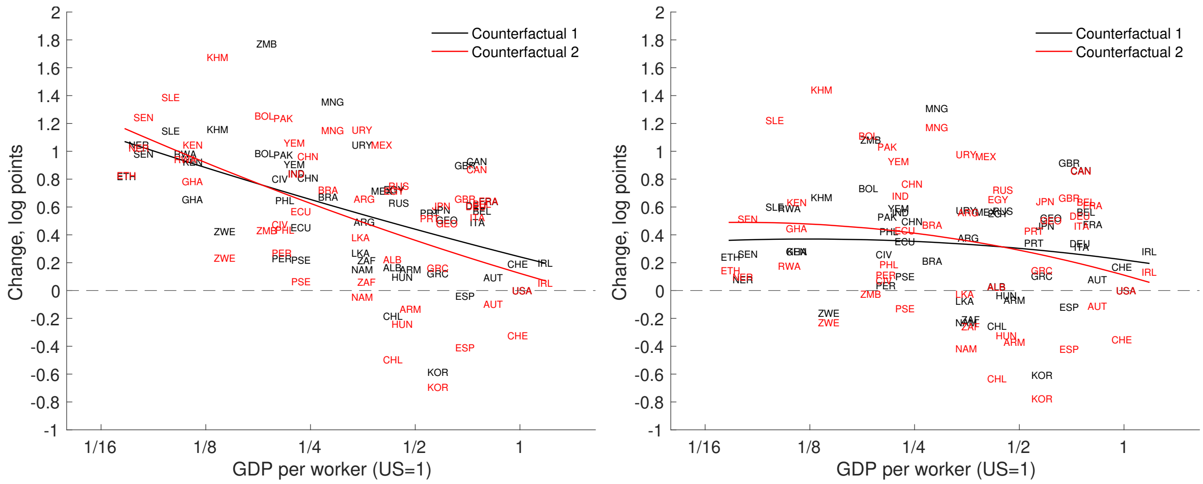
Figure 5 decomposes human capital by education and age. In both panels, we change human capital quality. In addition, the left panel shows experiments of endowing countries with the US education composition while keeping the age composition constant.[15] Analogously, in the second panel we vary the age composition while keeping that of education constant. Clearly, the composition of education has more leverage than that of age. The GDP difference due

[14] This refers to the linear-quadratic regression line evaluated at the average non-agricultural GDP per worker of the poorest quintile. It is 10.7 percent of the US level in 2019 and corresponds approximately to that of Rwanda in 2016.

[15] That is, within the group of young (old) workers, the educational distribution is that of the US.

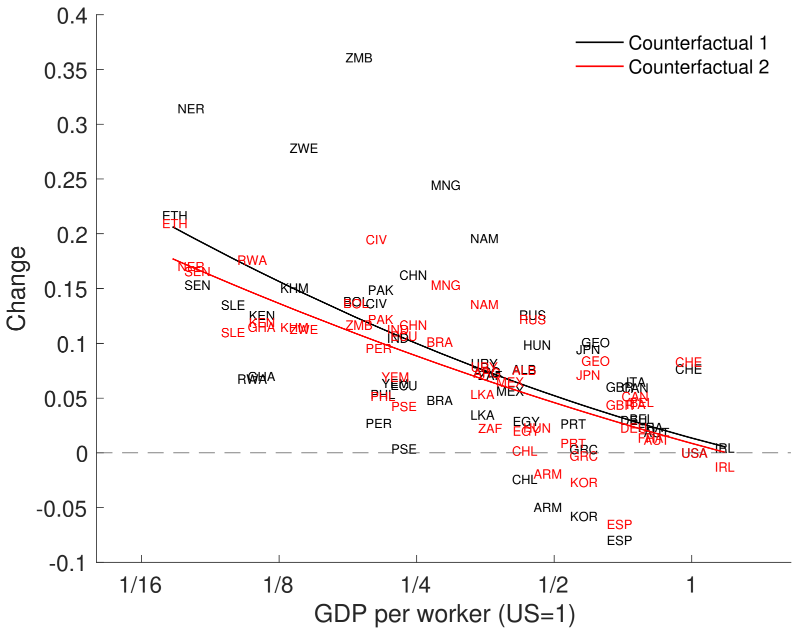
Figure 5: GDP change after shift to US human-capital quality and education or age composotion

(a) Education **(b)** Age



to the shift in education from the least-developed countries to the US is 93 percent in the first counterfactual and 98 percent in the second. For the age component, these numbers are smaller, 37 and 48 percent, respectively. There are two reasons for why education matters more than age. First, countries differ more strongly in their education composition than in their age composition. Second, the cross-country human-capital quality gap is larger in education than in age.

Figure 6: White-collar employment rate change after shift to US human capital



Next, we investigate how human capital affects occupational employment. Figure 6 plots the change in the white-collar employment rate associated with shifting to the US human capital composition. The poorest countries can expect an increase of 17 percentage points. Similarly, 15 percentage points of the US white-collar employment rate difference to the poorest countries are due to human capital.

Figure 7: Average wage premium change after shift to US human capital

(a) White-collar to blue-collar **(b)** High-skilled to low-skilled

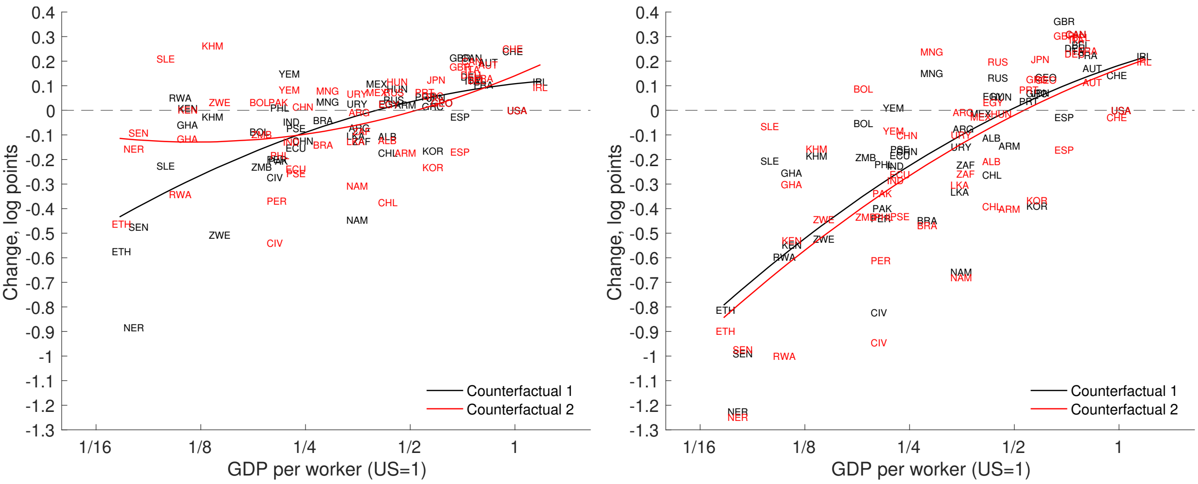


Figure 7 reports the change in relative wages. Panel (a) plots the average wage of white-collar relative to that of blue-collar workers. Endowing the poorest countries with US human capital leads to a drop of 31 percent in the white-collar relative wage. Higher levels of human capital prompt a shift toward white-collar employment, which subsequently dampens the wage rate of white-collar occupations. In addition, the shift drives down (up) the idiosyncratic productivity of white-collar (blue-collar) workers due self-selection. In the second counterfactual, that change is smaller, 13 percent. Next, panel (b) of Figure 7 plots the changes in the average wage of high-skilled relative to that of low-skilled workers. Both counterfactuals produce qualitatively and quantitatively similar results. Endowing the poorest countries with US human capital lowers the relative wage of high-skilled workers by 59 percent. In the second counterfactual, the drop amounts to 64 percent. Unsurprisingly, the education skill premium is strongly negatively related to the the abundance of human capital.

To complement this analysis, in Appendix 7.7.1 we run counterfactuals separately by either only human-capital quality or its composition. In Appendix 7.7.2 we measure how changes in human capital affect the the choice of endogenous technology, B. In Appendix 7.7.3 we present the changes in employment and relative wages by detailed human-capital and occupation groups.

5.2 Distortions

In this section we examine the impact of occupations distortions on aggregate GDP. We again run two counterfactuals that either endow countries with US distortions or else complement the US with its own distortions relative to those of other countries.

Figure 8 shows that in most countries, switching to US distortions typically increases GDP. In the first counterfactual, the poorest quintile of countries can expect a GDP increase of 6 percent, whereas in the second counterfactual is is 4 percent. This suggests that roughly 5 percent of the GDP difference between the US and the poorest countries is due to occupational wedges.

Figure 9 plots the change in the white-collar employment rate associated with shifting to US distortions. Most countries feature distortions that lower white-collar employment relative to the US. The distortion-driven difference in white-collar employment due between the US and the poorest countries ranges between 7 (first counterfactual) and 5 (second counterfactual)

Figure 8: GDP change after shift to US occupational distortions

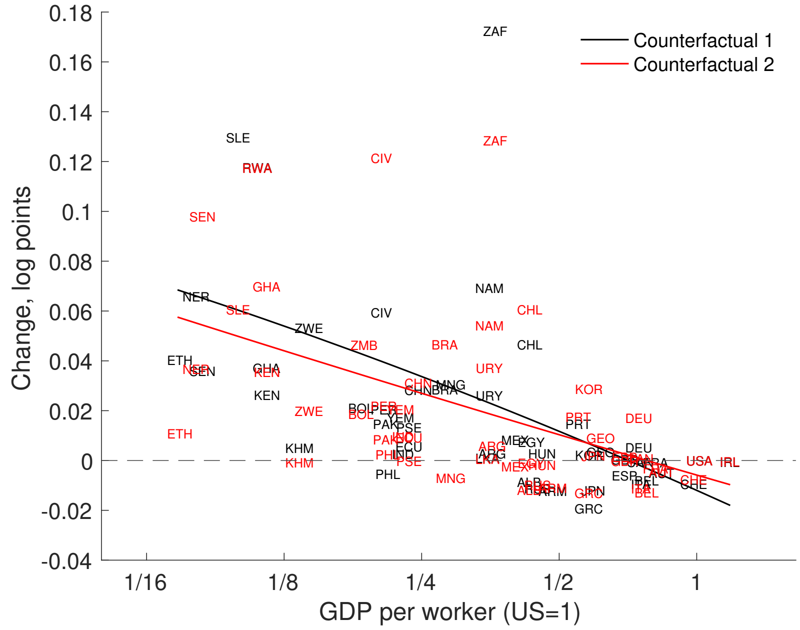
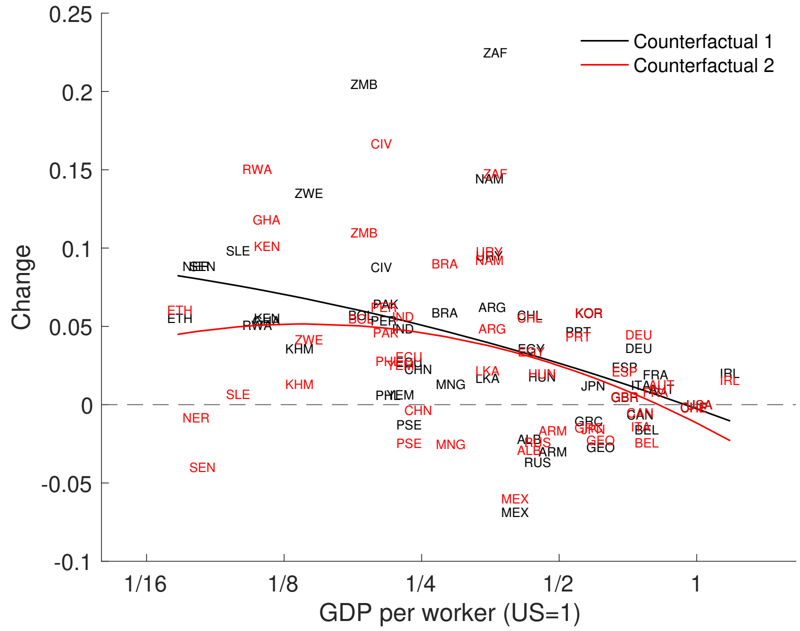


Figure 9: White-collar employment rate change after shift to US occupational distortions

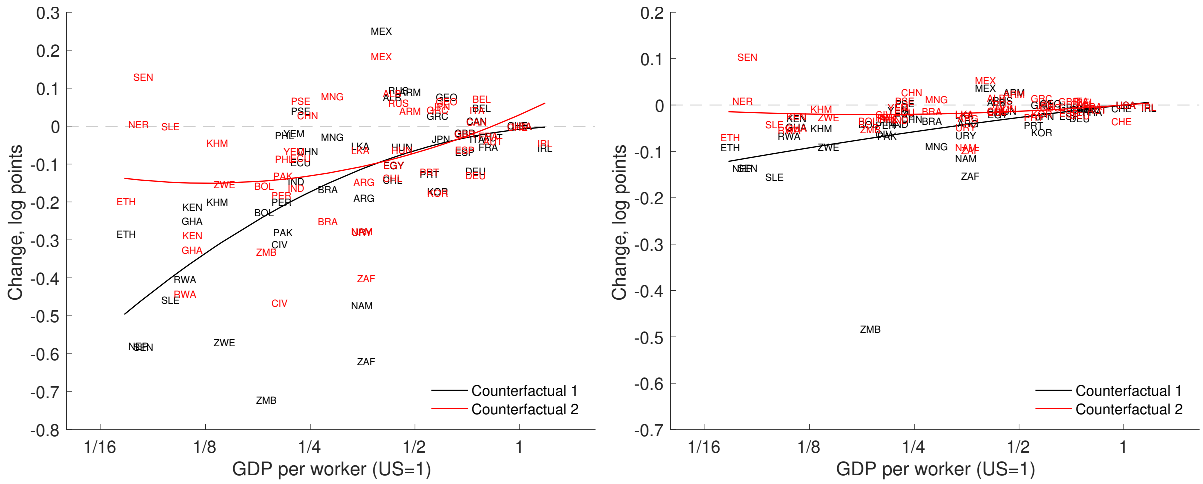


percentage points.

Panel (a) of Figure 10 shows that occupational distortions have a particularly large impact on the cross-country variation in the white-collar wage premium. Endowing the poorest countries with US human capital leads to a drop of 38 percent in the white-collar relative wage (first counterfactual). For the US itself, switching away from low-income distortions decreases the relative white-collar wage by 15 percent. This effect is more subdued because it typically generates a smaller change in white-collar employment and therefore a smaller drop in the average idiosyncratic productivity in that sector. Finally, note from panel (b) of Figure 10 that occupational distortions matter substantially less for the cross-country variation in the

Figure 10: Average wage premium change after shift to US occupational distortions

(a) White-collar to blue-collar **(b)** High-skilled to low-skilled



average wage of high-skilled to low-skilled workers. The two counterfactuals suggest that relative occupational distortions in the poorest countries account for 10 to 2 percent of the educational wage premium relative to the US.

5.3 Decomposition of aggregate statistics

In this subsection, we consider how GDP, occupational employment and wage premia are shaped by exogenous differences in countries' endowments. For this, consider $g^c = \log \frac{Y^c}{Y^{\mathrm{US}}}$, the non-agricultural GDP per worker ratio between country c and the US. The first decomposition we consider is

$$g^c = g^c(A) + g^c(hL) + g^c(R) + g^c(D) + g^c(COV). \tag{15}$$

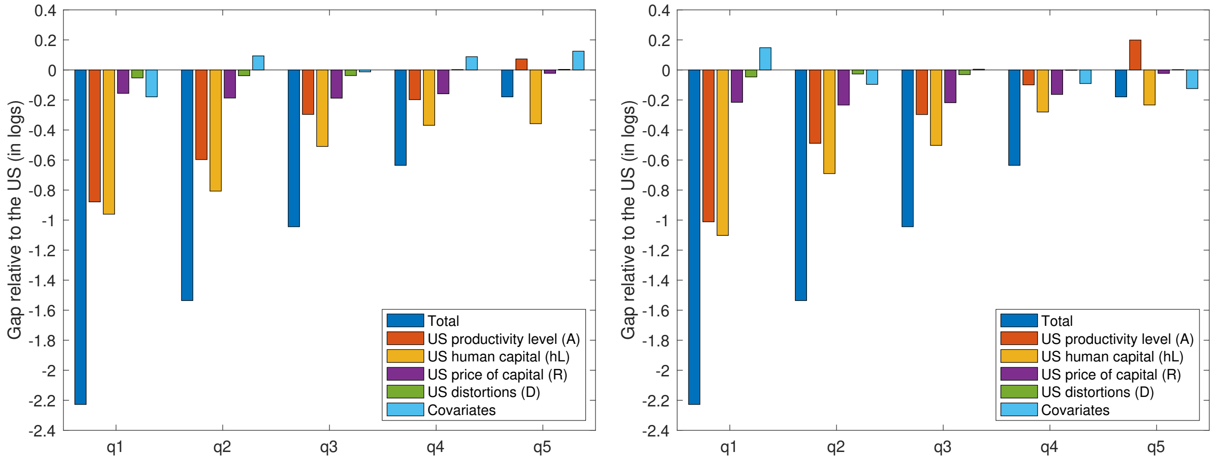
The term $g^c(A) = \log \frac{Y^c}{Y^c(A^{\mathrm{US}})}$ denotes the (log) ratio between the GDP of country c and the GDP of that country assuming it had US productivity, B. Analogously, the terms $g^c(hL)$, $g^c(R)$, and $g^c(D)$ capture the country's counterfactual (log) GDP ratio to the US under the assumption of US-level of human capital, price of equipment, and occupational distortions, respectively. Finally, the term $g^c(COV)$ captures all the covariate terms that makes equation (15) hold. The second decomposition that we consider is

$$g^c = \widetilde{g}^c(A) + \widetilde{g}^c(hL) + \widetilde{g}^c(R) + \widetilde{g}^c(D) + \widetilde{g}^c(COV). \tag{16}$$

Here, $\widetilde{g}^c(A) = \log \frac{Y^{US}(A^c)}{Y^{\mathrm{US}}}$ denotes the (log) ratio between the GDP of the US with productivity A of country c and the actual US. The remaining terms are constructed in an analogous way.

