From Skills to Occupations: Comparative Advantage and Cross-Country Income Differences

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Abstract

We revisit the role of human capital in cross-country income differences. We develop a general equilibrium model where workers of different skill groups sort into occupations by comparative advantage. Wages and employment depend on workers' skill quality, occupation-specific country-embedded productivity, and occupational distortions. Using harmonized microdata for 50 countries, we infer these components from the model's equilibrium conditions. Workers in rich countries exhibit higher skill quality and substantially greater productivity, especially in white-collar occupations. Human capital explains 52 percent of output-per-worker gaps, largely through the complementarity between skill composition and quality, and further amplified by technology choices biased toward skilled labor. Adopting the U.S. distribution of skill groups yields limited gains for poor countries without higher quality. Occupational distortions are more severe in low-income countries, reducing white-collar employment and raising wage premia, but with modest aggregate effects.

JEL Codes: O47, O15, J24, J31, E24

Keywords: Human capital; Development accounting; Occupational sorting; Country-embedded productivity; Wage premia.

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1 Introduction

Understanding the sources of large and persistent cross-country income differences remains a central goal of economics.[1] The main challenge is to isolate the role of *human capital*—the skills and know-how embodied in workers—from productivity factors embedded in countries. We revisit this question using a quantitative general-equilibrium model in which workers with different human capital sort across occupations according to comparative advantage. Combining the model with a new harmonized cross-country micro dataset, we conduct counterfactuals to assess how human capital shapes the allocation and productivity of workers across countries, and ultimately accounts for observed gaps in output per worker.

Educational attainment and other indicators of human capital vary widely across countries, yet the literature offers sharply divergent views on its quantitative contribution to income differences. Mankiw, Romer, and Weil (1992) attributed much of the variation to human and physical capital. In contrast, many authors instead argued that total factor productivity (TFP), not human or physical capital, drives output differences (Klenow and Rodríguez-Clare, 1997; Hall and Jones, 1999; Bils and Klenow, 2000; Caselli, 2005). The disagreement persists in richer models with imperfect substitution across skill groups. If skill-specific productivities are interpreted as embodied in workers, human capital explains most of the gap Jones (2014, 2019); if instead they are interpreted as country-embedded productivity, human capital explains little (Caselli and Coleman, 2006; Caselli and Ciccone, 2019). More recently, independent measures of human-capital quality—from test scores, migrant earnings, or life-cycle returns—have been introduced, typically yielding a contribution of human capital to GDP between those two extremes Hendricks and Schoellman (2018, 2023); Rossi (2022).

This paper makes three contributions. First, we assemble a novel dataset covering 50 countries that span the entire development spectrum. Drawing on harmonized labor force and household surveys, we measure employment and hourly wages across 64 worker–occupation cells in each country. Workers are grouped into four education categories crossed with two potential-experience levels, and occupations into eight broad

[1] Lucas (1988) put it starkly: "The consequences for human welfare involved in questions like these are simply staggering: once one starts to think about them, it is hard to think about anything else."

non-agricultural categories.[2] These data yield new stylized facts. In the richest quintile of countries, 59 percent of workers are in white-collar occupations (clerks, technicians, professionals, managers), compared with 16 percent in the poorest quintile. White-collar wage premia are also much larger in poor countries (150 percent) than in rich ones (51 percent), even after conditioning on education and experience. These patterns cannot be explained by labor force composition alone.

Second, we develop a general-equilibrium model of occupational sorting. Each worker type, defined by education and experience, is endowed with occupation-specific human-capital quality and faces occupation-specific wedges. Following Hsieh, Hurst, Jones, and Klenow (2019) and others, workers also draw idiosyncratic occupational skills, which makes self-selection analytically tractable. Occupations differ in their capital intensity, the elasticity of substitution between workers and capital, and country-embedded productivity, terms that are not embodied in workers but embedded in countries.[3] Firms adapt their production within occupation-specific productivity frontiers, extending Caselli and Coleman (2006). The equilibrium conditions allow us to disentangle human-capital quality from country-embedded productivity, while incorporating distortions that affect occupational choices.

Third, we calibrate the model to the United States and use the equilibrium conditions to infer, for each country, occupation-specific country-embedded productivity levels, the human-capital quality of each worker group, and the severity of occupational distortions. To anchor comparisons, we normalize the baseline skill level of workers with low education and little experience to be identical across all countries and occupations. For each country–occupation cell, our measure of human-capital quality for the remaining worker groups thus captures the incremental effects of higher education and experience on baseline skills, which determine both absolute and comparative advantage across occupations. Beyond the usual factors-versus-TFP decomposition, our quantitative results provide a multidimensional characterization of cross-country variation in worker skills and country productivity.

We document salient patterns across the development spectrum and along the skill

[2] Agricultural workers are excluded due to limited wage observations; throughout, "output" and "income" refer to non-agricultural GDP.

[3] See also Burstein and Monge-Naranjo (2009) and Alviarez, Cravino, and Ramondo (2023), who use equilibrium models and cross-country data to separate country-embedded productivity from worker- and firm-embedded skills.

complexity of occupations, shedding light on how human capital interacts with productivity in accounting for income differences across different segments of the development spectrum. First, workers in rich countries have substantially higher human-capital quality, especially among secondary-school and more experienced groups. Second, country-embedded productivity gaps between rich and poor countries are large and especially pronounced in white-collar occupations, implying that development is biased toward them. Third, endogenous technology choices in rich countries are directed toward more educated and experienced workers, who are relatively more abundant. Finally, occupational distortions are more prevalent in poor countries and discourage white-collar employment.

Quantitatively, we find that human capital accounts for about 52 percent of output-per-worker gaps relative to the US. For the poorest countries, adopting US human-capital composition and quality would more than double output. Composition and quality are strongly complementary: adopting only one yields substantially smaller gains. Gains from human capital are also mediated by technology adoption: holding technology fixed, increases in human capital generate little output growth in poor countries. Country-embedded productivity accounts for 32 percent of output gaps, equipment prices for 14 percent. Occupational distortions contribute little to aggregate output differences, though they matter for employment composition and wage premia.

This paper is related to a large literature on the role of human capital in accounting for cross-country income differences, particularly the recent strand that models skill groups as imperfect substitutes. A broad consensus holds that highly educated workers are especially productive in rich countries, as their rising supply is accompanied by only a modest decline in the skill premium (Caselli and Coleman, 2006).[4] Our contribution is to separate the human-capital quality embodied in workers from the occupation-specific country-embedded productivity of countries. Our results fall between the two extremes in the literature, e.g., (Jones, 2014, 2019) and (Caselli and Coleman, 2006; Caselli and Ciccone, 2019).