The left panel of Figure 11 visualizes the results of decomposition (15) with countries summarized into income groups. For each quintile, the first bar equals to the sum of the other bars. The right panel does the same for decomposition (16). Across both panels, we see that most of the GDP gap between relative to the US is driven by human capital, hL. For countries in the first and second quintile, productivity and human capital have roughly equal weight. For middle-income and rich countries, human capital matters more. The relative price of equipment, R, explains a smaller fraction of the GDP gap. Differences in wedges, D, play a comparatively minor role. Finally, the covariate term is typically positive in the left panel and negative in the right one.

Figure 11: Non-agricultural GDP-per-worker gap relative to the US (logs)



(a) Counterfactual versus country baseline **(b)** US baseline versus counterfactual

Table 10: Contribution to GDP ratio gap

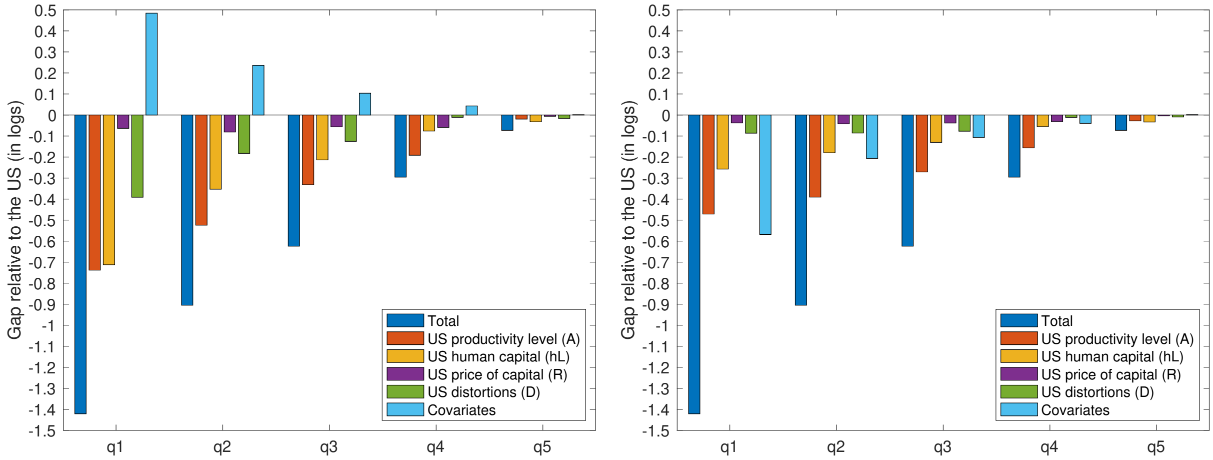
	Gap (in logs)						Contribution to gap (percent)					
	q1	q2	q3	q4	q5	all	q1	q2	q3	q4	q5	all
Total gap	-2.23	-1.54	-1.04	-0.64	-0.18	1.12	100	100	100	100	100	100
Productivity level, A	-0.95	-0.54	-0.30	-0.15	0.14	0.36	42	35	28	23	-76	32
Human capital, hL	-1.03	-0.75	-0.51	-0.32	-0.30	0.58	46	49	48	51	165	52
Price of capital, R	-0.19	-0.21	-0.20	-0.16	-0.02	0.16	8	14	19	25	13	14
Distortions, D	-0.05	-0.03	-0.03	0.00	0.00	0.02	2	2	3	0	-2	2
Covariance	-0.02	0.00	0.00	0.00	0.00	0.00	1	0	0	0	0	0

Table 10 summarizes these results. The left-hand side averages panels (a) and (b) of Figure 11. The right-hand side presents the relative contribution of each component to the aggregate GDP gap.[16] For the poorest quintile of countries, human capital accounts for 46 percent of the non-agricultural GDP per worker gap relative to the US. Averaging over all quintiles, the contribution of human capital to the GDP gap is 52 percent. The largest contribution is for the richest countries in the fifth quintile. By contrast, the relative contribution of productivity to the GDP gap to the US is 32 percent over the entire sample. In the richest quintile of countries, it is negative as these countries exhibit a higher productivity than the US. The relative price of equipment explains a relatively small fraction of the GDP gap in the poorer countries (8 percent in the poorest quintile), but matters quite substantially in middle-income countries. In the fourth quintile, its contribution is 25 percent. Finally, notice that occupational distortions play no major role, accounting for only 2 to 3 percent of the GDP to the US in the the poorest three quintiles.

Figure 12 visualizes the gap in the white-collar employment rate relative to the US. Qualitatively, the results are similar to those of the GDP gap. Table 11 summarizes the average of the two decompositions. For the first four quantiles of countries, about half of the white-collar employment gap relative to the US is due to productivity differences. The other important driver of the employment gap is human capital, accounting for 34 percent in the poorest quintile and 31 percent across the entire sample. This general-equilibrium result stands in contrast to the partial-equilibrium results depicted in Figure 1. There, we noted that most of the variation in

[16]That is, the left-hand side Table 10 presents the simple mean of decompositions (15) and (16). For instance, the average productivity component is $\overline{g}^c(A) = \frac{1}{2}\left[g^c(A) + \widetilde{g}^c(A)\right]$. The right-hand side is then $100 \times \frac{\overline{g}^c(A)}{g^c}$.

Figure 12: White-collar employment rate gap relative to the US (logs)



(a) Counterfactual versus country baseline

(b) US baseline versus counterfactual

Table 11: Contribution to white-collar gap relative to the US

	Gap (in logs)						Contribution to gap (percent)					
	q1	q2	q3	q4	q5	all	q1	q2	q3	q4	q5	all
Total gap	-1.42	-0.91	-0.62	-0.30	-0.07	0.66	100	100	100	100	100	100
Productivity level, A	-0.60	-0.46	-0.30	-0.17	-0.02	0.31	43	51	48	59	32	47
Human capital, hL	-0.48	-0.27	-0.17	-0.07	-0.03	0.20	34	29	28	22	45	31
Price of capital, R	-0.05	-0.06	-0.05	-0.05	-0.01	0.04	4	7	8	15	7	6
Distortions, D	-0.24	-0.13	-0.10	-0.01	-0.01	0.10	17	15	16	4	18	15
Covariance	-0.04	0.01	0.00	0.00	0.00	0.01	3	-2	0	-1	-2	1

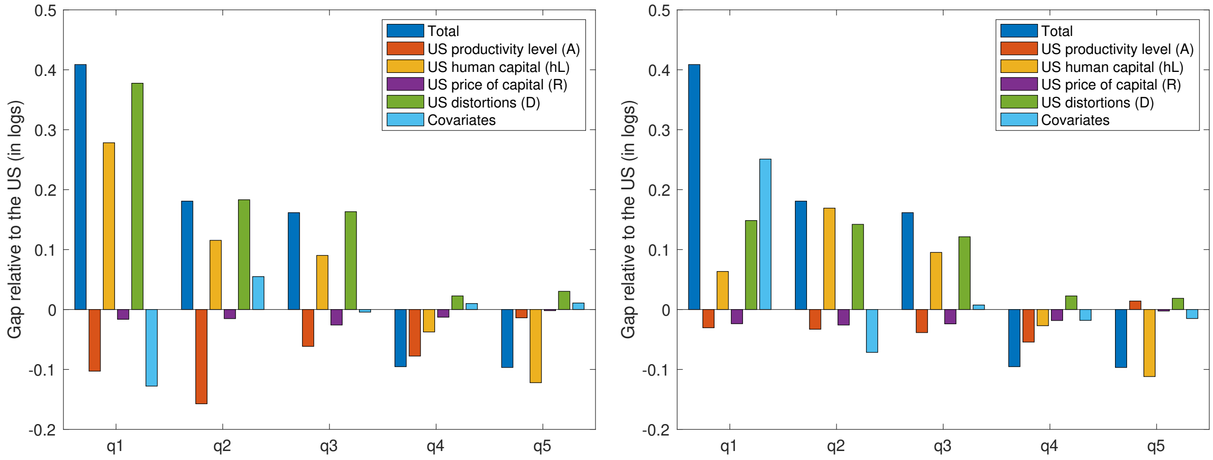
the white-collar employment rate across countries is accounted for by differences in human capital. This is no longer true once we consider general equilibrium forces: if an increase in human capital is not accompanied by other changes in exogenous factors, the increase in white-collar employment is dampened by the fall in the wages of those workers. Also, while distortions do not play a key role, their impact is not negligible, contributing on average roughly 15 percent to the gap over the entire sample of countries.

Table 12: Contribution to white-collar to blue-collar wage ratio gap relative to the US

	Gap (in logs)						Contribution to gap (percent)					
	q1	q2	q3	q4	q5	all	q1	q2	q3	q4	q5	all
Total gap	0.41	0.18	0.16	-0.10	-0.10	-0.11	100	100	100	100	100	100
Productivity level, A	-0.07	-0.10	-0.05	-0.07	0.00	0.06	-16	-53	-31	69	0	-50
Human capital, hL	0.17	0.14	0.09	-0.03	-0.12	-0.05	42	79	57	34	121	46
Price of capital, R	-0.02	-0.02	-0.02	-0.02	0.00	0.02	-5	-11	-15	16	2	-15
Distortions, D	0.26	0.16	0.14	0.02	0.02	-0.12	64	90	88	-24	-25	110
Covariance	0.06	-0.01	0.00	0.00	0.00	-0.01	15	-5	1	4	2	9

Figure 13 decomposes the gap in the average wage of white-collar to blue-collar workers. First, note that the white-collar wage premium relative to the US is positive for the quintiles 1 through 3, but negative for the two richer quintiles. We see in both panels that human capital is an important driver of the white-collar wage premium. The same is true for occupational distortions. That is, relative to the US, occupational distortions and lower human capital

Figure 13: White-collar to blue-collar wage ratio gap relative to the US (logs)

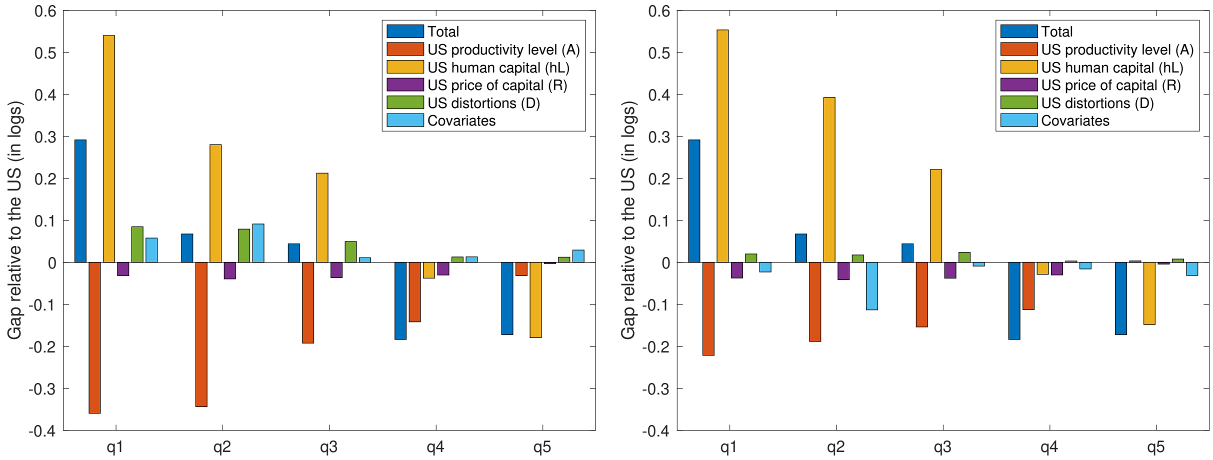


(a) Counterfactual versus country baseline

(b) US baseline versus counterfactual

attainment tend to the discourage white-collar employment, thus raising its price. The summary in Table 12 shows that occupational distortions and the composition of human capital both tend to contribute substantially and positively to the white-collar premium gap to the US for quintiles 1 through 3 for which the white-collar premium is positive.

Figure 14: High-skilled to low-skilled wage ratio gap relative to the US (logs)



(a) Counterfactual versus country baseline

(b) US baseline versus counterfactual

Finally, Figure 14 decomposes the gap in the average wage of high-skilled to low-skilled workers. The substantially higher wage skill premium in the lowest income countries is driven primarily by their lower level of human capital. This effect is counteracted by productivity differences, which push toward a smaller skill premium. For completion, Table (13) computes the contribution of the various exogenous factors to the high-skilled wage premium. These numbers are large because the overall gap to the US is small and varies non-monotonically over the development spectrum.

Table 13: Contribution to high-skilled to low-skilled wage ratio gap relative to the US

	Gap (in logs)						Contribution to gap (percent)					
	q1	q2	q3	q4	q5	all	q1	q2	q3	q4	q5	all
Total gap	0.29	0.07	0.04	-0.18	-0.17	-0.01	100	100	100	100	100	100
Productivity level, A	-0.29	-0.27	-0.17	-0.13	-0.01	0.17	-100	-394	-392	69	8	-1832
Human capital, hL	0.55	0.34	0.22	-0.03	-0.16	-0.18	187	498	491	18	95	1900
Price of capital, R	-0.03	-0.04	-0.04	-0.03	0.00	0.03	-12	-60	-84	16	2	-306
Distortions, D	0.05	0.05	0.04	0.01	0.01	-0.03	18	72	83	-4	-6	327
Covariance	0.02	-0.01	0.00	0.00	0.00	0.00	6	-16	2	1	1	11

6 Conclusion

Our key findings are as follows. Rich countries have particularly high productivity in more complex, white-collar occupation. They also have higher human-capital quality associated with almost all occupations, in particular amongst secondary-school educated workers and more experienced workers. For the poorest quintile of countries in the sample, a shift to the US composition of human capital doubles both GDP and white-collar employment while decreasing the wage of white relative to blue-collar workers by 30 percent. The composition of human capital explains approximately one-half the cross-country non-agricultural GDP per-worker gap and roughly one-third of the white-collar employment gap relative to the US. Occupational distortions are more pronounced in poor countries, depress white-collar employment and sustain a high white-collar wage premium, yet have a modest quantitative effect on aggregate output.

7 Appendix

7.1 Harmonization of surveys

7.1.1 Survey and sample selection

We use nationally representative household and labor force surveys. A full list of surveys can be found in Table 14. All selected surveys satisfy three conditions. First, they are nationally representative. Second, they report occupation codes for both wage and self-employed workers. Third, they contain information on wages and hours worked. In all surveys, we only keep individuals that provide information on age and sex and who are of working age (16-65).

7.1.2 Occupation codes

We use ISCO-08 occupation codes when these are provided in the data. For surveys that use country specific occupation codes, we do manual crosswalks into the ISCO-08 classification. We discard surveys that use ISCO-88 occupation codes and do not attempt to crosswalk ISCO-88 codes into ISCO-08.

7.1.3 Education

The individual education information in the dataset is drawn from two surveys questions, one on years of education and one on completed degrees. When information on years of education is available we use that. If not, we apply to each degree some years of education such that a primary, secondary, high-school, vocational, university, (undergraduate), university (postgraduate) correspond to 6, 9, 12, 14, 15 and 17 years of education, respectively.

7.1.4 Wage measurement

We measure wages using survey questions on wages, in-kind payments and hours worked. Some surveys provide disaggregated information on in-kind payments. We consider in-kind payments to be allowances, gratuities, housing, food and transport. Wages and in-kind payments are reported for specific reference periods. We use this information to scale the wage series to a weekly frequency. With this information, we can have up to three wage series per survey: wage without in-kind, wage with in-kind and total labor income.

We measure hours worked using survey questions that ask about actual or usual hours worked in the reference week. We use available data series on hours worked and weekly wages to compute hourly wages. Since we may have two series of hours worked and two wage series, we apply two rules to build our hourly wage data. First, we prioritize actual over usual hours. Second, we prioritize wages with in-kind payments over wages without in-kind payments.

7.1.5 Weights

When surveys provide individual weights, we use these. If only household weights are provided, we use households weights which we multiply by the number of household members to obtain individual weights as suggested in Deaton (1997).

7.1.6 Survey list

7.2 Construction of employment shares and wages

Our goal is to construct, for each country c, employment shares L^c_{sj} and average wages $\overline{w}^c_{sj}$ where s is one of the eight human-capital groups and j is one of the eight occupations. In principle, we could simply compute them as raw moments from the data. In practice, the samples in many labor force and household surveys are too small for raw averages to yield precise moment estimates, with some rarely occurring cell pairs sj often showing up as completely empty.[17] Instead, we propose to estimate L^c_{sj} via multinomial logistic regressions and $\overline{w}^c_{sj}$ via wage regressions. We do this for each country-year-survey separately.

7.2.1 Shares

We start with the construction of employment shares. Let

$$\mathbb{I}^\star_{ij} = const_j + X_i\beta_j + \varepsilon_{ij}$$

be a latent variable determining the likelihood that the main job of individual i is in occupation j. The explanatory variables in vector X include the broadest plausible set of human-capital attributes that we can harmonize across surveys, namely: years of education (level and quadratic terms), age (level and quadratic terms), and gender. The realized occupational choice is

$$\mathbb{I}_{ij} = \begin{cases} 1 & \text{if } \mathbb{I}^\star_{ij} > \mathbb{I}^\star_{ij'},\ \forall j' \neq j, \\ 0 & \text{otherwise.} \end{cases}$$

[17] For example primary-school young workers in professional occupations or college-educated old workers in elementary occupations. The most binding constraint is to compute average wages since wage observations are a subset of all observations.

Table 14: List of data sources.

Country	Survey	Years	Number of Years	Sample Size
ALB	Labour Force Survey	2009-2013	5	131'269
ALB	Living Standards Measurement Survey	2002	1	7'973
ARM	Labour Force Survey	2014-2019	6	160'773
ARM		2013	1	0
AUS	Household, Income and Labour Dynamics in Australia	2001-2017	17	341'170
AUT	European Union Statistics on Income and Living Conditions	2004-2020	17	228'063
BEL	European Union Statistics on Income and Living Conditions	2004, 2005	2	25'728
BEN	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018	1	42'343
BEN	Enquête Modulaire Intégrée sur les Conditions de Vie des ménages	2010	1	7'568
BEN		2015	1	0
BFA	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018	1	45'612
BGR	European Union Statistics on Income and Living Conditions	2007-2020	14	210'570
BOL	Encuesta de Hogares	2005-2009, 2011-2020	15	447'300
BRA	Pesquisa Nacional por Amostra de Domicílios	2002-2009, 2011-2015	13	4'982'683
BWA	Labor Force Survey	2005	1	30'206
CAN	Labour Force Survey	1997-2015, 2017-2019	22	22'000'000
CHE	European Union Statistics on Income and Living Conditions	2007-2020	14	239'301
CHL	Encuesta de Caracterización Socioeconómica Nacional	1990, 1992, 1994, 1998, 2000, 2003, 2006, 2009, 2011, 2013, 2015, 2017	12	2'637'377
CHN	Family Panel Studies	2014, 2016	2	91'082
CHN		2012	1	0
CIV	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018	1	61'116
DEU	Socio-economic Panel	2005-2019	15	703'967
ECU	Encuesta de Condiciones de Vida	2005	1	55'666
ECU	Encuesta Nacional de Empleo, Desempleo y Subempleo	2007-2018	12	2'776'950
EGY	Harmonized Labor Force Survey	2007-2017	11	3'826'856
ESP	European Union Statistics on Income and Living Conditions	2004-2012	9	329'657
ETH	National Labour Force Survey	2005, 2013	2	471'340
FRA	Enquête emploi annuelle	2003-2010	8	1'001'541
FRA	Enquête emploi en continu	2011, 2013, 2014, 2016, 2017	5	874'946
FRA		2018, 2019	2	0
GBR	British Household Panel Survey	1991-2008	18	239'626
GBR	European Union Statistics on Income and Living Conditions	2005-2018	14	328'040
GEO	Labour Force Survey	2017-2021	5	373'626
GHA	Ghana Living Standard Survey	1987, 1988, 1991, 1998	4	77'230
GHA	Living Standard Survey	2005, 2008, 2017	3	135'473
GMB	Integrated Household Survey	2015	1	106'681
GNB	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018	1	42'839
GRC	European Union Statistics on Income and Living Conditions	2004-2020	17	444'211
HRV	European Union Statistics on Income and Living Conditions	2010-2020	11	186'627
HUN	European Union Statistics on Income and Living Conditions	2006-2020	15	322'844
IND	Indian National Sample Survey	2004-2007, 2009, 2011	6	2'773'075
IND		2017	1	0
IRL	European Union Statistics on Income and Living Conditions	2004-2019	16	206'240
ISL	European Union Statistics on Income and Living Conditions	2004-2011, 2013	9	78'683
ITA	European Union Statistics on Income and Living Conditions	2004-2020	17	821'610
JOR	Hamonized Labor Force Survey	2005-2014, 2016	11	2'584'948
KEN	Kenya Continuous Household Survey Programme	2019, 2020	2	171'506
KHM	Cambodia Labor Force and Child Labor Survey	2012	1	48'290
KHM	Cambodia Labor Force Survey	2019	1	40'497
KOR	Korean Labor and Income Panel Study	1998-2015, 2017, 2018	20	255'195
LKA	Labor Force Survey	2000, 2017	2	142'414
LUX	European Union Statistics on Income and Living Conditions	2012, 2014, 2015	3	34'906
MEX	Encuesta Nacional de Ocupación y Empleo	2005-2019	15	15'000'000
MLI	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018	1	46'014
MNG	Labor Force Survey	2002, 2006-2008, 2010-2018	13	537'892
NAM	Labor Force Survey	2012, 2013, 2016, 2018	4	156'606
NER	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018	1	35'406
NER	National Survey on Household Living Conditions and Agriculture	2011, 2014	2	47'796
NGA	Living Standards Measurement Survey	2010, 2012	2	113'152
PAK	Social & Living Standards Measurement	2001, 2005-2008, 2010-2015, 2018	12	3'395'482
PER	Encuesta Nacional de Hogares	2007-2019	13	1'453'907
PHL	Labor Force Survey	2005-2018	14	10'518'942
POL	European Union Statistics on Income and Living Conditions	2005-2019	15	592'352
PRT	European Union Statistics on Income and Living Conditions	2004-2020	17	326'463
PSE	Hamonized Labor Force Survey	2000-2007, 2012	9	1'016'935
PSE		2008-2011, 2013-2016	8	0
RUS	Russia Longitudinal Monitoring Survey	2004-2017	14	244'223
RWA	Enquête Intégrale sur les Conditions de Vie des Ménages	2013, 2016	2	130'395
SEN	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018	1	66'119
SLE	Labor Force Survey	2014	1	25'645
SRB	European Union Statistics on Income and Living Conditions	2013-2020	8	139'907
TGO	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018	1	27'480
UGA	Uganda National Panel Survey	2018, 2019	2	37'317
URY	Encuesta Continua de Hogares	2006-2017	12	1'678'605
USA		1990-1998, 1998-2000, 2000-2002, 2002-2004, 2004-2021	36	584'664
YEM	Labor Force Survey	2013	1	85'850
ZAF	Labor Market Dynamics	2010-2019	10	3'088'974
ZMB	Labour Force Survey	2017	1	45'569
ZWE	Labour Force and Child Labour Survey	2014, 2019	2	79'653

Note: The first column reports the ISO3 country code. The second column reports the survey name. The third column reports the years covered. The fourth column reports the number of years covered. The six column reports total sample size of the dataset across all years.

Assuming that the disturbances ε_{ij} follow a standard type-I extreme-value distribution obtains the estimated probability of individual i taking on occupation j,

$$\widehat{\pi}_{ij} = \exp\left\{const_j + X_i\beta_j\right\}.$$

In the estimation we use standardized regression weights ω_i that multiply the individual's survey weight by their hours worked.

We then use the predicted values $\widehat{\pi}_{ij}$ to construct the estimated shares

$$L_{sj} = \sum_{i \in s} \widehat{\pi}_{ij} \omega_i \tag{17}$$

where s is one of the final eight human-capital groups. Note that the multinomial logistic regression forces the aggregate occupational share to coincide exactly with the raw data moment,

$$L_j = \sum_s L_{sj} = L_j^{raw} \text{ where } L_j^{raw} \equiv \sum_i \mathbb{I}_{ij} \omega_i. \tag{18}$$

Also, note that the aggregate share of human-capital groups equals the raw data,

$$L_s = L_s^{raw} = \sum_{i \in s} \omega_i.$$

7.2.2 Wages

Next, we turn to wages. We start with the wage regression

$$\ln w_i = \sum_j \mathbb{I}_{ij} \left(\gamma_j + X_i \beta_j \right) + \varepsilon_i \tag{19}$$

where w is the observed hourly wage of individual i and γ_j is the coefficient on occupational fixed effects. We again include the same set of explanatory variables in X as before and allow their coefficient to differ by occupation, β_j. The wage regressions are obtained via OLS using weights ω_i. We then predict the wage of individual i in any occupation j, $\widehat{w}_{ij}$, which we use to construct the predicted average of human-capital group s in occupation j as

$$\overline{w}_{sj} = \zeta_j \frac{\sum_{i \in s} \widehat{w}_{ij} \widehat{\pi}_{ij} \omega_i}{\sum_{i \in s} \widehat{\pi}_{ij} \omega_i}. \tag{20}$$

It includes the adjustment factor ζ_j which is set so that the estimated aggregate average wage in occupation j coincides exactly with the raw data moment,

$$\overline{w}_j = \frac{\sum_s \overline{w}_{sj} L_{sj}}{\sum_s L_{sj}} = \overline{w}_j^{raw} \quad \text{where} \quad \overline{w}_j^{raw} \equiv \frac{\sum_i \mathbb{I}_{ij} w_i \omega_i}{\sum_i \mathbb{I}_{ij} \omega_i}. \tag{21}$$

This adjustment is necessary given that the average predictions obtained from wage regression (19) are biased downward due to the logarithmic transformation. To ensure that the adjustment is plausible, we discard any surveys for which the adjustment factor ζ_j in any occupation is larger than twofold (up or down), which removes a handful of surveys. Note, however, the adjustment does not imply that the predicted average wages for any *human-capital group* necessarily coincide with the raw data moment,

$$\overline{w}_s = \frac{\sum_j \overline{w}_{sj} L_{sj}}{\sum_j L_{sj}} \neq \overline{w}_s^{raw} \quad \text{where} \quad \overline{w}_s^{raw} \equiv \frac{\sum_{i \in s} w_i \omega_i}{\sum_{i \in s} \omega_i}.$$

Again, to ensure that our wage predictions are plausible, we discard any surveys for which $\overline{w}_s$ differs from $\overline{w}_s^{raw}$ by more than factor 2 in any human-capital group s. This removes a few surveys. We then set a number of additional conditions that the surveys need to satisfy. One is that the ratio between the largest and smallest average wage by human-capital group does not exceed 10. This procedure discards a handful of countries for which we suspect abnormal levels of wage measurement error due to implausibly large wage inequality (Botswana and Vietnam).[18] Finally, to ensure that the wage measures are representative, we discard all surveys for which we do not have at least 10 wage observations for each human-capital groups s. This removes a small number of rich country surveys where there are very few observations of either young or old workers with only a primary-school level of education attainment. Finally, we only consider surveys for which we have at least 10 wage observations for each occupation j, which is satisfied in all cases.

7.3 Projections

Here, we describe the construction of the projections in Figures 1- **??**. Recall from combining (17) and (18) that the estimated employment share of workers in human-capital group s and occupation j in country c is

$$L_j^c = \sum_s L_{sj}^c = \sum_s \sum_{i \in s} \widehat{\pi}_{ij}^c \omega_i^c = \sum_i \widehat{\pi}_{ij}^c \omega_i^c.$$

The projection based on the US distribution of human capital is then

$$\widetilde{L}_j^c = \sum_i \widehat{\pi}_{ij}^c \omega_i^{US}$$

where ω_i^{US} is the weight that an individual corresponding to individual i in terms education, age and gender carries in the US survey. The projected white-collar employment share in Figure 1 is hence $\widetilde{L}_{WC}^c = \sum_{j \in WC} \widetilde{L}_j^c$.

We next turn to the projection of wages. Using (20), the average white-collar wage in country c is

$$\overline{w}_{WC}^c = \frac{\sum_{j \in WC} \sum_i \zeta_j^c \widehat{w}_{ij}^c \widehat{\pi}_{ij}^c \omega_i^c}{\sum_{j \in WC} \sum_i \widehat{\pi}_{ij}^c \omega_i^c}$$

The partial projection uses only the US human capital composition while the full projection in addition uses occupational employment propensity,

$$\overset{\simeq}{w}_{WC}^{c,part} = \frac{\sum_{j \in WC} \sum_i \zeta_j^c \widehat{w}_{ij}^c \widehat{\pi}_{ij}^c \omega_i^{US}}{\sum_{j \in WC} \sum_i \widehat{\pi}_{ij}^c \omega_i^{US}} \quad \text{and} \quad \overset{\simeq}{w}_{WC}^{c,full} = \frac{\sum_{j \in WC} \sum_i \zeta_j^c \widehat{w}_{ij}^c \widehat{\pi}_{ij}^{US} \omega_i^{US}}{\sum_{j \in WC} \sum_i \widehat{\pi}_{ij}^{US} \omega_i^{US}}.$$

Similarly, the projected high-skilled average wages are

$$\overset{\simeq}{w}_{HS}^{c,part} = \frac{\sum_j \sum_{i \in HS} \zeta_j^c \widehat{w}_{ij}^c \widehat{\pi}_{ij}^c \omega_i^{US}}{\sum_j \sum_{i \in HS} \widehat{\pi}_{ij}^c \omega_i^{US}} \quad \text{and} \quad \overset{\simeq}{w}_{HS}^{c,full} = \frac{\sum_j \sum_{i \in HS} \zeta_j^c \widehat{w}_{ij}^c \widehat{\pi}_{ij}^{US} \omega_i^{US}}{\sum_j \sum_{i \in HS} \widehat{\pi}_{ij}^{US} \omega_i^{US}}.$$

The projections for blue-collar and low-skilled average wages are computed in an analogous way. Finally, the projections in Figures 1-**??** based on global average simply use global averages for weights ω_i and $\widehat{\pi}_{ij}$.

[18] To put this in perspective, for the US in 2019 (CPS), that ratio equals 2.9. The ratio is still within bounds in countries with notoriously high wage inequality, such as Brazil in 2015 (PNAD) where it is 4.6 and South Africa in 2019 (LMD) where it is 7.0.

7.4 Summary conditional employment shares and average wages

Table 1 reports unconditional employment shares and average wages. As a complement, Table 15 reports the occupational employment shares and relative wages conditional on education. Among low-skilled workers, development is still associated with a rise in white-collar employment and a drop in the white-collar premium. The white-collar employment shares increases from 7 percent in the poorest quintile to 26 percent in the richest, while the white-collar wage premium drops from 77 to 21 percent. Among high-skilled workers, this pattern is more muted. The white-collar employment share does not vary strongly over the first four quintiles, while the white-collar wage drops, but less dramatically, from 91 percent in the poorest quintile to 50 percent in the richest.

Table 15: Employment shares and wages conditional on education

	Employment shares					Relative wages				
All occupations	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Elementary, LS	20	21	24	19	18	1.00	1.00	1.00	1.00	1.00
Services, LS	41	33	27	22	24	0.84	0.92	0.92	1.02	0.96
Operators, LS	9	13	12	18	14	1.29	1.29	1.32	1.31	1.17
Craft, LS	23	21	24	25	19	1.21	1.26	1.21	1.28	1.10
Clerks, LS	1	2	4	5	7	1.53	1.48	1.15	1.27	1.10
Technicians, LS	2	3	4	7	12	1.85	1.44	1.60	1.31	1.22
Professionals, LS	2	1	1	1	3	1.96	1.81	1.76	1.59	1.39
Managers, LS	1	5	3	3	5	2.33	1.64	1.86	1.67	1.55
Main occupations	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Blue-collar, LS	93	89	87	84	74	1.00	1.00	1.00	1.00	1.00
White-collar, LS	7	11	13	16	26	1.84	1.47	1.44	1.19	1.22
All occupations	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Elementary, HS	5	7	7	5	4	1.00	1.00	1.00	1.00	1.00
Services, HS	24	24	19	17	14	1.02	1.08	1.01	1.11	1.07
Operators, HS	6	8	7	7	5	1.28	1.30	1.28	1.36	1.17
Craft, HS	10	9	11	11	9	1.14	1.23	1.25	1.35	1.27
Clerks, HS	7	8	9	10	9	1.72	1.59	1.24	1.42	1.25
Technicians, HS	11	13	15	16	21	1.96	1.86	1.71	1.53	1.47
Professionals, HS	30	23	22	25	28	2.13	2.25	2.43	1.98	1.85
Managers, HS	7	9	10	7	10	2.83	2.64	2.66	2.34	2.04
Main occupations	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Blue-collar, HS	45	47	44	41	32	1.00	1.00	1.00	1.00	1.00
White-collar, HS	55	53	56	59	68	1.97	1.82	1.87	1.49	1.50

Analogously, Table 16 reports the occupational employment shares and relative wages conditional on occupation. Among blue-collar workers, the share of high-skilled workers rises in development, from 13 to 64 percent between the poorest and richest quintile. The high-skilled wage premium drops from 58 to 16 percent. A similar pattern emerges for white-collar workers. The employment share of high-skilled workers rises from 66 to 92 percent in the inter-quintile range. This implies that a substantial fraction of complex tasks in the poorest countries is carried out by low-skilled workers, while almost none is the richest countries. Also, the high-skilled premium drops from 70 to 45 percent. The larger (unconditional) skill premium in poor countries is hence not only due to occupational choice.