In this vein, our work aligns with a substantial empirical literature that documents the lower embodied quality of human capital in poorer countries. Standardized test scores reveal inferior schooling quality (Hanushek and Woessmann, 2008; Hanushek and

[4] A related phenomenon is the joint evolution of the supply of skills and the education premium over time (Katz and Murphy, 1992).

Woessman, 2012a,b). Immigrant wage comparisons show large pre- and post-migration gaps (Hendricks, 2002; Schoellman, 2012; Hendricks and Schoellman, 2018), with high-skill workers particularly disadvantaged (Rossi, 2022). Similar evidence arises from wage comparisons of college graduates, employees in multinational firms, and international trade flows (Hjort, Malmberg, and Schoellman, 2023; Malmberg, 2022). Experience-based human capital also appears weaker in poor countries, with lower life-cycle returns (Lagakos, Moll, Porzio, Qian, and Schoellman, 2018a,b). We contribute by measuring human-capital quality not only by schooling and experience, but also across occupations. At the aggregate level, our accounting results are compatible with those in (Hendricks, 2002; Schoellman, 2012; Hendricks and Schoellman, 2018; Gethin, 2025) which employ very different methods and data.

A related literature study examines how substitutability across skills influences the contribution of human capital to output. Building on Caselli and Coleman (2006), recent work endogenizes the elasticity of substitution through directed technological choice (Okoye, 2016; Hendricks and Schoellman, 2023; Bils, Kaymak, and Wu, 2024). We extend this approach by allowing endogenous technology within occupations, while separately identifying country-embedded productivity terms for each occupation rather than relying on a single aggregate TFP. Our quantitative results show that productivity is not so much biased toward more skilled workers *per se*, but systematically tilted toward white-collar activities, where these workers have a stronger comparative advantage. Moreover, with endogenous technology choice, richer countries direct productivity disproportionately toward higher skills.

Our paper closely relates to research on occupational sorting, distortions, and structural transformation. Models of sectoral and occupational change emphasize how skills and technology shape employment patterns over time (Duernecker and Herrendorf, 2022; Bárány and Siegel, 2018, 2021; Acemoglu and Autor, 2011; Aum, Lee, and Shin, 2018; Dvorkin and Monge-Naranjo, 2019), while more recent contributions study these forces across countries (Vizcaino, 2021; Peña and Siegel, 2024; Engbom, Malmberg, Porzio, Rossi, and Schoellman, 2024; Bandiera, Kotia, Lindenlaub, Moser, and Prat, 2024). Adopting the modeling strategy of Hsieh, Hurst, Jones, and Klenow (2019), we also uncover stronger occupational distortions in poorer countries, which likely reflect institutional frictions (Grobovšek, 2020; Akcigit, Alp, and Peters, 2021). Yet, in contrast

to those studies, we find that such distortions, though relevant for wages and sorting, contribute little to aggregate output. Our empirical measures of skills and wage premia also connect to the broader literature on Mincerian returns, where we document patterns consistent with, but more granular than, existing cross-country evidence (Caselli, Ponticelli, and Rossi, 2016; Psacharopoulos and Patrinos, 2018; Jedwab, Romer, Islam, and Samaniego, 2023).[5]

Finally, as in most papers on development accounting, we take the cross-sectional distributions of workers and their labor market skills in each country as exogenous. Thus, we abstract from education decisions and endogenous skill formation as studied by Erosa, Koreshkova, and Restuccia (2010); Córdoba and Ripoll (2013); Manuelli and Seshadri (2014) and other authors. We also abstract from labor force participation and home production decisions. We restrict attention to the non-agricultural sector and thus abstract from 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).

The remainder of the paper is organized as follows. Section 2 presents the data. Section 3 introduces the model. Section 4 discusses the parameterization of the model and analyzes the inferred differences in human-capital quality and country-embedded productivity across countries. Section 5 reports on the counterfactual accounting exercises. Section 6 concludes. An online supplemental appendix contains details on the data, the model and its calibration, and further explains and expands the results.

2 Skills and Occupations Across Countries

2.1 Data

The main database is the Harmonized World Labor Force Survey, a large micro dataset that harmonizes household and labor force surveys for many countries (Gottlieb, 2025). From this dataset, we only use surveys that: (i) have individual-level hourly wages and hours worked; (ii) are nationally representative; (iii) have information on the ISCO-08

[5] Flabbi and Gatti (2018) and Rossi (2020) review the various channels explored in the literature for the impact of human capital on growth.

occupational classification. We restrict our sample to civilian non-agriculture workers.[6] See Appendix A for details.

As we are interested in cross-country differences, we only consider the most recent year for each country.[7] The resulting sample includes 50 countries and spans the entire development spectrum, ranging from Ethiopia, Niger, and Senegal to Switzerland, United States, and Ireland.[8]

We classify the workers in each country into eight skill groups, based both on their formal education attainment and their (potential) experience. The education bins are labeled as follows: "primary" for those with 0 to 8 years of schooling, "lower secondary" with 9 to 11 years, "upper secondary" with 12 to 14; and "tertiary", with 15 years or more.[9] For potential experience, we group workers into two groups: "inexperienced" workers, those with ages between 16 to 40, and "experienced," those with 41 years or more. Likewise, we classify the workers' occupations into eight categories: "Elementary occupations," "Service workers," "Operators," "Craft and trade workers," "Clerical workers," "Technicians," "Professionals," and "Managers." In what follows, we refer to the first four occupations are "blue-collar" occupations and to the second four occupations are "white-collar."

For each country, we compute the employment shares and the average earnings of each group of workers in each occupation.[10] The resulting 8×8 matrices of employment

[6]Specifically, we discard all workers whose main employment is in occupation "Skilled agricultural workers" and/or the agricultural sector (ISIC 4 code: A), as well as those whose main occupation is "Armed forces."

[7]We stop at 2019 to discard the years of the Covid pandemic. In a sequel to this paper, we are extending our results to the evolution over time of for those countries for which the data are available.

[8]Ordered by non-agricultural output 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).

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

[10]We use survey weights and hours worked in the main job to compute average wages and employment shares. The employment shares include the hours of the self-employed under the assumption that wages

shares provide the information about the assignment of the different types of workers across the different occupations, while the 8×8 matrices of average wages provide the information about the wages of the workers according to their selection of occupations.[11]

2.2 Employment Shares and Wages

We now report how employment shares and average wages evolve across countries at different stages of development. To organize the information, we group countries into quintiles ordered by output per worker. Here, "q1" indicates the lowest quintile, "q2" the second lowest, and so on, up to"q5," the quintile of countries in the highest income group. Table 1 summarizes the data on employment shares and relative wages by occupation and skill group.