Table 16: Employment shares and wages conditional on occupation

	Employment shares					Relative wages				
All human-capital groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Primary, young, BC	44	27	13	4	3	1.00	1.00	1.00	1.00	1.00
Primary, old, BC	23	19	18	9	7	1.18	1.21	1.12	1.03	1.17
Lower secondary, young, BC	15	19	20	10	10	1.30	1.15	1.13	1.05	1.03
Lower secondary, old, BC	6	10	13	15	17	1.66	1.45	1.32	1.10	1.29
Upper secondary, young, BC	9	13	17	23	23	1.61	1.32	1.29	1.10	1.15
Upper secondary, old, BC	3	5	14	23	25	2.03	1.68	1.51	1.20	1.38
Tertiary, young, BC	1	5	4	8	8	2.48	1.67	1.71	1.27	1.26
Tertiary, old, BC	0	2	2	7	7	3.11	2.06	1.98	1.39	1.48
Main human-capital groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Low-skilled, BC	87	75	63	39	37	1.00	1.00	1.00	1.00	1.00
High-skilled, BC	13	25	37	61	63	1.58	1.32	1.25	1.13	1.13
All human-capital groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Primary, young, WC	9	5	2	0	0	1.00	1.00	1.00	1.00	1.00
Primary, old, WC	9	6	4	2	1	1.40	1.46	1.25	1.14	1.35
Lower secondary, young, WC	12	8	8	3	2	1.07	1.00	1.10	1.01	1.09
Lower secondary, old, WC	7	6	6	5	6	1.61	1.46	1.48	1.17	1.54
Upper secondary, young, WC	19	16	18	16	13	1.39	1.25	1.39	1.15	1.32
Upper secondary, old, WC	10	9	16	17	21	2.02	1.88	1.85	1.36	1.79
Tertiary, young, WC	21	29	25	28	24	2.22	1.93	2.17	1.53	1.71
Tertiary, old, WC	15	19	20	30	32	3.22	2.89	2.78	1.91	2.28
Main human-capital groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Low-skilled, WC	36	26	20	10	10	1.00	1.00	1.00	1.00	1.00
High-skilled, WC	64	74	80	90	90	1.69	1.64	1.62	1.40	1.38

7.5 Aggregate data

7.5.1 Non-agricultural output

Here we explain how we construct a measure of Y_{ct}, non-agricultural output in country c at time t. We start with the GGDC Productivity Level Database (PLD) which provides data on sectoral current nominal value added in local currency ("VA"), purchasing power parity ("PPP_va"), and sectoral employment ("EMP") for a large number of countries in the years 2005, 2011, and 2017. For each country c and year t, we compute the share of real non-agricultural GDP out of aggregate real GDP as $s_{ct}^{VA} \equiv \frac{\sum_{i \neq \text{agr}}^{I}(\text{VA}_{i,ct}/\text{PPP\_va}_{i,ct})}{\sum_{i=1}^{I}(\text{VA}_{i,ct}/\text{PPP\_va}_{i,ct})}$ where i denotes the sector and agr is agriculture. Next, we linearly interpolate s_{ct}^{VA} for each country between the years 2005 and 2017. We use the values of 2005 (2017) for the years prior to (beyond) 2005 (2017). We proceed in an analogous way to determine non-agricultural employment, s_{ct}^{EMP}. Finally, real non-agricultural GDP per worker is $Y_{ct} = \frac{s_{ct}^{VA}}{s_{ct}^{EMP}} \frac{\text{rgdpe}_{ct}}{\text{emp}_{ct}}$ where "rgdpe" is the PWT measure of real aggregate GDP and "emp" is the PWT measure of employment.

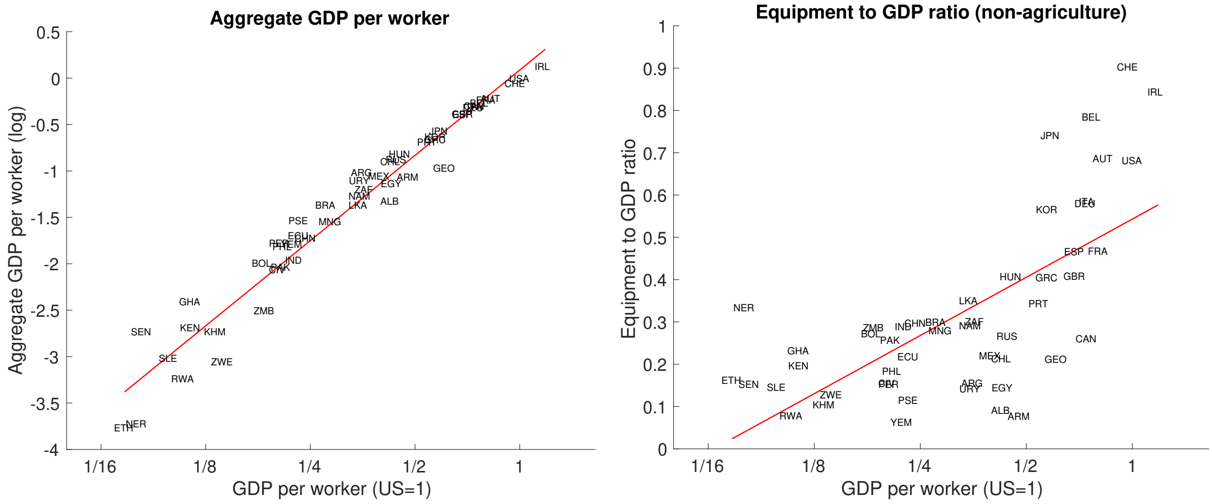
There are a number of countries in the micro dataset for which we do not have sectoral data in the PLD.[19] For these countries, we follow Herrendorf, Rogerson and Valentinyi (2022) by assuming that agricultural goods, being tradable, command the same nominal price in all countries. First, we take their agricultural employment share from from the World Bank database to compute the non-agricultural employment share, s_{ct}^{EMP}. Second, we assume that the real non-agricultural value-added share is $s_{ct}^{VA} = 1 - a_{ct}\left(\frac{1}{P_{US,t}/P_{US,17}}\right)\left(\frac{NY_{ct}/NY_{US,17}}{\text{rgdpo}_{ct}/\text{rgdpo}_{US,17}}\right)$. The first term is a_{ct}, which is the nominal value-added share of agriculture, taken from the World Bank database. We assume that it coincides with the real value-added share of agriculture in the

[19]These are

benchmark country-year, namely the US in 2017. For other country-years, the nominal share is adjusted by the price of agriculture (second term) relative to the price of aggregate GDP (third term). The price of agriculture, P, is the index of US agricultural prices, taken from FRED. The third term is the relative change of current-US dollar nominal GDP, NY, relative to the change in real GDP.[20]

The left panel of Figure 15 plots the cross-country relationship between non-agricultural GDP per non-agricultural worker (on the x-axis) and aggregate GDP per worker (on the y-axis). Both are normalized to the US non-agricultural GDP per non-agricultural worker.

Figure 15



(a) (b)

7.5.2 Non-agricultural equipment

Here we explain how we measure K_{ct}, the stock of non-agricultural equipment in country c at time t. There are three challenges. The first is that this is a real measure, priced in units of real non-agricultural GDP, Y_{ct}. The second is to isolate equipment from other types of capital (structures). The third challenge is to isolate non-agricultural from agricultural capital.

We start with the Capital Detail of the Penn World Table 10.01 that reports investment at current national prices and current-cost net capital stocks across countries and across time for the following items: residential and non-residential structures ("Struc"), machinery ("Mach"), transport equipment ("TraEq"), and other assets ("Other"). Let $\widetilde{V}^S_{i,ct}$ and $\widetilde{V}^S_{n,ct}$ denote investment in structures and the net capital stock of structures, respectively, after converting to current US dollars using the exchange rate of PWT. We define equipment as the sum of all the remaining items except structures, denoted by $\widetilde{V}^K_{i,ct}$ for investment and $\widetilde{V}^K_{n,ct}$ for the net capital stock, respectively. Also, define the share of the equipment value as $s_{i,ct} \equiv \frac{\widetilde{V}^K_{i,ct}}{\widetilde{V}^S_{i,ct}+\widetilde{V}^K_{i,ct}}$ and $s_{n,ct} \equiv \frac{\widetilde{V}^K_{n,ct}}{\widetilde{V}^S_{n,ct}+\widetilde{V}^K_{n,ct}}$. The tilde notation defines aggregate values as opposed to non-agricultural ones (without the tilde).

[20] In the World Bank database, the agricultural employment is "SL.AGR.EMPL.ZS," the agricultural nominal value-added share a_{ct} is "NV.AGR.TOTL.ZS," and current-US dollar nominal GDP NY is "NY.GDP.MKTP.CD."

Let the real stock of equipment be $\widetilde{K}_{ct} = \frac{\widetilde{V}^K_{n,ct}}{P^K_{n,ct}}$ where $P^K_{n,ct}$ is the price level of equipment relative to a benchmark country-year. To construct $P^K_{n,ct}$, we proceed as follows. The Penn World Table reports the price level of (aggregate) capital formation, $P_{i,ct}$, normalized to the price of real GDP in 2017. It also provides the price level of the capital stock, $P_{n,ct}$, which is normalized to one for the US in 2017.[21] We assume that these price indices are geometric means of the prices of equipment and structures, weighted by their nominal value shares, namely: $P_{i,ct} = \left(P^K_{i,ct}\right)^{s_{i,ct}} \left(P^S_{i,ct}\right)^{1-s_{i,ct}}$, and $P_{n,ct} = \left(P^K_{n,ct}\right)^{s_{n,ct}} \left(P^S_{n,ct}\right)^{1-s_{n,ct}}$. The solution to these two equations allows to infer $P^K_{n,ct}$ and hence the real stock of aggregate equipment, $\widetilde{K}_{ct}$.

The last step is to isolate the fraction of the capital stock used in non-agriculture. For this we set $K_{ct} = \phi_{ct}\widetilde{K}_{ct}$ where $\phi_{ct} \equiv 1 - \frac{\widehat{V}_{n,ct}}{\widetilde{V}^S_{n,ct}+\widetilde{V}^K_{n,ct}}$ where $\widehat{V}_{n,ct}$ is the value of the net agricultural capital stock, obtained from FAOSTAT.[22] The implicit assumption is therefore that the capital stocks in agriculture and non-agriculture equal in their composition between structures and equipment. Finally, we divide by the number of non-agricultural workers to arrive at K_{ct}.

The resulting cross-country ratio of non-agricultural equipment to non-agricultural GDP, $\frac{K_c}{Y_c}$, is plotted in the right panel of Figure 15.

7.5.3 Income share of equipment

We calibrate the parameters α_j, $\forall j \in \{1, 2, ..., J\}$, to the aggregate equipment capital income share of the US. First, we assume that the occupational incomes shares are all identical and equal to the aggregate, $\frac{RK_j}{p_jY_j} = \frac{RK}{Y}$, $\forall j$.[23] Second, we assume that the equipment capital income share in non-agriculture is identical to that of the aggregate economy. The next step is to separate the aggregate capital income share into equipment and structures: $\frac{RK}{Y} = \frac{RK}{RK+R_SS}\widetilde{\alpha} = \frac{RK/(R_SS)}{RK/(R_SS)+1}\widetilde{\alpha}$ where R_SS is the aggregate income of structures and $\widetilde{\alpha}$ is the aggregate capital income share. The latter is readily available from the data while the ratio $\frac{RK}{R_SS}$. We deduce it as follows from a neoclassical growth model with two types of capital.

Suppose that the representative household's budget constraint is

$$C + P_KK' + P_SS' = (1-\delta_K)\,P_KK + R_KK + (1-\delta_S)\,P_SS + R_SS$$

where C is consumption, δ_i is the depreciation rate of capital type $i \in \{K, S\}$, and P_i is the price (relative to GDP) of capital type $i \in \{K, S\}$. The household's intertemporal problem in steady state results in $P_K = \beta\left[(1-\delta_K)\,P_K + R\right]$ and $P_S = \beta\left[(1-\delta_S)\,P_S + R_S\right]$ where β is the household's discount factor. We thus have

$$\frac{RK}{R_SS} = \left(\frac{1-\beta\,(1-\delta_K)}{1-\beta\,(1-\delta_S)}\right)\frac{P_KK}{P_SS} = \left(\frac{r+\delta_K}{r+\delta_S}\right)\frac{P_KK}{P_SS}$$

where $r = \frac{1-\beta}{\beta}$ is the the steady-state interest rate. The Capital Detail of PWT 10.01 provides data on $\frac{P_KK}{P_SS}$. In addition, we determine δ_i from the steady-state relationships $\delta_K = \frac{P_KI_K}{P_KK}$ and $\delta_S = \frac{P_SI_S}{P_SS}$ where P_KI_K and P_KI_K denote investment for which data is also available in the Capital Detail of PWT 10.01.[24]

[21] In the PWT, the two series are denoted as pl_i and pl_n, respectively.

[22] This series is denoted as element code 6109 and item code 22030 in FAOSTAT.

[23] An alterantive is to equate the parameters $\alpha_j = \alpha$, $\forall j \in \{1, 2, ..., J\}$ and set α so as to hit the aggregate ratio $\frac{RK}{Y}$. In this case, occupational shares in the benchmark country differ by occupation. However, the resulting cross-country productivity differences and all counterfactuals are almost identical to the baseline calibration.

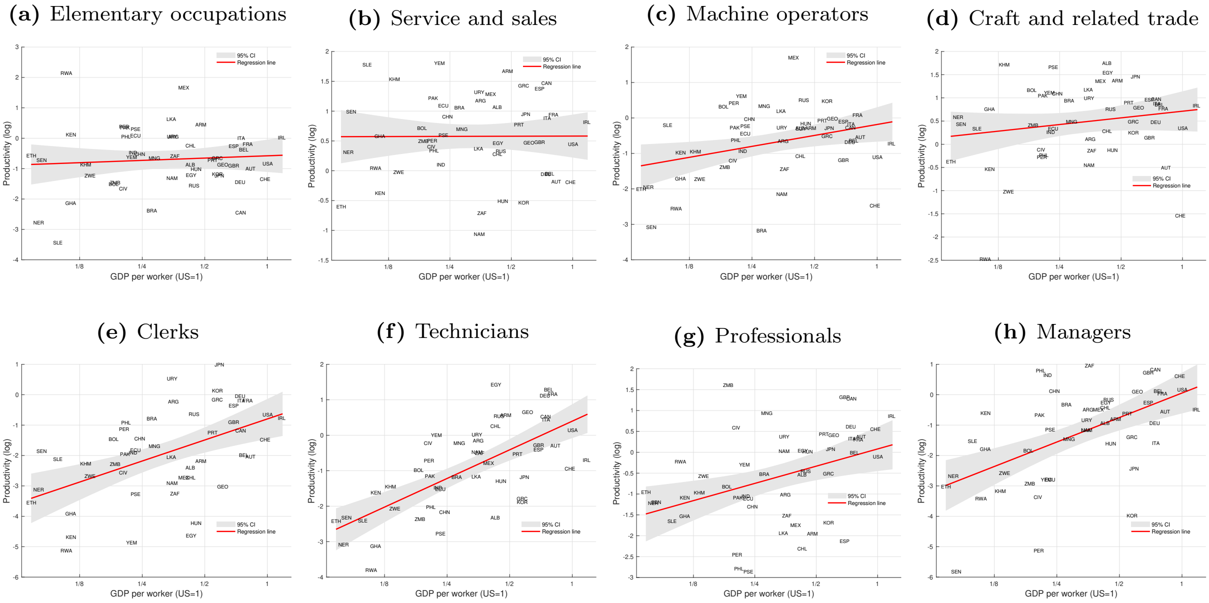
[24] These data are described in the previous subsection where the notation is $P_KK = \widetilde{V}^K_n$, $P_SS = \widetilde{V}^S_n$, $P_KI_K =$

Finally, we set $r = 0.03$. For the US in 2019, we find that $\frac{R_K K}{R_S S} = 0.872$ and $\widetilde{\alpha} = 0.416$, which gives $\frac{RK}{Y} = 0.193$. Note that using the same procedure for other countries (and imposing $r = 0.03$ everywhere) obtains a cross-country mean value of $\frac{RK}{Y}$ that is almost equal to that of the US, 0.190.

7.6 Inferred productivity, human capital quality, and distortions

Figure 16 portrays the inferred productivity terms, A, for each occupation. Figures 17-24 plots the inferred human-capital quality terms, h, for each human capital level, conditional on each occupation. Figures 33-40 depict the inferred distortions, D, for each occupation, conditional on each level of human capital.

Figure 16: Productivity, A



(a) Elementary occupations **(b)** Service and sales **(c)** Machine operators **(d)** Craft and related trade **(e)** Clerks **(f)** Technicians **(g)** Professionals **(h)** Managers

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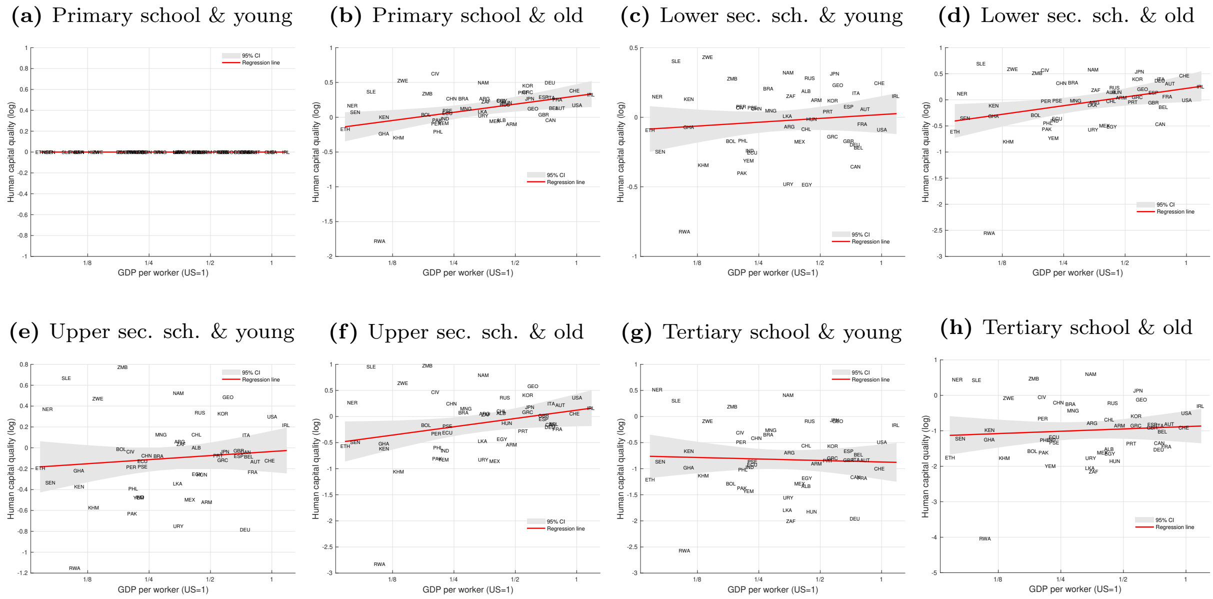
$\widetilde{V}_i^K$, and $P_S I_S = \widetilde{V}_i^S$.