Table 1 shows that as countries develop, their employment in the less complex blue-collar occupations declines and their employment in the more complex white-collar occupations increases. The share of white-collar work is only 16% in the poorest quintile of countries, while it is 59% in the richest one. The upper right part Table 1 also shows that the wage differential between white-collar and blue-collar occupations is substantially larger in poorer countries. Indeed, white-collar workers earn 2.5 times the wages of blue-collar workers in the poorest quintile, while that ratio is only 1.51 in the richest quintile.

As expected, the lower-left panel of Table 1 reports that workers' educational attainment and age are higher in more developed countries. Naming all workers with strictly less than 12 years of formal education as "low-skilled workers," we see that they account for 79% in the poorest countries. Interestingly, almost exactly the converse holds in the richest quintile of countries, where the share of low-skilled workers is only 21%. Using these two groups of workers to define the wage skill premium, the lower right part of Table 1 shows that the skill premium is larger in poor than in rich countries. High-skilled

are a good proxy for their self-employed income.

[11]For some countries, splitting the workers' data into these 8×8 matrices leads to raw moments that are not precisely measured due to small samples. For example, very few low-educated workers are in managerial occupations. To deal with this problem, we use the micro data to estimate those moments using a multinomial logistic regression for occupational choice as well as wage regressions. Our resulting estimates are precise in the sense that the unconditional employment shares and average wages by occupation as well as the unconditional skill group shares coincide exactly with the raw moments of the data. The procedure is laid out in Appendix B.

Table 1: Employment shares and relative wages for occupations and skill groups by country income group

	Employment shares					Relative wages				
All occupations	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Elementary occ.	17	16	15	8	7	1.00	1.00	1.00	1.00	1.00
Service & sales	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 & trade	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 skill groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Primary & inexperienced	39	21	9	2	1	1.00	1.00	1.00	1.00	1.00
Primary & experienced	21	16	13	6	3	1.22	1.25	1.14	1.05	1.21
Lower secondary & inexperienced	14	16	16	7	5	1.35	1.17	1.15	1.05	1.06
Lower secondary & experienced	6	9	10	11	11	1.87	1.56	1.43	1.14	1.39
Upper secondary & inexperienced	10	14	18	20	17	1.85	1.45	1.49	1.17	1.25
Upper secondary & experienced	4	6	14	20	22	2.62	2.06	1.92	1.34	1.65
Tertiary & inexperienced	4	11	11	17	18	3.33	2.37	2.57	1.63	1.68
Tertiary & experienced	3	7	8	18	22	4.90	3.56	3.31	2.03	2.26
Main skill 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

Notes. The left part of the table reports average shares of employment hours across income quintiles of countries (by non-agricultural GDP per worker). Employment shares are expressed in percentages and sum up to 100 in the columns of each sub-table. The right part of the table reports average hourly wage premia across countries in each quintile. The wage premium in each occupation is expressed relative to elementary occupations, while the wage premium in each main occupation is expressed relative to the blue-collar occupation. The wage premium for each skill group is expressed relative to inexperienced (young) workers with primary education or less, while the wage premium in each main skill group is expressed relative to the white-collar occupation.

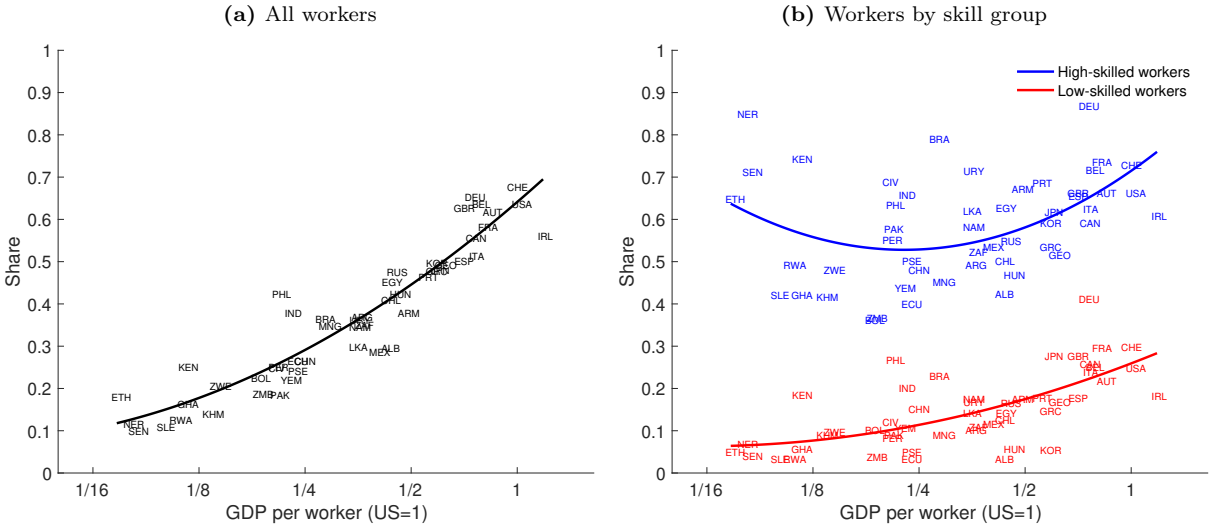
workers earn 127% more than low-skilled ones in the poorest quintile of countries, whereas in the richest quintile that differential is only 43%.

In sum, the cross-development patterns in employment and wage premia are similar for occupations and human-capital groups. In Appendix D we report additional patters, i.e. employment shares and earnings for each occupation conditional on human capital, and for human capital conditional on occupational employment.

To visualize these patterns for the fifty countries in our sample, Figure 1 plots in its left panel the strong positive relationship between the share of white-collar employment (vertical axis) with the country's output per worker (horizontal axis). The right panel of Figure 1 plots the white-collar employment separating low-skilled workers and high-skilled workers as defined above. Clearly, for high-skilled workers, there is a U-shaped relationship and not a monotonic gradient with the country's output per worker.[12] For

[12] Engbom, Malmberg, Porzio, Rossi, and Schoellman (2024) similarly document that conditioning on

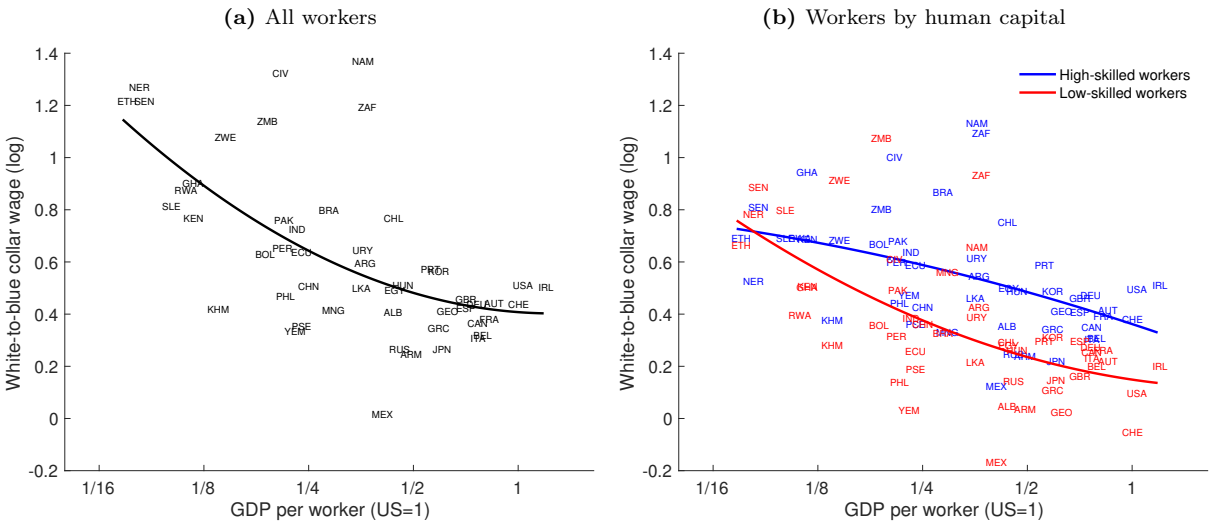
Figure 1: White-collar employment across countries



Notes: Panel (a) plots the aggregate employment share of white-collar workers for each country against non-agricultural GDP per worker, normalized to the US. Panel (b) plots the white-collar employment share for low-skilled and high-skilled workers, respectively. The lines of best fit are based on a regression with linear and quadratic terms.

low-skilled workers, instead, there is a clear positive gradient. This finding contradicts the plausible hypothesis that poorer countries, lacking a large reservoir of educated workers, disproportionately resort to filling white-collar jobs with low-educated workers. Instead, richer countries are the ones that assign those workers more intensively into white-collar occupations.

Figure 2: White-collar wage premium across countries



Notes: Panel (a) plots the log of the ratio between the average white-collar hourly wage and the average blue-collar hourly wage against non-agricultural GDP per worker, normalized to the US. Panel (b) plots the analogous log ratio for low-skilled and high-skilled workers, respectively. The lines of best fit are based on a regression with linear and quadratic terms.

human capital, the aggregate white-collar employment share is surprisingly flat across countries.

Similarly, Figure 2 plots in the left panel the white-collar wage premium (the ratio of the average wages between white- and blue-collar workers) against the countries' output 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 or due to high-skilled workers (who have a higher propensity to be employed in white-collar occupations) earning a high premium. To explore this, the right panel of Figure 2 suggests that both channels are at work. Partitioning workers by skill group, the occupational wage premium remains decreasing in output for each of the groups, albeit at a smaller rate. The upshot is that the high white-collar premium in poor countries is likely a consequence of additional factors beyond the scarce supply of high-skilled workers.

Next, we develop a structural general equilibrium framework to understand the emergence of these patterns from occupational and technological choices, and then infer the skill-content of human capital and country-embedded productivity across occupations.

3 The Model

We consider a model economy populated by heterogeneous workers endowed with multi-dimensional skills. Workers choose their occupations and competitive firms hire workers and capital into multiple occupations to produce a final good. Firms also adapt their production technologies for each type of occupation according to the skills of their workers. We first lay out the environment and then derive the key equilibrium conditions.

3.1 Environment

Workers. The population of workers is distributed across S skill groups indexed by $s = 1, \ldots, S$. The shares $L_s \geq 0$ sum to unity, $\sum_s L_s = 1$, and are exogenously given. All individual workers in group s are endowed with baseline skill $h_{s,j} \geq 0$ for each of the $j = 1, \ldots, J$ occupations. Following recent usage, we call these values $h_{s,j}$ the *skill quality* of workers s in occupations j. Throughout our analysis, we normalize their values for all occupations j relative to the lowest skill group, $s = 1$, i.e., $h_{1,j} = 1$. Therefore, for each country, the values $h_{s,j}$ indicate how much different levels of human capital augment the baseline skills of workers within each country.

In addition to skill quality $h_{s,j}$, each individual worker in group s draws a random

vector $z \in \mathbb{R}_+^J$ of idiosyncratic skills in each occupation. These random skills drive cross-sectional heterogeneity within each group s, accounting for cross-sectional dispersion of earnings of those workers in each occupation, as well as for non-degenerate probabilities in the assignment of workers to occupations. In particular, they account for the possibility that some low-educated workers might be exceptionally suited to perform white-collar jobs typically occupied by more educated individuals; conversely, they can account for the observation that sometimes highly educated individuals end up employed in blue-collar occupations. We assume that for all workers in skill group s, the vectors z are drawn from a correlated Fréchet distribution with c.d.f.

$$G_s\left(z_1, \ldots, z_J\right) = \exp\left(-\left[\sum_{j=1}^{J} z_j^{-\frac{\theta_s}{1-\rho}}\right]^{1-\rho}\right). \tag{1}$$

The shape parameter $\theta_s > 1$ is allowed to vary by skill group s. The correlation of the vector z is governed by ρ, the parameter of a Gumbel copula. It ranges from $\rho = 0$ (no correlation) to $\rho = 1$ (perfect positive correlation). These parameters ultimately govern the dispersion and correlation of the comparative advantage of s-workers across occupations.

In the competitive labor markets described below, workers know their vector of skills $[h_{s,1}z_1, \ldots, h_{s,J}z_J]$ and choose the occupations that maximize their utility. The equilibrium decisions are determined by skill prices (or wages per efficiency unit) $w_{s,j}$ as determined by the marginal product for firms described below. These occupational choices are also driven by non-pecuniary wedges, $D_{s,j}$, that proportionally reduce (if $D_{s,j} > 1$) or augment (if $D_{s,j} < 1$) the utility of a worker in each occupation. These wedges capture institutional constraints, discrimination, or simply taste-shifters that uniformly affect all workers in group s.[13] Occupational decisions are only affected by the relative value of these non-pecuniary costs. We thus set $D_{s,1} = 1$ for all s.

Production. A representative competitive firm produces output using labor and capital across all occupations $j = \{1, 2, \ldots, J\}$. Aggregate output, Y, is a CES composite of

[13]For example, licensing requirements or lack of networks can make professional jobs inaccessible to workers with low-educational attainment

occupational output, Y_j:

$$Y = \left(\sum_{j=1}^{J} Y_j^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where $\sigma > 0$ is the elasticity of substitution. Each occupational product Y_j combines capital, K_j, and a bundle of efficiency units of labor, Q_j, according to

$$Y_j = \left(\alpha_j K_j^{\frac{\gamma_j-1}{\gamma_j}} + (1-\alpha_j) Q_j^{\frac{\gamma_j-1}{\gamma_j}} \right)^{\frac{\gamma_j}{\gamma_j-1}}, \tag{3}$$

with occupation-specific elasticities of substitution $\gamma_j > 0$ and intensities $\alpha_j \in (0,1)$. The efficiency units of labor Q_j are given by

$$Q_j = \left(\sum_{s=1}^{S} (B_{s,j} H_{s,j})^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{4}$$

where $\varepsilon > 0$ is the elasticity of substitution. Thus, Q_j is a composite bundle of distinct technology-augmented human-capital services $H_{s,j}$ provided to occupation j by workers in skill group s.