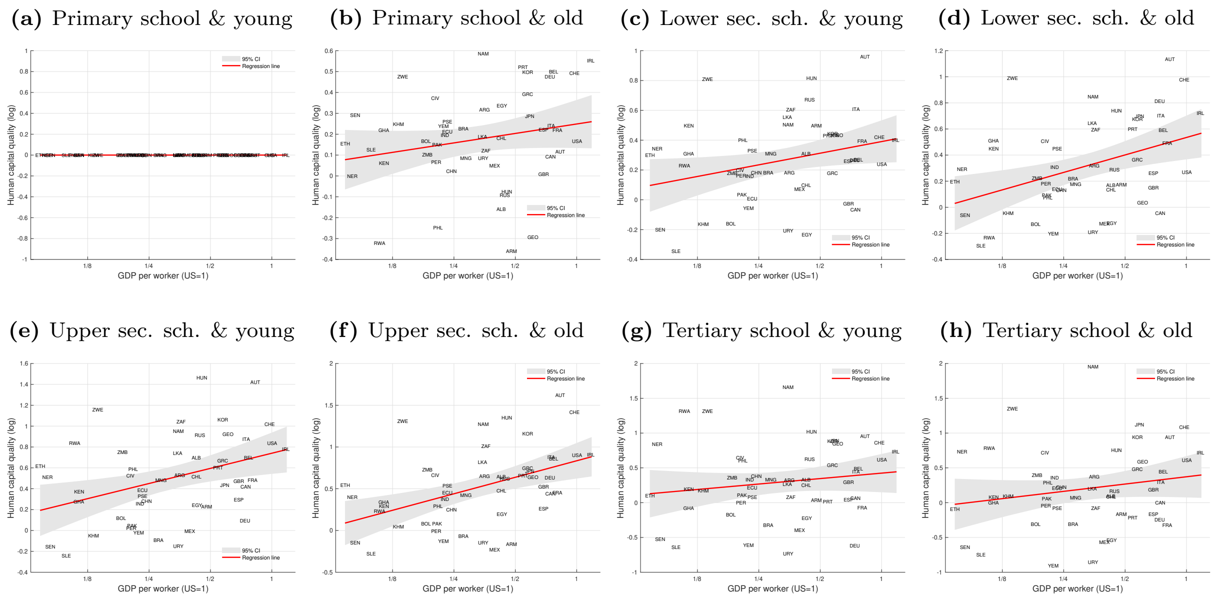
Figure 17: Human capital quality, h: elementary occupations



(a) Primary school & young **(b)** Primary school & old **(c)** Lower sec. sch. & young **(d)** Lower sec. sch. & old

(e) Upper sec. sch. & young **(f)** Upper sec. sch. & old **(g)** Tertiary school & young **(h)** Tertiary school & old

Figure 18: Human capital quality, h: service and sales occupations

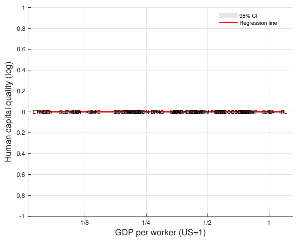


(a) Primary school & young **(b)** Primary school & old **(c)** Lower sec. sch. & young **(d)** Lower sec. sch. & old

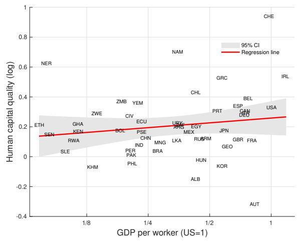
(e) Upper sec. sch. & young **(f)** Upper sec. sch. & old **(g)** Tertiary school & young **(h)** Tertiary school & old

Figure 19: Human capital quality, h: machine and plant operators

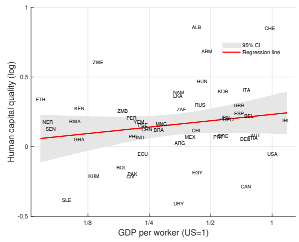
(a) Primary school & young



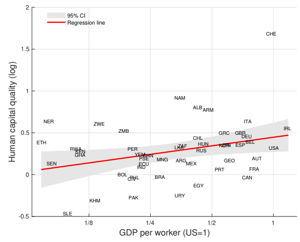
(b) Primary school & old



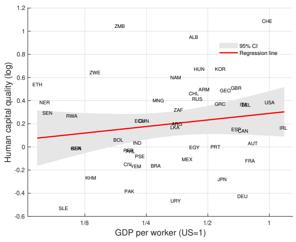
(c) Lower sec. sch. & young



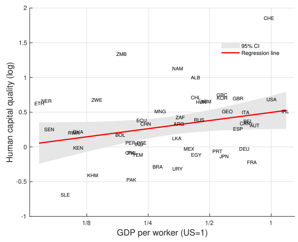
(d) Lower sec. sch. & old



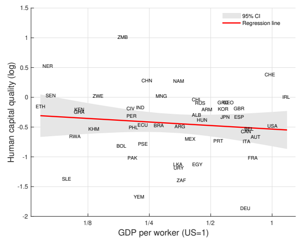
(e) Upper sec. sch. & young



(f) Upper sec. sch. & old



(g) Tertiary school & young



(h) Tertiary school & old

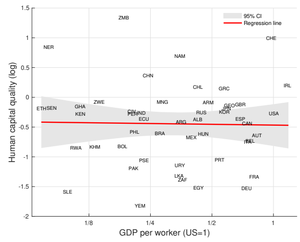
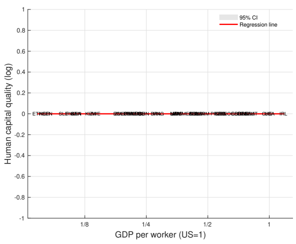
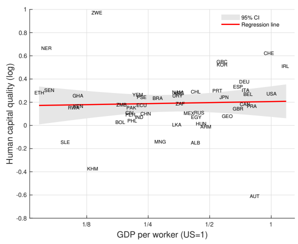


Figure 20: Human capital quality, h: craft and related trade

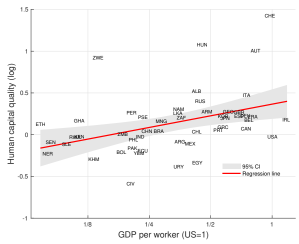
(a) Primary school & young



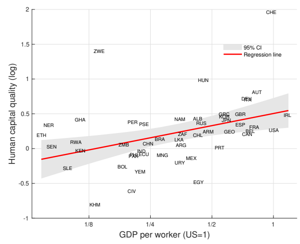
(b) Primary school & old



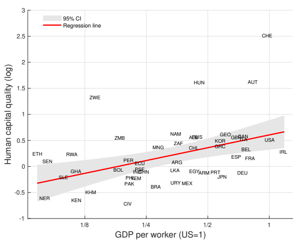
(c) Lower sec. sch. & young



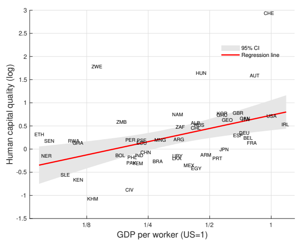
(d) Lower sec. sch. & old



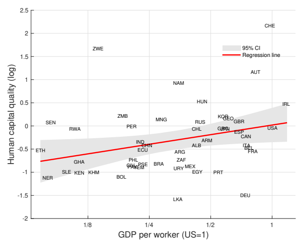
(e) Upper sec. sch. & young



(f) Upper sec. sch. & old



(g) Tertiary school & young



(h) Tertiary school & old

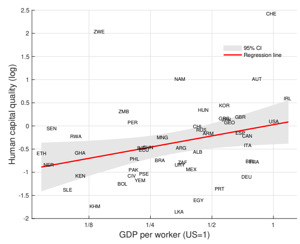
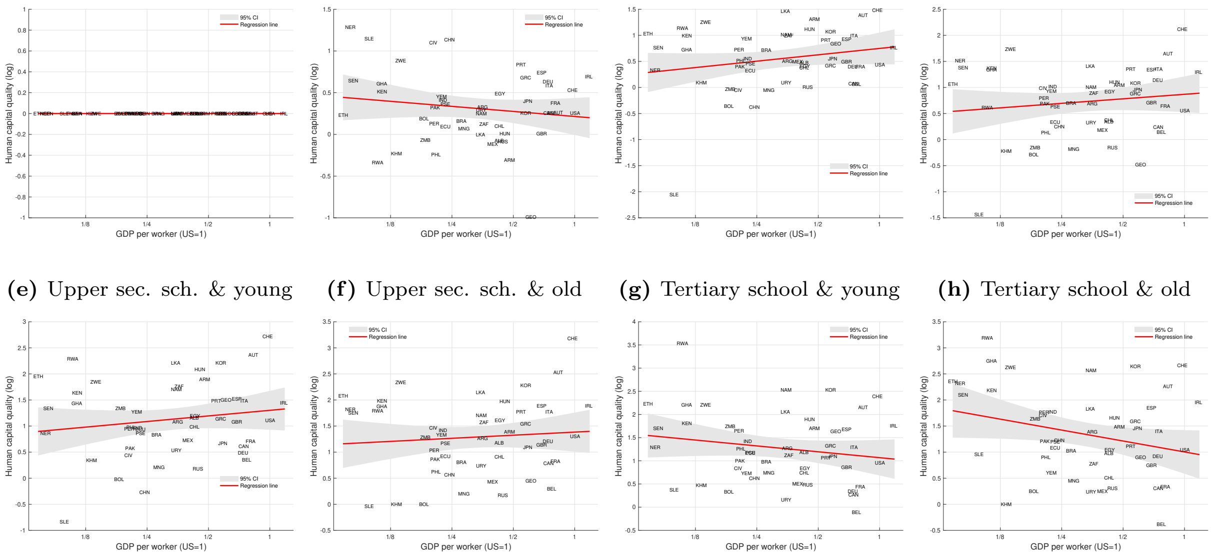
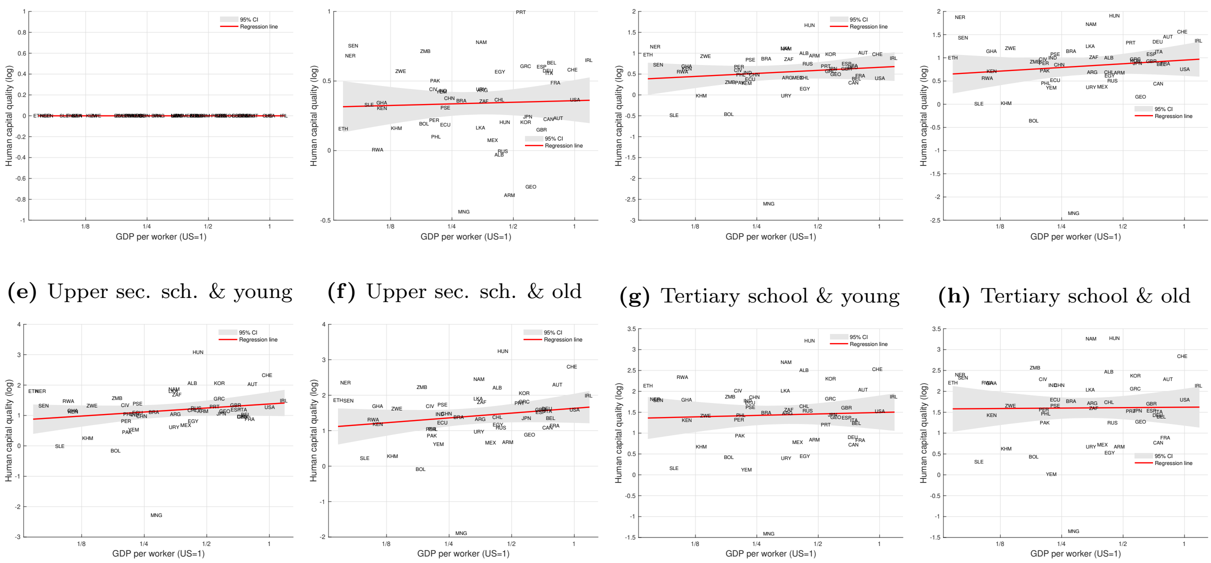


Figure 21: Human capital quality, h: clerks



(a) Primary school & young (b) Primary school & old (c) Lower sec. sch. & young (d) Lower sec. sch. & old (e) Upper sec. sch. & young (f) Upper sec. sch. & old (g) Tertiary school & young (h) Tertiary school & old

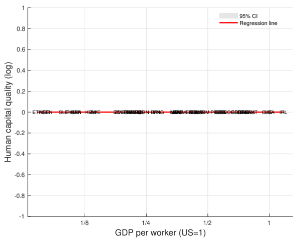
Figure 22: Human capital quality, h: technicians and associate professionals



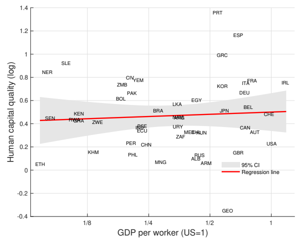
(a) Primary school & young (b) Primary school & old (c) Lower sec. sch. & young (d) Lower sec. sch. & old (e) Upper sec. sch. & young (f) Upper sec. sch. & old (g) Tertiary school & young (h) Tertiary school & old

Figure 23: Human capital quality, h: professionals

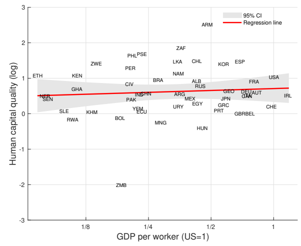
(a) Primary school & young



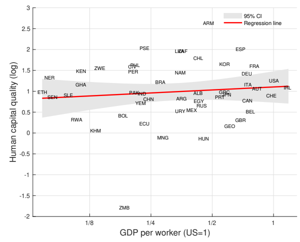
(b) Primary school & old



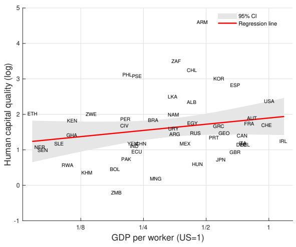
(c) Lower sec. sch. & young



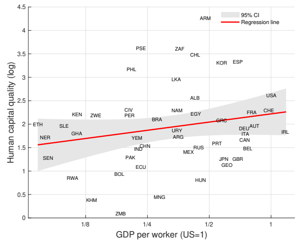
(d) Lower sec. sch. & old



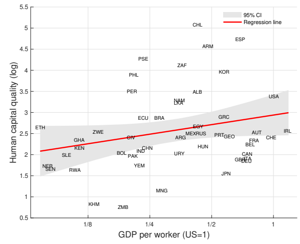
(e) Upper sec. sch. & young



(f) Upper sec. sch. & old



(g) Tertiary school & young



(h) Tertiary school & old

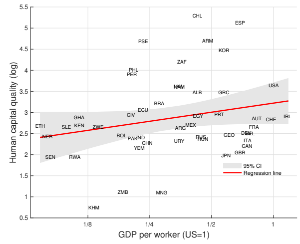
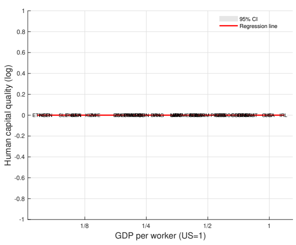
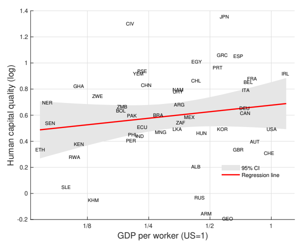


Figure 24: Human capital quality, h: managers

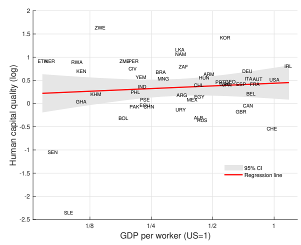
(a) Primary school & young



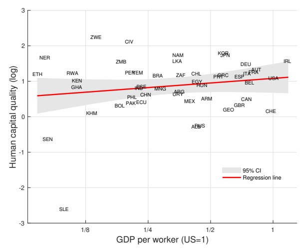
(b) Primary school & old



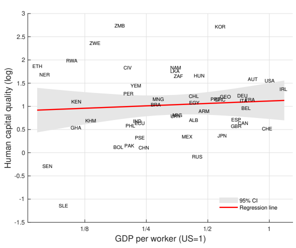
(c) Lower sec. sch. & young



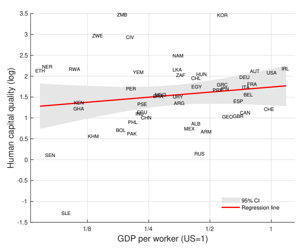
(d) Lower sec. sch. & old



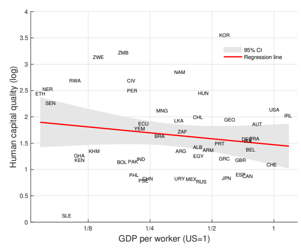
(e) Upper sec. sch. & young



(f) Upper sec. sch. & old



(g) Tertiary school & young



(h) Tertiary school & old

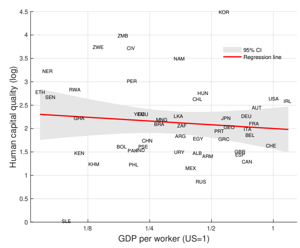
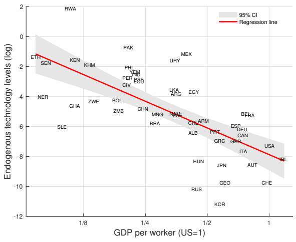
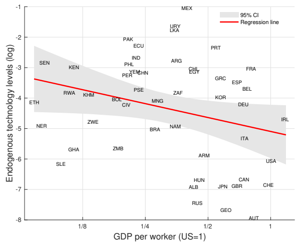