As in Caselli and Coleman (2006), Acemoglu (2007), Hendricks and Schoellman (2023), and Bils, Kaymak, and Wu (2024), firms also choose the technology terms $B_{s,j}$ from the technological menu

$$\left(\sum_{s} B_{s,j}^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}} \leq A_j, \tag{5}$$

with the parameter restriction $\nu > 0$ and $\nu(2-\varepsilon) > 1$. In our model, (5) is specific to each occupation and hence allows technologies $B_{s,j}$ to be directed toward the relatively abundant skill group s within each occupation. We take the productivity level for each occupation, A_j, to be exogenously given.

3.2 Equilibrium

We now characterize the individual optimality conditions and market clearing conditions that define a competitive equilibrium in this economy. We denote by R the rental rate of capital and by $w_{s,j}$ the unit wage rate of skill type s in occupation j, all of which are

taken as given by workers and firms.[14]

Taking as given factor prices and technology menus, the representative firm maximizes profits by choosing the amount of physical and human capital as well as technology levels:

$$\max_{K_j, H_{s,j}, B_{s,j}} \left\{ Y - \sum_j \left(RK_j + \sum_s w_{s,j} H_{s,j} \right) \right\} \tag{6}$$

subject to the technological menu (5).

Workers take wages rates as given and choose their occupation to maximize their net utility:

$$\max_j \left\{ \frac{w_{s,j} h_{s,j} z_j}{D_{s,j}} \right\}_{j=1}^{J}. \tag{7}$$

The numerator represents the worker's labor income while the denominator denotes the occupational wedges. Apart from the wage rates $w_{s,j}$, workers' choices are governed by the baseline skill quality $h_{s,j}$ of group s and the realized random value of skills z_j for each worker in occupation j.

Given the idiosyncratic skills component, the optimal occupation choices of workers are characterized by non-degenerate probabilities. We denote by $\pi_{s,j}$ the fraction of workers in skill group s that choose occupation j. These probabilities also determine the average level of the idiosyncratic skills of workers of type s in occupation j. We denote these selected averages by $\overline{z}_{s,j}$.

The aggregate resource constraints and market clearing conditions are as follows. Given $\pi_{s,j}$, the mass of s-workers in occupation j is

$$L_{s,j} = \pi_{s,j} L_s, \tag{8}$$

while the aggregate supply of skills to that occupation is

$$H_{s,j} = h_{s,j} \overline{z}_{s,j} L_{s,j}. \tag{9}$$

We assume that the supply of physical capital is perfectly elastic at an exogenous gross rental rate R.

Definition. *Given an exogenous distribution of worker skill groups L_s, the price of capital*

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

R, sectoral productivity levels A_j, skill quality levels $h_{s,j}$, and distortions $D_{s,j}$, a competitive equilibrium consists of unit wage rates $w_{s,j}$, capital allocations K_j, human capital allocations $H_{s,j}$, technology choices $B_{s,j}$, occupational probabilities $\pi_{s,j}$, and average idiosyncratic efficiencies $\overline{z}_{s,j}$, such that:

1. *The representative firm chooses K_j, $H_{s,j}$, and $B_{s,j}$ to maximize profits subject to the technological menu constraint (5);*

2. *Individual workers choose their occupation to maximize utility;*

3. *The labor market clears, namely the occupational choices imply $\pi_{s,j}$ and $\overline{z}_{s,j}$ such that (8) and (9) hold.*

3.3 Characterization

Under the assumed functional forms, the equilibrium conditions are tractable. First, the extreme-value distribution of idiosyncratic skills implies that the probability of an individual of skill s choosing occupation j is

$$\pi_{s,j} = \frac{\left(w_{s,j}\frac{h_{s,j}}{D_{s,j}}\right)^{\frac{\theta_s}{1-\rho}}}{\sum_{i=1}^{J}\left(w_{s,i}\frac{h_{s,i}}{D_{s,i}}\right)^{\frac{\theta_s}{1-\rho}}}. \tag{10}$$

The selection of workers across occupations leads to an average of idiosyncratic skills equal to

$$\overline{z}_{s,j} = \Gamma_s \pi_{s,j}^{-\frac{1-\rho}{\theta_s}}, \tag{11}$$

where $\Gamma_s \equiv \Gamma\left(1-\theta_s^{-1}\right)$ and $\Gamma(\cdot)$ is the Gamma function. Selection clearly plays a role. As more workers of type s select into occupation j, their average productivity diminishes, which is reflected in the term $\pi_{s,j}^{-(1-\rho)/\theta_s}$. Note that the higher is the correlation parameter ρ, the smaller is this effect.

Since $L_{s,j} = \pi_{s,j}L_s$, the *total supply of human capital services* from group s to occupation j is

$$H_{s,j} = \Gamma_s h_{s,j}\pi_{s,j}^{1-\frac{1-\rho}{\theta_s}}L_s. \tag{12}$$

The firm's optimality conditions with respect to physical and human capital are stan-

dard:

$$\alpha_j \left(\frac{Y}{Y_j}\right)^{\frac{1}{\sigma}} \left(\frac{Y_j}{K_j}\right)^{\frac{1}{\gamma_j}} = R, \tag{13}$$

and

$$(1-\alpha_j) \left(\frac{Y}{Y_j}\right)^{\frac{1}{\sigma}} \left(\frac{Y_j}{Q_j}\right)^{\frac{1}{\gamma_j}} \left(\frac{Q_j}{H_{s,j}}\right)^{\frac{1}{\varepsilon}} B_{s,j} = w_{s,j}. \tag{14}$$

The optimality conditions with respect to technology terms $B_{s,j}$ imply the technological choice

$$B_{s,j} = A_j H_{s,j}^{\frac{\nu(\varepsilon-1)}{\nu-\varepsilon}} \left(\sum_{s'} H_{s',j}^{\frac{(\nu-1)(\varepsilon-1)}{\nu-\varepsilon}}\right)^{\frac{-\nu}{\nu-1}}. \tag{15}$$

Substituting the technology choices from (15) into (4) leads to a simple expression for the bundles of technology-augmented skills Q_j:

$$Q_j = A_j H_j, \tag{16}$$

where

$$H_j = \left(\sum_{s=1}^{S} H_{s,j}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \tag{17}$$

are human capital CES aggregators with elasticity of substitution $\eta = \frac{\nu-\varepsilon}{\nu(2-\varepsilon)-1} > \varepsilon$ that combine human-capital services directed to j from all groups s. Importantly, the equilibrium H_j is not directly by the productivity terms A_j or the wedges $D_{s,j}$. These factors only impact the equilibrium H_j through the country's availability of workers' skills and occupational choices.

3.4 Inferring Workers' Skills & Countries' Productivity

The equilibrium conditions of our framework explicitly capture the selection of workers' skills across occupations and firms' optimal allocation of country-embedded productivity for each occupation across different types of workers employed. Under the parameterization discussed in the next section, we use these conditions to separate the skill quality of worker skill groups s across occupations j, $h_{s,j}$, from the country-embedded productivity levels, A_j, and their allocation across worker types, $B_{s,j}$. We also infer the (normalized) non-pecuniary wedges $D_{s,j}$ that distort the allocation of skills within each country. These values, along with the observed shares L_s, provide the basis for our counterfactual ac-

counting exercises.

Skill Quality. Selection constitutes a key driver of observed relative wage differences. Using the model's equilibrium selection conditions and the normalization $h_{1,j} = 1$ for all j, the baseline skill level of worker type s in occupation j is given by

$$h_{s,j} = \left(\frac{\overline{w}_{s,j}}{\overline{w}_{1,j}}\right)\left(\frac{\Gamma_1}{\Gamma_s}\right)\left(\frac{\pi_{s,j}^{\frac{\theta_s+(1-\rho)(\eta-1)}{\theta_s(\eta-1)}}}{\pi_{1,j}^{\frac{\theta_1+(1-\rho)(\eta-1)}{\theta_1(\eta-1)}}}\right)\left(\frac{\overline{w}_{s,j}L_s}{\overline{w}_{1,j}L_1}\right)^{\frac{1}{\eta-1}}, \tag{18}$$

where $\overline{w}_{s,j} \equiv w_{s,j}h_{s,j}\overline{z}_{s,j}$ denotes the observed average wage of workers s in occupation j.

Variations in the ratios $\frac{\overline{w}_{s,j}}{\overline{w}_{1,j}}$ drive the predictions for the magnitudes of cross-country differences in $h_{s,j}$. Under the model's functional forms and calibration, we control for selection and infer by how much education and experience enhance worker skills across occupations in each country.

Two special cases illuminate the model's mechanics. First, when $\theta_s \to \infty$, selection plays no role and the model boils down to

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

echoing the interpretation in Jones (2014) and Jones (2019), but applied to each occupation.

Second, if workers of different skill groups s are perfect substitutes in all occupations ($\eta \to \infty$), the model converges to

$$h_{s,j} = \left(\frac{\overline{w}_{s,j}}{\overline{w}_{1,j}}\right)\frac{\Gamma_1}{\Gamma_s}\left(\frac{\pi_{s,j}^{\frac{1}{\theta_s}}}{\pi_{1,j}^{\frac{1}{\theta_1}}}\right)^{1-\rho}.$$

Country-Embedded Productivity. The values of (17) and its components (9) do not depend *directly* on the country-embedded productivity levels A_j. For a multi-occupation model, this result echoes the insight of Hendricks and Schoellman (2023) that the long-run elasticity of substitution η subsumes any endogenous technological choices resulting from changes in the supply of workers' skills available to firms. Their result proves par-

ticularly relevant to the debate between Caselli and Ciccone (2019) and Jones (2019), showing that human-capital aggregators with either skill-neutral or skill-biased technology both constitute plausible representations of the same data, depending on the elasticity of substitution between worker skill groups.

In our model, countries' technologies are not skill-neutral. Country-embedded productivity levels A_j vary across occupations, but we allow firms to choose the levels $B_{s,j}$ according to the workforce composition in terms of $H_{s,j}$. Given workers' optimal occupation choices, firms' technology choices, and the normalization $h_{1,j} = 1$, we can back out A_j from the model as

$$A_j = \overline{w}_{s,j} \frac{1}{h_{s,j}} \frac{\pi_{s,j}^{\frac{1-\rho}{\theta_s}}}{\Gamma_s} x_j^{\frac{1}{\sigma-1}} x_{s,j}^{\frac{1}{\eta-1}} \left(\frac{1}{1-\alpha_j} \right)^{\frac{\gamma_j}{\gamma_j - 1}} \left(\lambda_j^{\frac{\sigma-\gamma_j}{\gamma_j-1}} \lambda \right)^{\frac{1}{\sigma-1}}, \tag{19}$$

where

$$x_j \equiv \frac{\sum_s \overline{w}_{s,j} L_{s,j}}{\sum_j \sum_s \overline{w}_{s,j} L_{s,j}}$$

is the relative labor income share of occupation j,

$$x_{s,j} \equiv \frac{\overline{w}_{s,j} L_{s,j}}{\sum_s \overline{w}_{s,j} L_{s,j}}$$

is the relative labor income share of human-capital group s in occupation j,

$$\lambda_j \equiv \frac{\sum_s \overline{w}_{s,j} L_{s,j}}{\sum_s \overline{w}_{s,j} L_{s,j} + RK_j}$$

is the labor share within occupation j, and

$$\lambda \equiv \frac{\sum_j \sum_s \overline{w}_{s,j} L_{s,j}}{Y}$$

is the aggregate labor share. Using our data on average wages and employment shares, normalizing $h_{1,j} = 1$, and solving for the equilibrium value of λ_j, we obtain A_j.[15]

Several implications emerge from equation (19). First, technological efficiency in

[15] In the absence of capital ($\alpha_j = 0$), A_j could be pinned down directly by the data as

$$A_j \propto \overline{w}_{1,j} \pi_{1,j}^{\frac{1-\rho}{\theta_1}} x_j^{\frac{1}{\sigma-1}} x_{1,j}^{\frac{1}{\eta-1}}.$$

occupation j increases with the *average wage* of the bottom group ($s = 1$) in that occupation—a direct implication of the normalization $h_{1,j} = 1$. Second, it increases with the selection of the bottom skill group toward that occupation: for a given average wage, a higher fraction of workers in that occupation implies lower average idiosyncratic productivity and therefore a higher A_j. Third, for the plausible $\sigma > 1$ calibrated below, A_j increases with the income share of that occupation, x_j. The observation that more complex occupations comprise a large fraction of total labor earnings in rich countries indicates that country-embedded productivity in those countries is higher in more complex, white-collar occupations. At the occupation level, this finding aligns with those in Caselli and Ciccone (2013) and Caselli and Ciccone (2019). Finally, for the plausible $\eta > 1$ calibrated below, A_j increases with the within-occupation income share of the lowest human-capital group, $x_{1,j}$. This pattern influences the implied cross-country productivity gaps.