Figure 25: Endogenous productivity, B: elementary occupations

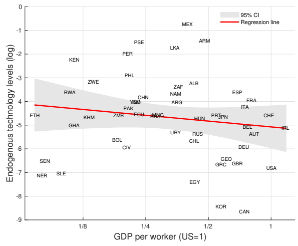
(a) Primary school & young



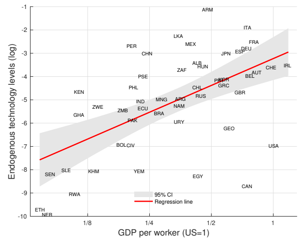
(b) Primary school & old



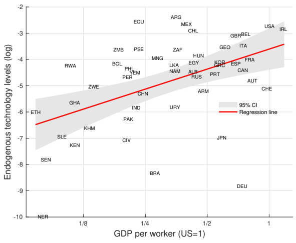
(c) Lower sec. sch. & young



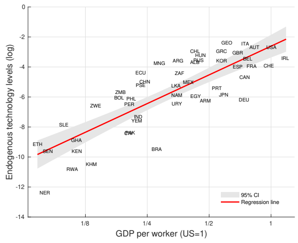
(d) Lower sec. sch. & old



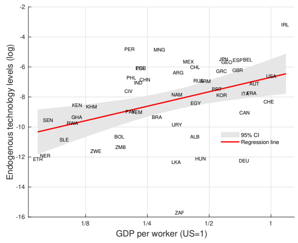
(e) Upper sec. sch. & young



(f) Upper sec. sch. & old



(g) Tertiary school & young



(h) Tertiary school & old

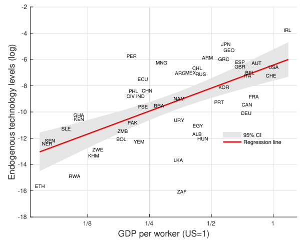
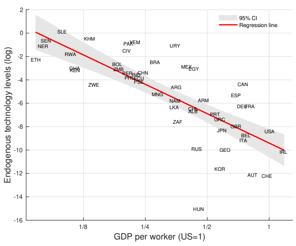
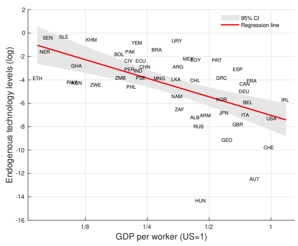


Figure 26: Endogenous productivity, B: service and sales occupations

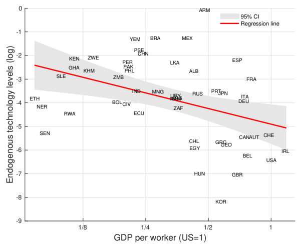
(a) Primary school & young



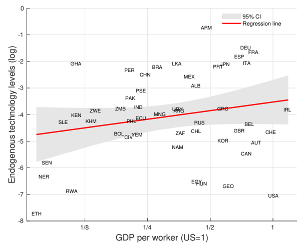
(b) Primary school & old



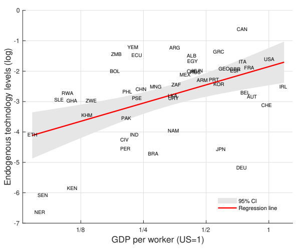
(c) Lower sec. sch. & young



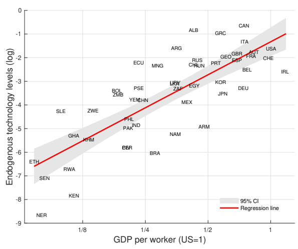
(d) Lower sec. sch. & old



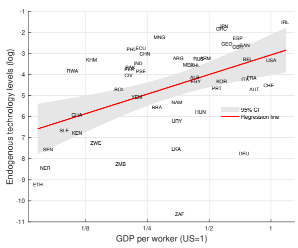
(e) Upper sec. sch. & young



(f) Upper sec. sch. & old



(g) Tertiary school & young



(h) Tertiary school & old

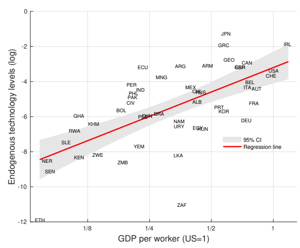
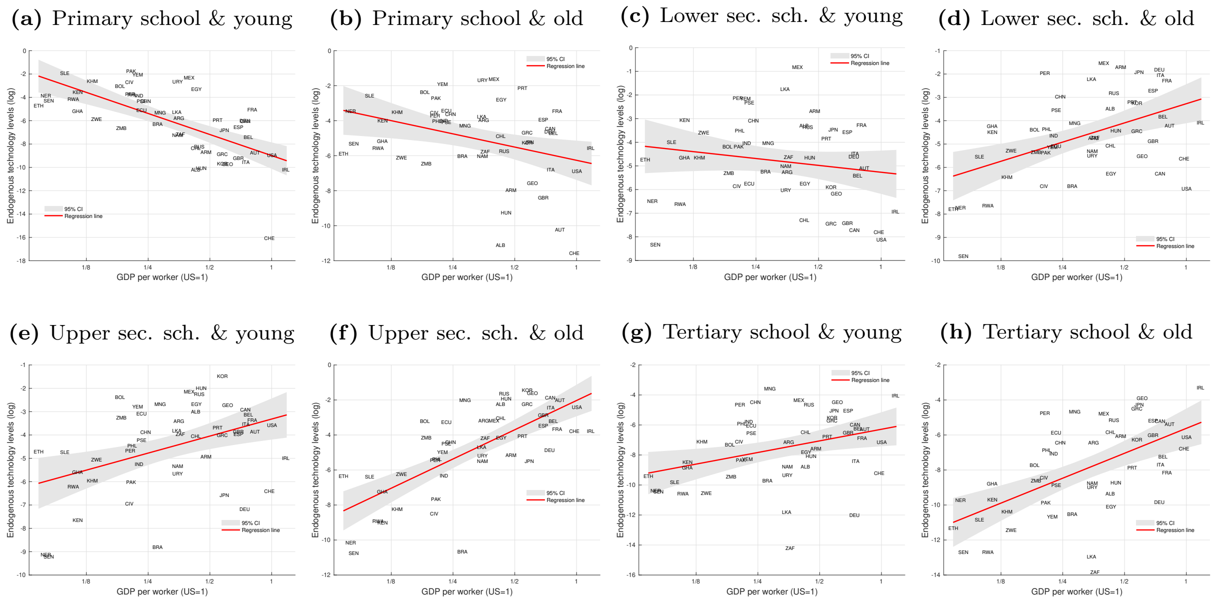


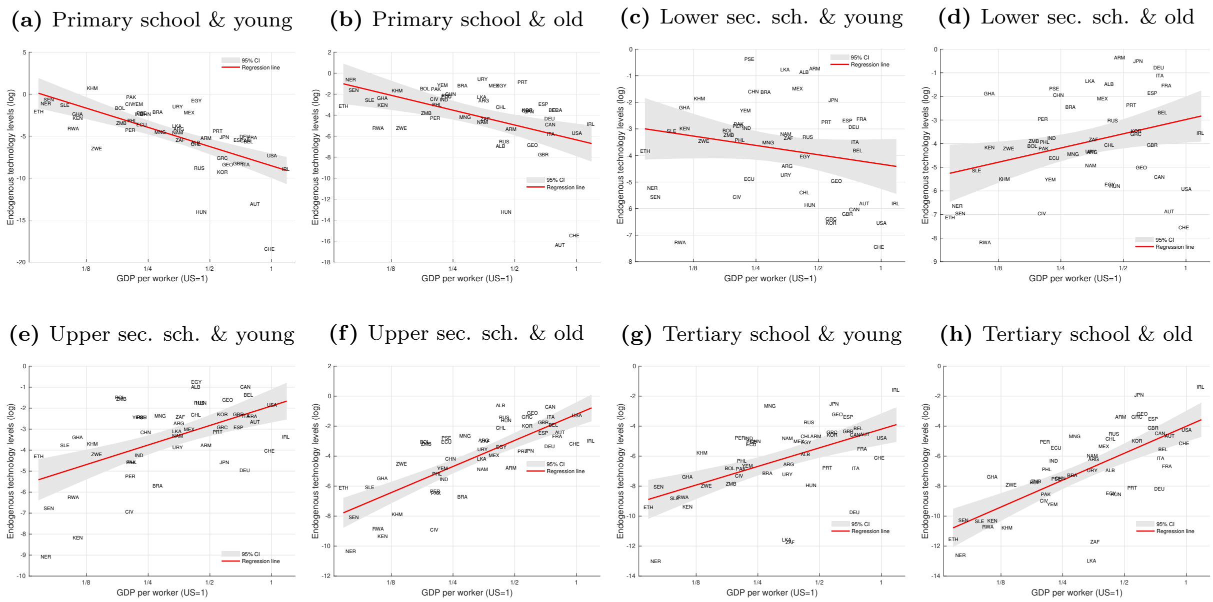
Figure 27: Endogenous productivity, B: machine and plant operators



(a) Primary school & young (b) Primary school & old (c) Lower sec. sch. & young (d) Lower sec. sch. & old

(e) Upper sec. sch. & young (f) Upper sec. sch. & old (g) Tertiary school & young (h) Tertiary school & old

Figure 28: Endogenous productivity, B: craft and related trade

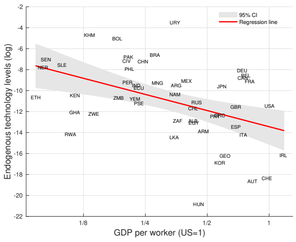


(a) Primary school & young (b) Primary school & old (c) Lower sec. sch. & young (d) Lower sec. sch. & old

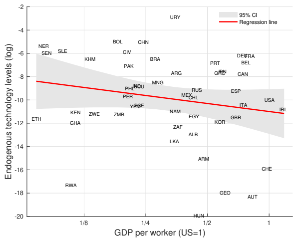
(e) Upper sec. sch. & young (f) Upper sec. sch. & old (g) Tertiary school & young (h) Tertiary school & old

Figure 29: Endogenous productivity, B: clerks

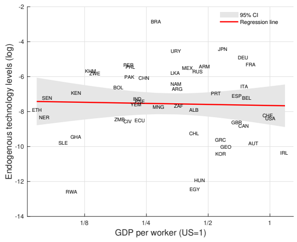
(a) Primary school & young



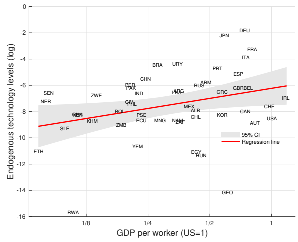
(b) Primary school & old



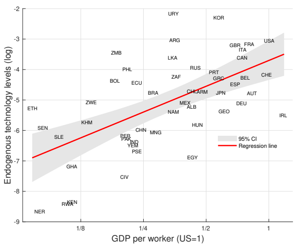
(c) Lower sec. sch. & young



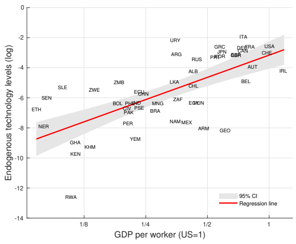
(d) Lower sec. sch. & old



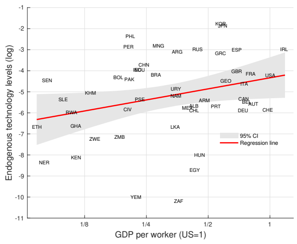
(e) Upper sec. sch. & young



(f) Upper sec. sch. & old



(g) Tertiary school & young



(h) Tertiary school & old

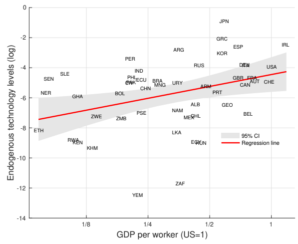
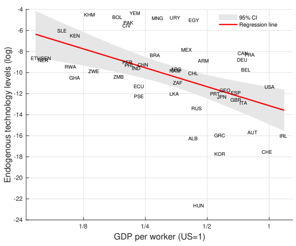
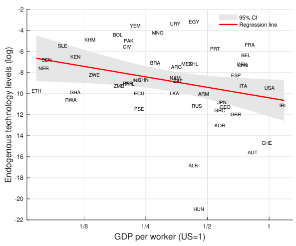


Figure 30: Endogenous productivity, B: technicians and associate professionals

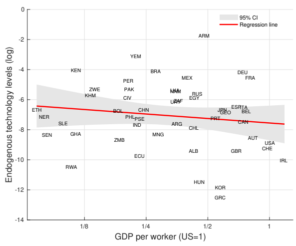
(a) Primary school & young



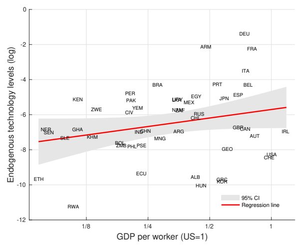
(b) Primary school & old



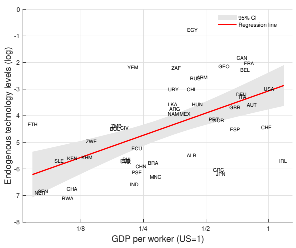
(c) Lower sec. sch. & young



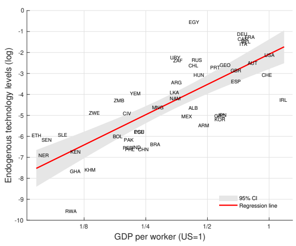
(d) Lower sec. sch. & old



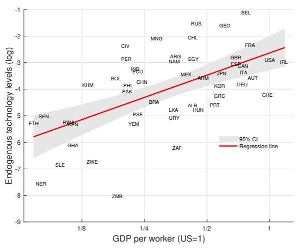
(e) Upper sec. sch. & young



(f) Upper sec. sch. & old



(g) Tertiary school & young



(h) Tertiary school & old

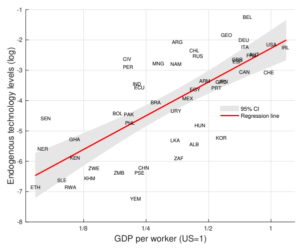
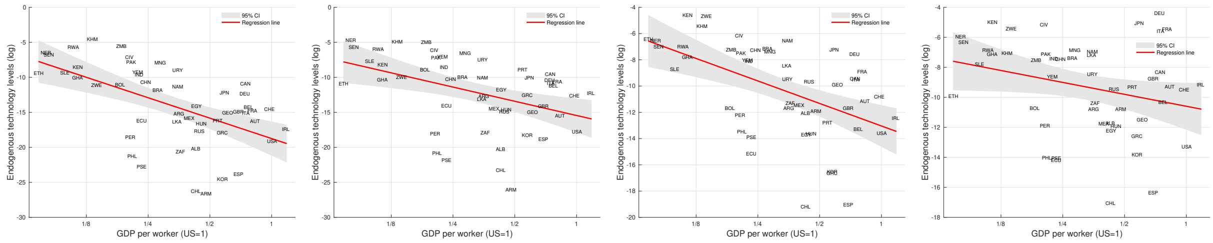


Figure 31: Endogenous productivity, B: professionals

(a) Primary school & young **(b)** Primary school & old **(c)** Lower sec. sch. & young **(d)** Lower sec. sch. & old



(e) Upper sec. sch. & young **(f)** Upper sec. sch. & old **(g)** Tertiary school & young **(h)** Tertiary school & old

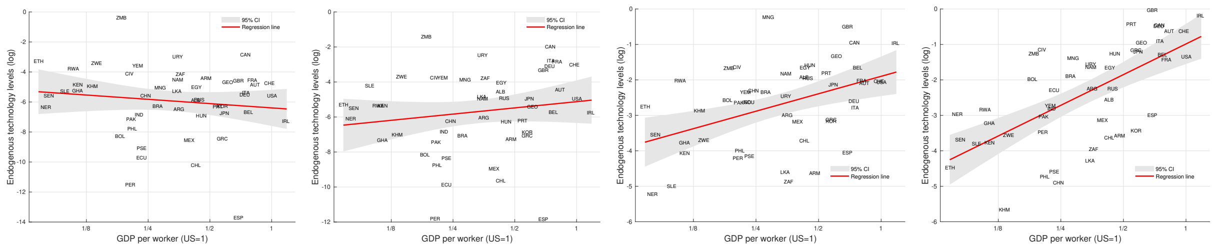
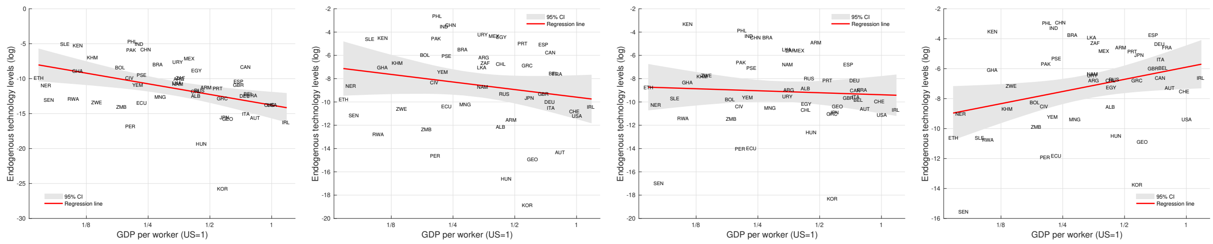


Figure 32: Endogenous productivity, B: managers

(a) Primary school & young **(b)** Primary school & old **(c)** Lower sec. sch. & young **(d)** Lower sec. sch. & old



(e) Upper sec. sch. & young **(f)** Upper sec. sch. & old **(g)** Tertiary school & young **(h)** Tertiary school & old

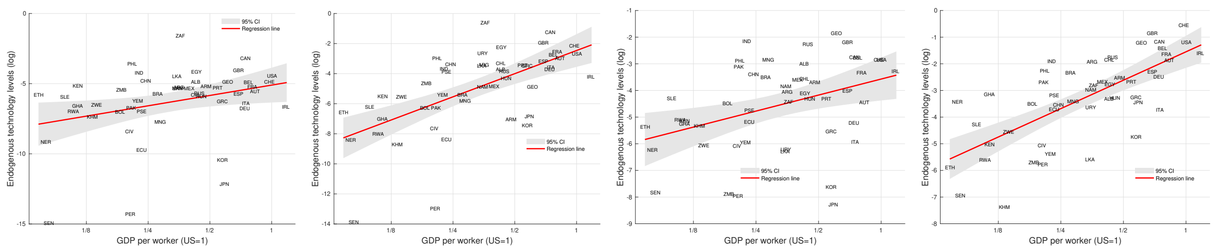
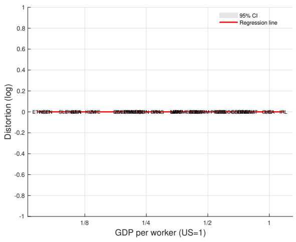
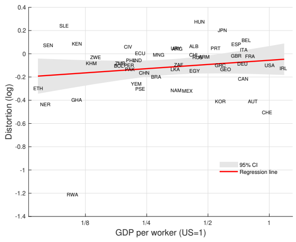


Figure 33: Distortions, D: primary school and young

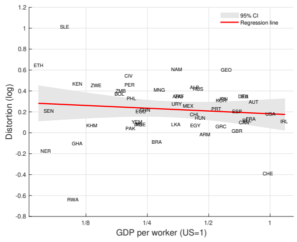
(a) Elementary occupations



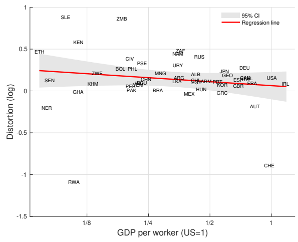
(b) Service and sales



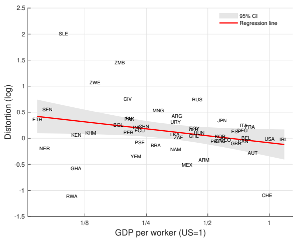
(c) Machine operators



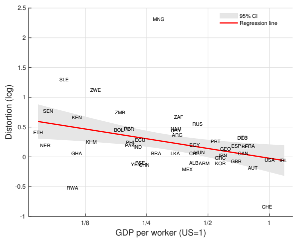
(d) Craft and related trade



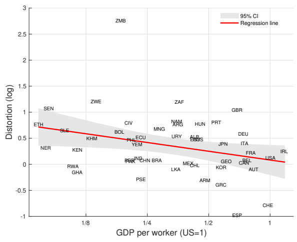
(e) Clerks



(f) Technicians



(g) Professionals



(h) Managers

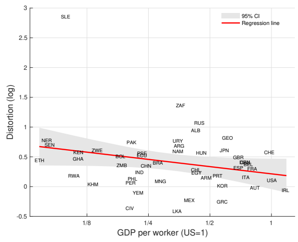
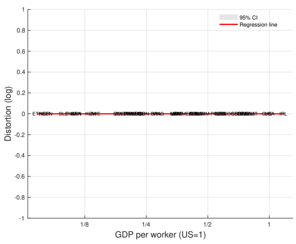
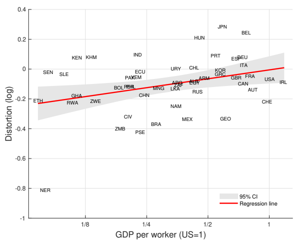


Figure 34: Distortions, D: primary school and old

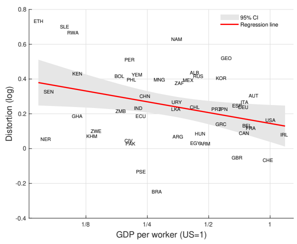
(a) Elementary occupations



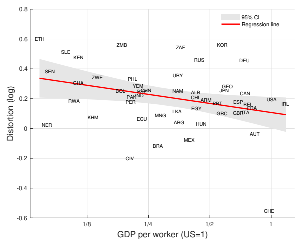
(b) Service and sales



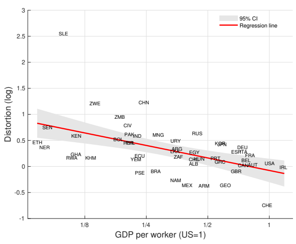
(c) Machine operators



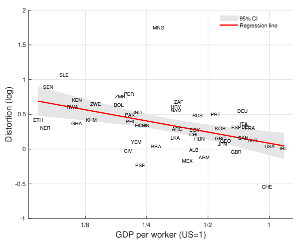
(d) Craft and related trade



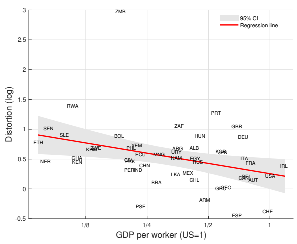
(e) Clerks



(f) Technicians



(g) Professionals



(h) Managers

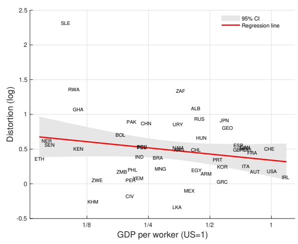
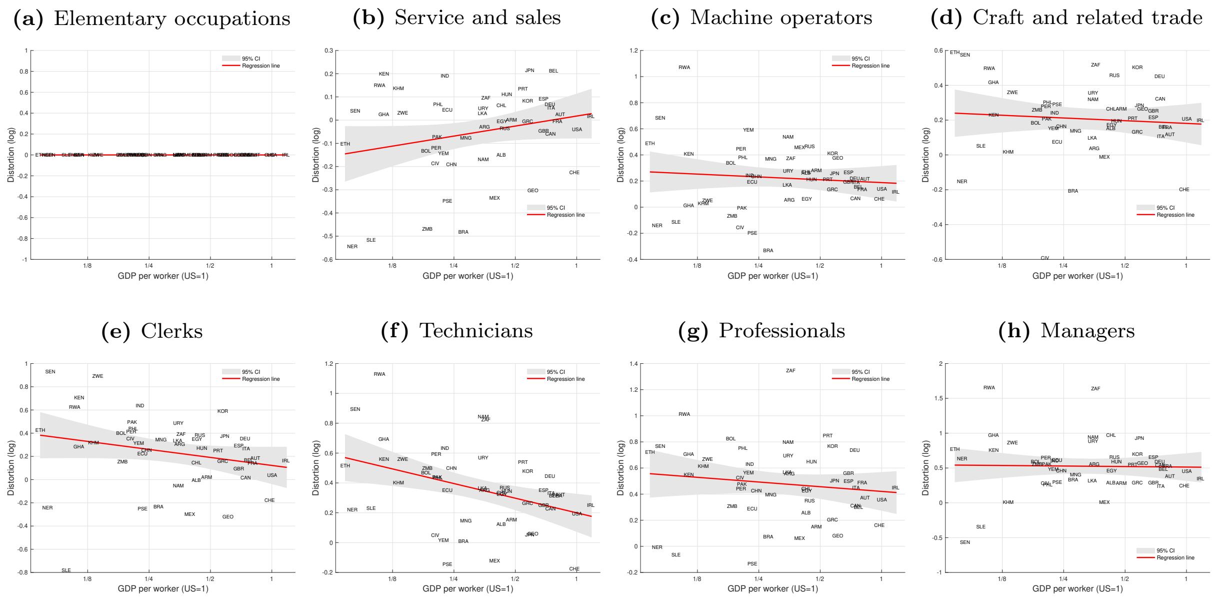


Figure 35: Distortions, D: lower secondary school and young

(a) Elementary occupations **(b)** Service and sales **(c)** Machine operators **(d)** Craft and related trade

(e) Clerks **(f)** Technicians **(g)** Professionals **(h)** Managers

Figure 36: Distortions, D: lower secondary school and old

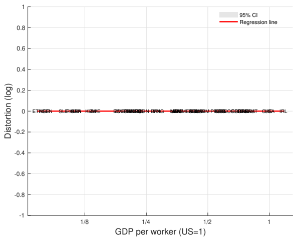


(a) Elementary occupations **(b)** Service and sales **(c)** Machine operators **(d)** Craft and related trade

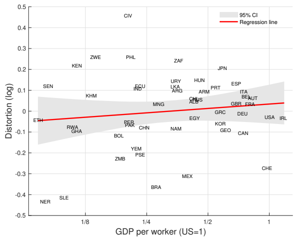
(e) Clerks **(f)** Technicians **(g)** Professionals **(h)** Managers

Figure 37: Distortions, D: upper secondary school and young

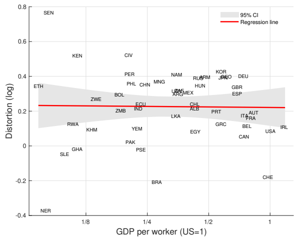
(a) Elementary occupations



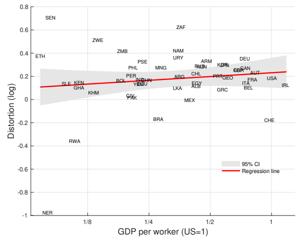
(b) Service and sales



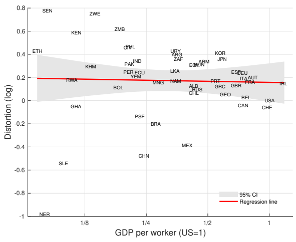
(c) Machine operators



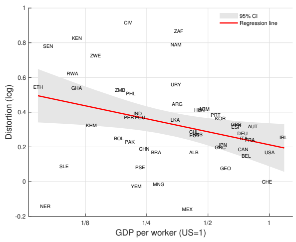
(d) Craft and related trade



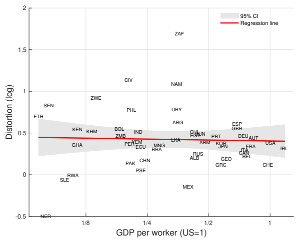
(e) Clerks



(f) Technicians



(g) Professionals



(h) Managers

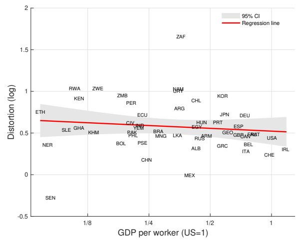
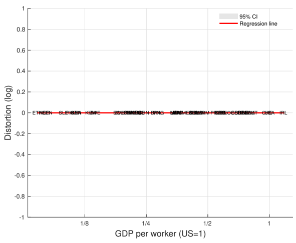
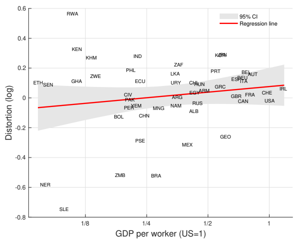


Figure 38: Distortions, D: upper secondary school and old

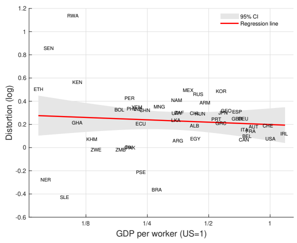
(a) Elementary occupations



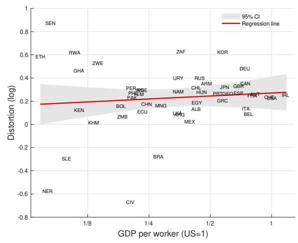
(b) Service and sales



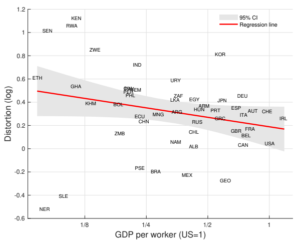
(c) Machine operators



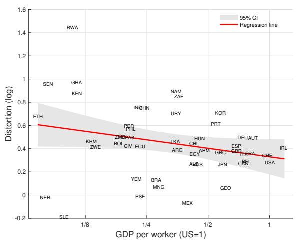
(d) Craft and related trade



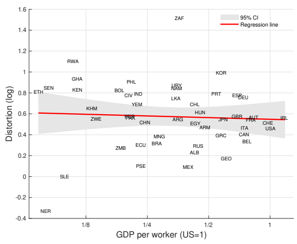
(e) Clerks



(f) Technicians



(g) Professionals



(h) Managers

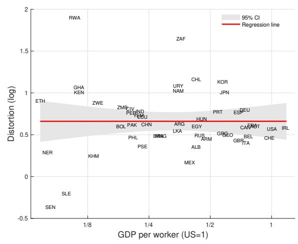
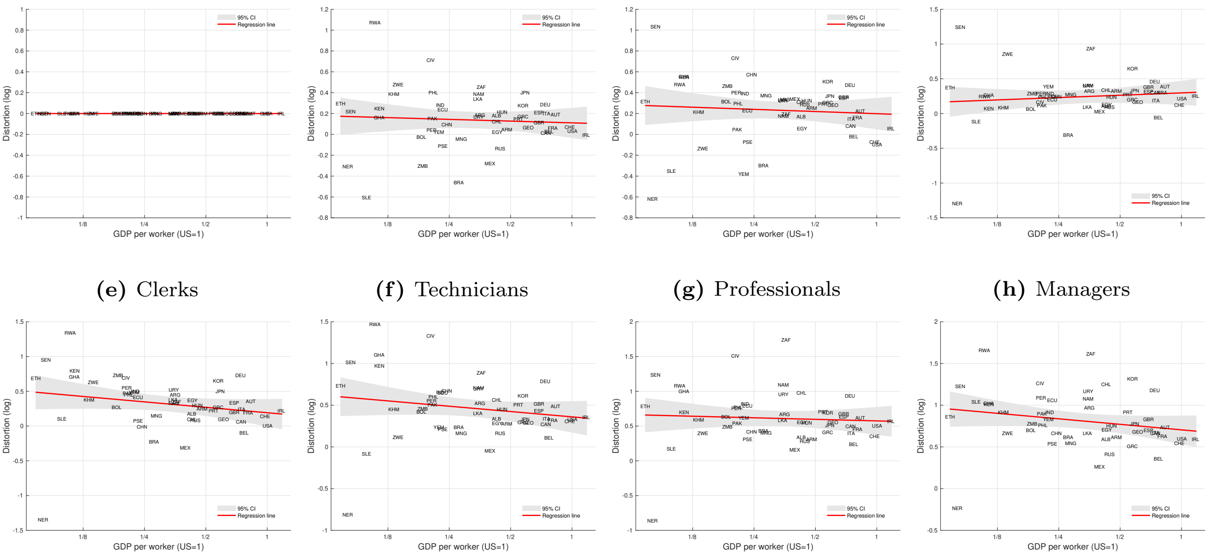


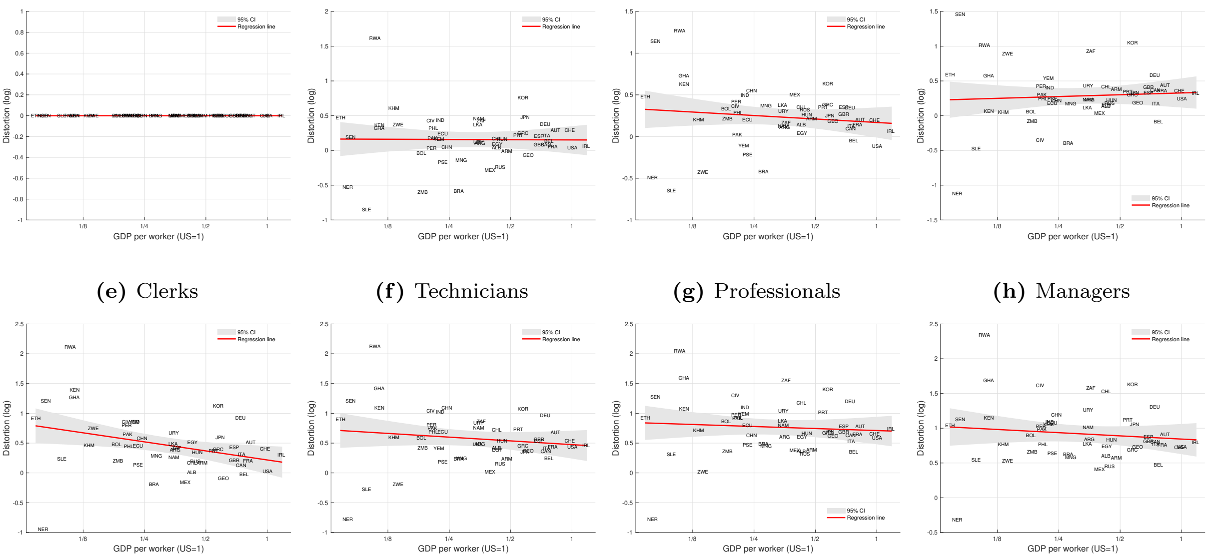
Figure 39: Distortions, D: tertiary school and young



(a) Elementary occupations (b) Service and sales (c) Machine operators (d) Craft and related trade

(e) Clerks (f) Technicians (g) Professionals (h) Managers

Figure 40: Distortions, D: tertiary school and old



(a) Elementary occupations (b) Service and sales (c) Machine operators (d) Craft and related trade

(e) Clerks (f) Technicians (g) Professionals (h) Managers

7.7 Additional counterfactual results

7.7.1 Human capital quality versus composition

In the left panel of Figure 41 we vary human-capital quality, h, while in the right panel we vary the composition of human capital, L. Changing human-capital quality produces substantially more variation than changing its composition, with many countries exhibiting higher human-capital quality than the US. Also, on average, poor countries stand more to gain from acquiring the US composition of human capital than its quality.