Occupational Wedges. Under the normalization $D_{s,1} = 1$ for all s, the implied non-pecuniary wedges for workers type s across all other occupations $j = 2, \ldots, J$ are:

$$D_{s,j} = \frac{\overline{w}_{s,j}}{\overline{w}_{s,1}}. \tag{20}$$

This specification follows from the Fréchet-distributed skills in the model, which Burstein, Morales, and Vogel (2019) find to approximate well the cross-sectional distribution of earnings.

4 Quantification of the Model

4.1 Calibration

Following Section 2, we classify occupations into $J = 8$ categories, retaining the ordering introduced there. The first four correspond to blue-collar, or low-complexity, occupations, while the remaining four correspond to white-collar, or high-complexity, occupations. This classification enables us to externally calibrate the production functions using recent parameter estimates for one-digit SOC occupations in the United States. Similarly, we adopt $S = 8$ human-capital groups, defined by formal schooling and labor

market experience, as in Section 2. For each group, we internally calibrate the curvature of the idiosyncratic skill distribution so as to match the earnings dispersion observed in the U.S. economy.

Table 2 reports the parameter values, indicating the sources for the externally calibrated parameters and the targets for the internally calibrated ones.

Table 2: Calibrated parameters

Set parameters	Value	Source
EoS between occupations, σ	1.81	Burstein, Morales & Vogel (2019)
EoS elementary occ., γ_1	1.32	Caunedo, Jaume & Keller (2023)
EoS service & sales, γ_2	1.38	Caunedo, Jaume & Keller (2023)
EoS machine & plant operators, γ_3	1.41	Caunedo, Jaume & Keller (2023)
EoS craft & related trade, γ_4	2.06	Caunedo, Jaume & Keller (2023)
EoS clerks, γ_5	2.18	Caunedo, Jaume & Keller (2023)
EoS technicians, γ_6	0.65	Caunedo, Jaume & Keller (2023)
EoS professionals, γ_7	0.86	Caunedo, Jaume & Keller (2023)
EoS managers, γ_8	0.93	Caunedo, Jaume & Keller (2023)
Calibrated parameters	**Value**	**Target**
EoS between human-capital groups, η	6.97	Long-run EoS between low & high skilled
Gumbel dependence param, ρ	0.35	Spearman rank correlation
Fréchet param. primary & inexp., θ_1	2.90	US var. of log wages, primary & inexp.
Fréchet param. primary & exp., θ_2	2.77	US var. of log wages, primary & exp.
Fréchet param. lower sec. & inexp., θ_3	2.67	US var. of log wages, lower sec. & inexp.
Fréchet param. lower sec. & exp., θ_4	2.47	US var. of log wages, lower sec. & exp.
Fréchet param. upper sec. & inexp., θ_5	2.68	US var. of log wages, upper sec. & inexp.
Fréchet param. upper sec. & exp., θ_6	2.58	US var. of log wages, upper sec. & exp.
Fréchet param. tertiary & inexp., θ_7	2.42	US var. of log wages, tertiary & inexp.
Fréchet param. tertiary & exp., θ_8	2.33	US var. of log wages, tertiary & exp.
Capital inten., elementary occ., α_1	0.25	US equipment share elementary occ.
Capital inten., service & sales, α_2	0.36	US equipment share service & sales
Capital inten., machine & plant operators, α_3	0.26	US equipment share machine & plant op.
Capital inten., craft & related trade, α_4	0.48	US equipment share craft & related trade
Capital inten., clerks, α_5	0.47	US equipment share clerks
Capital inten., technicians, α_6	0.04	US equipment share technicians
Capital inten., professionals, α_7	0.11	US equipment share professionals
Capital inten., managers, α_8	0.16	US equipment share managers

Notes. The upper part of the table reports parameter values as taken from the literature. The lower part of the table reports jointly calibrated parameter values and their targets. For parameter η, the target value is the (endogenous) long-run elasticity of substitution between low-skilled and high-skilled workers of 4.53, as described in the text. For parameter ρ, the target value is the Spearman rank correlation between the logarithm of idiosyncratic skills of 0.35, as described in the text. For θ_s, we target the variance of log wages of the different skill groups in the US, which are reported in Table 3. For the capital intensity parameters α_j, in each occupation we set them such that the occupation's equipment income share in the US equals the aggregate US equipment income share of 0.193, as described in the text.

The upper panel of Table 2 reports the parameter values of the production function, all externally calibrated. The elasticity of substitution (EoS) across occupational

Table 3: Variance of log wages, US

Skill group	Model	Data
Primary school & inexperienced	0.207	0.207
Primary school & experienced	0.226	0.226
Lower sec. school & inexperienced	0.245	0.245
Lower sec. school & experienced	0.289	0.289
Upper sec. school & inexperienced	0.252	0.252
Upper sec. school & experienced	0.287	0.287
Tertiary school & inexperienced	0.322	0.322
Tertiary school & experienced	0.356	0.356

Occupation	Model	Data
Elementary occupations	0.253	0.257
Service & 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

Notes. The upper part of the table reports the model and data values of the variance of log wages by skill group in the US, as targeted in the calibration. The lower part of the table reports analogous moments for occupations, which are not targeted.

tasks, σ, is set to 1.81 following Burstein, Morales, and Vogel (2019). The elasticity between equipment capital and efficiency units of labor is taken from Caunedo, Jaume, and Keller (2023), focusing on equipment rather than structures given its heterogeneous complementarity with labor across occupations. The elasticities of substitution exceed one in all blue-collar occupations, indicating substitutability between workers and equipment, while in white-collar occupations they are below one, with the exception of clerks, implying complementarity.[16] Capital-equipment intensity parameters α_j are set so that equipment shares equal the U.S. aggregate value of 0.193. Appendix C.3 provides additional details.

The lower panel of Table 2 reports the distributional parameters of idiosyncratic skills by worker group s. The Fréchet shape parameters θ_s are chosen to match the within-group variance of log wages as measured in the U.S. in 2019. Within-group wage dispersion reflects both idiosyncratic productivity and occupational sorting. Higher-skilled workers

[16]The estimates in Caunedo, Jaume, and Keller (2023) are based on SOC occupations, while here we employ ISCO. Most categories map one-to-one, but in some cases we adopt the closest crosswalk: "clerical support workers" correspond to "administrative service workers"; "elementary occupations" to "low-skilled service workers"; and "craft-related trades workers" to "precision occupations."

exhibit lower θ_s, consistent with greater wage variation. The dependence parameter ρ is set to 0.35, targeting a Spearman rank correlation of 0.5 across draws $\log z$, balancing the assumption of independence with evidence of cross-occupational skill correlation (Alvarez-Cuadrado, Amodio, and Poschke, 2021).