Figure 41: GDP change after shift to either US human capital quality or composition

(a) Human capital quality, h (b) Human capital composition, L

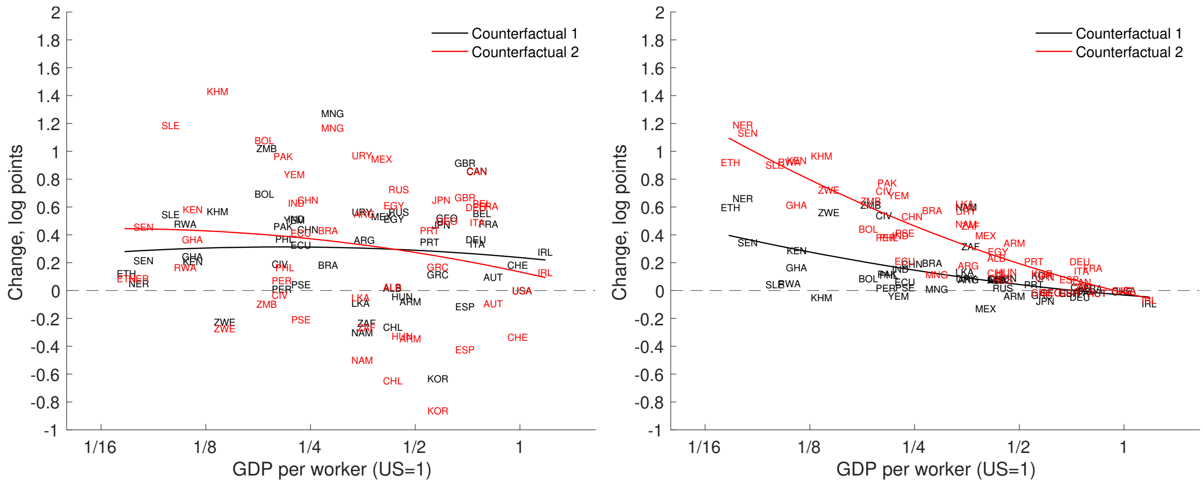
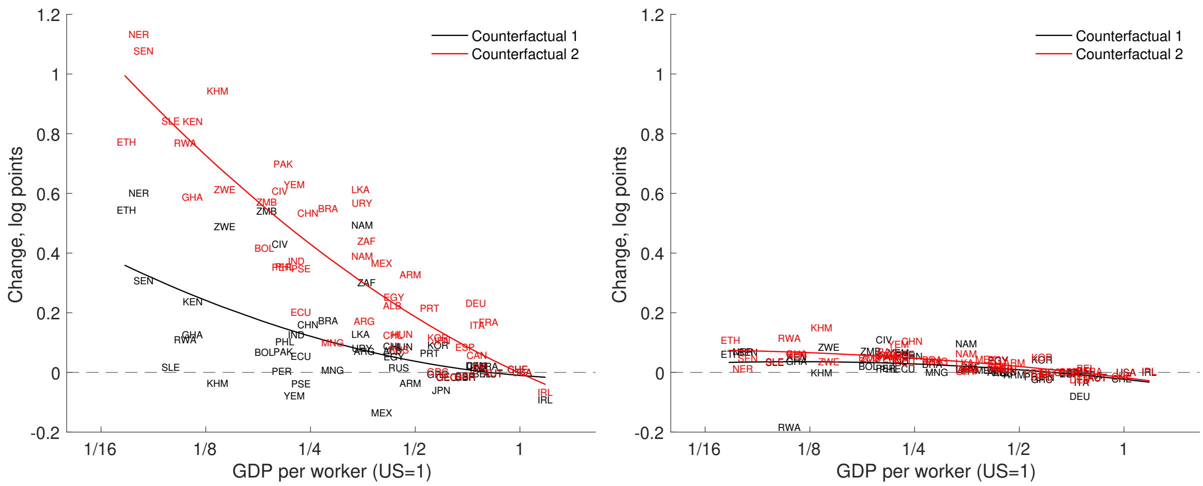


Figure 42: GDP change after shift to either US education or age composition

(a) Education (b) Age



In Figure 42 we focus only on the human-capital composition and keep human-capital quality unaltered. The left panel shows experiments of endowing countries with the US education composition while keeping the age composition constant. Analogously, in the right panel we vary the age composition while keeping that of education constant. Clearly, education matters substantially more than age.

Figure 43 plots the change in the white-collar employment rate associated with shifting toward the US human capital. We see from the left panel that the variation in human-capital does not systematically contribute to the relationship between white-collar employment and aggregate income. That relationship is driven primarily by the composition of human capital, portrayed in the right panel.

Figure 44 plots the changes in the average wage of white-collar relative to that of blue-collar workers. As can be seen from the left panel, shifting to US human-capital quality tends to increase the white-collar wage premium in rich countries almost as much as in poor countries.

Figure 43: White-collar employment rate change after shift to either US human capital quality or composition

(a) Human capital quality, h **(b)** Human capital composition, L

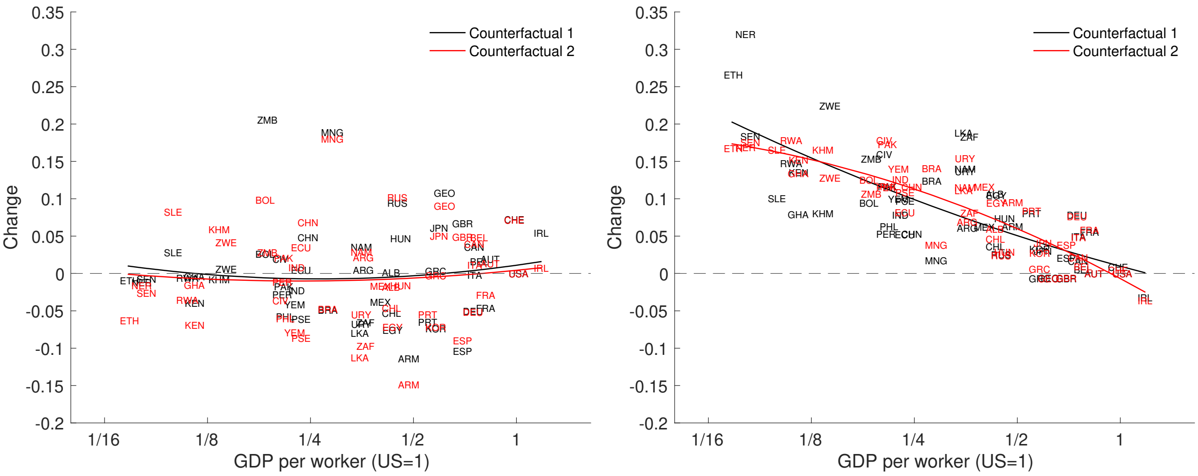
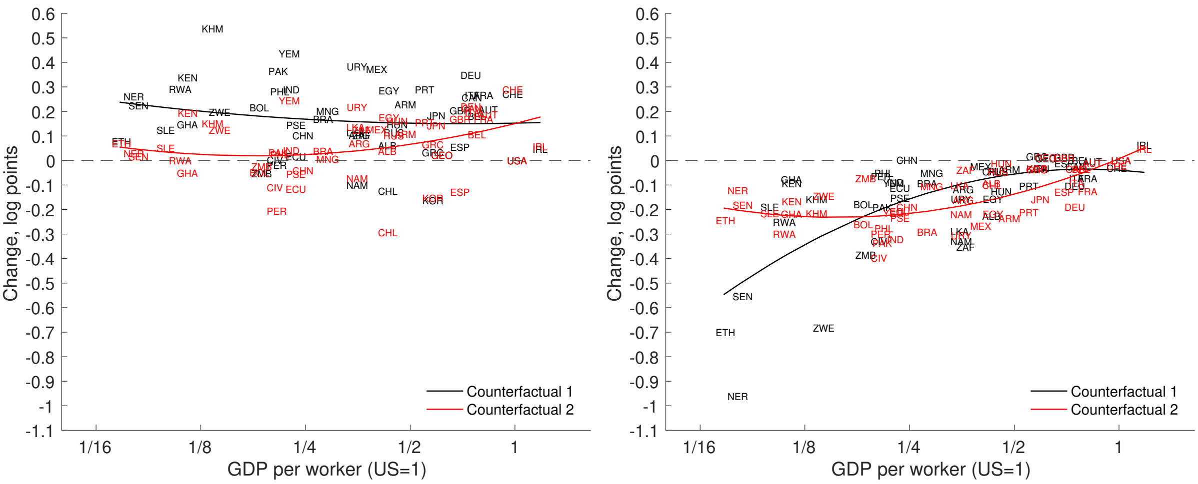


Figure 44: White-collar to blue-collar average wage change after shift to either US human capital quality or composition

(a) Human capital quality, h **(b)** Human capital composition, L



Shifting to the US human-capital composition, on the other, tends to lower the white-collar wage premium in poor countries.

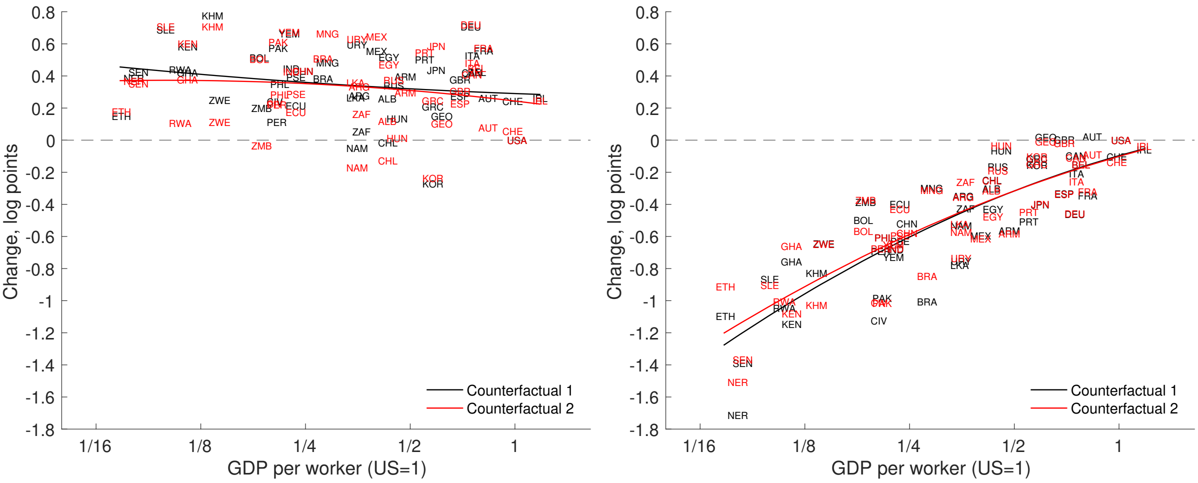
Finally, Figure 45 shows that the the impact of US human capital on the high-skill wage premium follows a similar and even more pronounced trend to that on the white-collar wage premium. Acquiring US human capital trends to increase the premium as the US has particularly high productivity of high-skilled workers. Acquiring the US human-capital composition, on the hand, strongly decreases the premium.

7.7.2 Counterfactual human capital and endogenous technology

In this subsection we recompute the endogenous technology terms B_{sj} under the two counterfactuals of either (i) endowing all countries with the US human-capital quality and composition or (ii) endowing the US with the human-capital quality of and composition of other countries.

Figure 45: High-skilled to low-skilled average wage change after shift to either US human capital quality or composition

(a) Human capital quality, h **(b)** Human capital composition, L



We then regress the resulting parameters on GDP per worker and present the elasticities in Tables 17 and 18.

Table 17: Elasticity of endogenous technology, B, with respect to GDP: Counterfactual 1

	Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
Primary, young	0.37	-0.15	0.95	-0.19	2.73	2.36	1.01	3.07
Primary, old	0.84	-0.27	1.00	-0.38	2.47	2.03	0.80	2.83
Lower second., young	0.17	0.08	0.69	0.18	2.37	2.03	0.24	2.51
Lower second., old	0.73	0.03	0.82	0.09	2.04	1.64	0.04	2.40
Upper second., young	-0.12	0.15	0.42	0.29	1.94	1.92	0.56	2.08
Upper second., old	0.39	0.15	0.62	0.30	1.67	1.62	0.30	2.06
Tertiary, young	-0.70	-0.26	-0.41	-0.14	0.52	0.97	0.72	0.92
Tertiary, old	-0.20	-0.25	-0.12	0.01	0.23	0.69	0.58	0.91

Consider first Table 17 and compare the elasticities to the original values reported in Table 8. When human capital is equalized across countries, there is no longer a clear pattern of directed technology distinguishing rich from poor countries. This suggests that cross-country differences in human capital are key in driving the inferred specialization in the baseline calibration. Next, compare 18 to the original Table 8. We see that when all countries are identical in all endowments *except* human capital, the specialization pattern becomes even starker. In that scenario, economies with a higher share of educated and older workers would specialize technology even more toward those groups.

7.7.3 Counterfactuals by detailed human-capital group and occupation

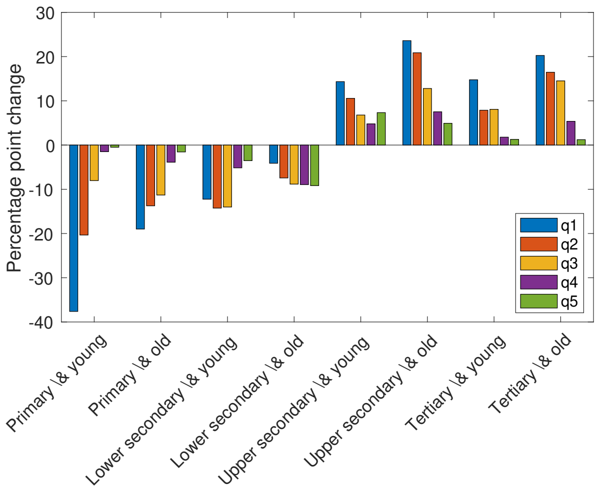
Here, we complement the results presented in Figures 6-7 in Section 5.1. For concision, we group countries by quintiles according to non-agricultural GDP per worker. The left panel of Figure 46 shows the change in human capital composition. In most countries, a switch to the US endowment lowers the share of low-skilled workers and leads to a relative drop in young workers. Naturally, this pattern is more pronounced in less developed countries. The equilibrium change in occupational employment is shown in the right panel of Figure 46. In all country groups,

Table 18: Elasticity of endogenous technology, B, with respect to GDP: Counterfactual 2

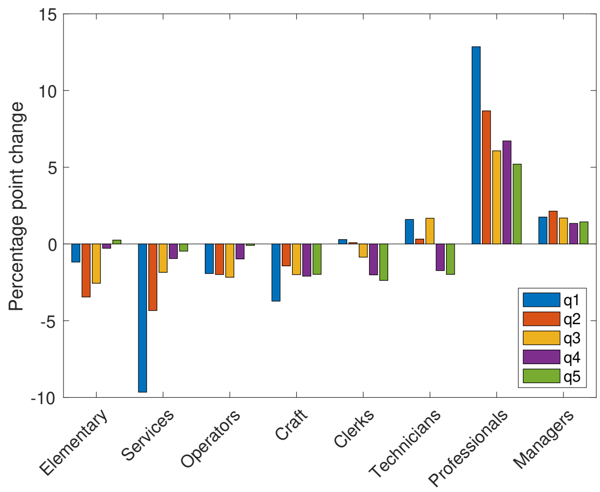
	Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
Primary, young	-2.74	-3.53	-3.16	-3.14	-4.02	-4.28	-5.24	-4.84
Primary, old	-1.34	-2.11	-1.75	-1.74	-2.60	-2.85	-3.79	-3.40
Lower second., young	-0.32	-1.08	-0.72	-0.70	-1.55	-1.80	-2.73	-2.34
Lower second., old	1.03	0.30	0.64	0.66	-0.16	-0.41	-1.30	-0.93
Upper second., young	1.41	0.65	1.01	1.02	0.17	-0.08	-1.00	-0.62
Upper second., old	2.44	1.69	2.04	2.06	1.22	0.98	0.07	0.45
Tertiary, young	2.22	1.50	1.84	1.85	1.04	0.80	-0.08	0.28
Tertiary, old	2.76	2.04	2.38	2.40	1.60	1.36	0.49	0.85

employment shifts from blue-collar to white-collar work. Among blue-collar occupations, there is a particularly strong decline in elementary occupations, service and sales, and craft and trade. Among white-collar occupations, the increase is strongest amongst professionals.

Figure 46



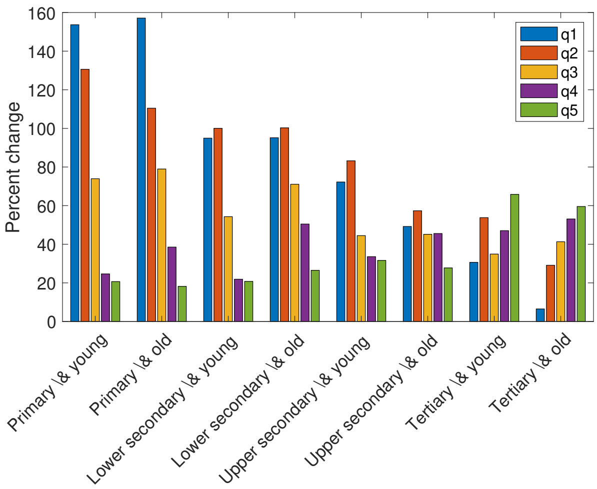
(a) Change in human capital composition



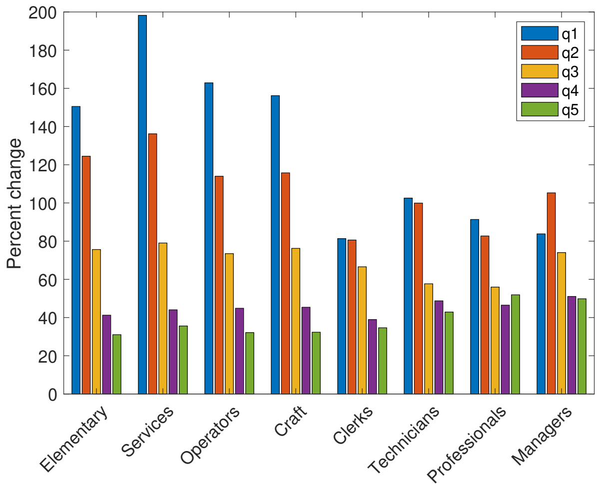
(b) Change in occupational composition

Continuing with the above experiment, Figure 47 portrays the change in average wages by human capital (left panel) and by occupation (right panel). The left panel mirrors that of the left panel of Figure 46. An increase in the number of skilled workers leads to a drop in their wages as the relative demand for their labor decreases. What is more surprising is the right panel. We see that the average wage increases in practically all occupations. It rises more strongly in blue-collar occupations where employment drops. It is due to sorting as the remaining white-collar workers are more positively selected.

Figure 47



(a) Change in average wages by human capital



(b) Change in average wages by occupation

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