The within-occupation elasticity of substitution across human-capital groups, η, is calibrated to 6.97. The target is the elasticity between low- and high-skilled workers, estimated at 4.53 by Hendricks and Schoellman (2023) across countries.[17] This calibration is also consistent with Bils, Kaymak, and Wu (2024), who establish a lower bound of 4 using as identification assumption that technology is non-regressing.

Table 3 evaluates the calibration. The upper panel shows that the targeted variances of log earnings by worker group are matched exactly. The lower panel reports non-targeted moments: the variance of log wages across occupations. The model reproduces these closely, capturing in particular the greater wage dispersion within high- versus low-complexity occupations.

4.2 Workers' Skills and Countries' Productivities

To build a comprehensive picture of how richer and poorer countries differ in both fundamentals and misallocation, we now provide a quantitative characterization of cross-country differences in workers' skills, country-embedded productivity levels, technology choices, and distortions. Specifically, we infer human-capital quality $h^c_{s,j}$, country-embedded productivity A^c_j and their endogenous allocations, $B^c_{s,j}$, distortions $D^c_{s,j}$, and the relative price of capital R^c for each of the $c = 1, \ldots, 50$ countries in the sample. These objects are obtained from the inverted equilibrium system of Section 3.3, applied to country data on the distribution of workers across skill groups and occupations, $L^c_{s,j} = \pi^c_{s,j} L^c_s$, and average wages $\overline{w}^c_{s,j}$ described in Section 2.[18] To identify the capital price R^c, we target real equipment stocks K^c constructed from the auxiliary capital data in the Penn World Table 10.01 (Feenstra, Inklaar, and Timmer, 2015), following Appendix C.2.

Because the inferred objects $h^c_{s,j}, A^c_j, B^c_{s,j}, D^c_{s,j}$ are high-dimensional, we focus on their

[17] We compute the elasticity for each country and target the cross-country average. Most values cluster around the mean, ranging from 2.80 (Rwanda) to 6.29 (Canada). The U.S., a country with relatively few low-skilled workers, exhibits a value of 6.20.

[18] Wages are observed in nominal units. We infer relative values, while levels are pinned down by country output per worker, measured as described in Section 2.

systematic variation with development, namely their relationship with output per worker across countries. Detailed figures are deferred to Appendix E. Our analysis proceeds in four steps. We first examine cross-country patterns in human-capital quality h, establishing a foundation for understanding skill differences. We then turn to country-embedded productivity A, which captures how efficiently occupations transform skills into output. Third, we study endogenous technology B, which determines how productivity is allocated across worker types. Finally, we consider distortions D, and how they vary across countries, occupations and workers' groups.

4.2.1 Skill quality, h

We begin with the quality of human capital, $h_{s,j}$. Education and experience typically increase human capital within each occupation, and we investigate how these gains vary systematically with country's development level, measured by its income per worker.

For each human-capital group s and occupation j, we estimate

$$\log h^c_{s,j} = \alpha + \beta^h_{s,j} \log Y^c + \varepsilon^c_{s,j},$$

where Y^c denotes country output per worker.

The estimated elasticities $\widehat{\beta}^h_{s,j}$, reported in Table 4, are almost uniformly positive.[19] Hence, the baseline quality of human capital is higher in richer countries. The gradient is particularly pronounced in service and sales, craft and trade, and professional occupations. Within occupations, the income gradient is steeper for more experienced workers than for less experienced ones, consistent with Lagakos, Moll, Porzio, Qian, and Schoellman (2018b), who document that experience-related wage gains are larger in richer countries. Across education groups, the quality advantage of richer countries is most evident among secondary-educated workers. By contrast, some tertiary-educated workers—particularly machine operators, clerks, and managers—display lower relative quality in richer economies.

To better understand these patterns, we decompose the cross-country variation in $h^c_{s,j}$

[19] By construction, the first row ($\widehat{\beta}^h_{1,j}$) equals zero since our baseline is $h_{1,j} = 1$.

Table 4: Elasticity of human-capital quality, h, with respect to GDP per worker

	Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
Primary & inexp.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Primary & exp.	0.17	0.07	0.05	0.01	-0.09	0.02	0.03	0.07
Low. sec. & inexp.	0.04	0.11	0.07	0.20	0.18	0.11	0.08	0.08
Low. sec. & exp.	0.24	0.19	0.15	0.25	0.12	0.11	0.10	0.19
Up. sec. & inexp.	0.06	0.21	0.08	0.35	0.15	0.19	0.25	0.08
Up. sec. & exp.	0.23	0.29	0.17	0.41	0.09	0.20	0.25	0.18
Tertiary & inexp.	-0.04	0.11	-0.09	0.30	-0.18	0.05	0.33	-0.16
Tertiary & exp.	0.09	0.15	-0.02	0.35	-0.30	0.02	0.31	-0.12

Notes. Each number represents, separately for each skill group and occupation, the estimated coefficient $\hat{\beta}^{h}_{s,j}$ from the cross-country linear regression of the inferred skill quality $\log h_{s,j}$ on the log of non-agricultural GDP per worker.

using equation (18):

$$\begin{aligned}\log h^c_{s,j} = &\underbrace{\log \overline{w}^c_{s,j} - \log \overline{w}^c_{1,j}}_{\substack{\text{Observed}\\ \text{wages}}} + \underbrace{\log \Gamma_1 - \log \Gamma_s + \tfrac{1-\rho}{\theta_s}\left(\log \pi^c_{s,j} - \log \pi^c_{1,j}\right)}_{\substack{\text{Observed}\\ \text{selection effect}}} \\ &+ \underbrace{\tfrac{1}{\eta-1}\left[\log\left(\overline{w}^c_{s,j} L^c_{s,j}\right) - \log\left(\overline{w}^c_{1,j} L^c_{1,j}\right)\right]}_{\substack{\text{Observed}\\ \text{endowment effect}}}.\end{aligned} \tag{21}$$

We separate each component into human-capital and occupation components by estimating, for each country c, the fixed-effects regression

$$\log X^c_{s,j} = \alpha^c + \mathrm{FE}^c_s + \mathrm{FE}^c_j + \varepsilon^c_{s,j}, \tag{22}$$

The dependent variable X is either $h_{s,j}$ or one of the three components from equation (21). In a second stage, we regress the skill-group fixed effects FE^c_s on $\log Y^c$. Results are reported in Table 5.

The first column shows that skill quality is generally higher in richer countries, particularly for secondary-educated and experienced workers. The next columns reveal the role of each component. The second column shows lower elasticities for high-skilled workers: conditional on occupations, their relative wages are higher in poorer countries. This is reinforced by the selection effect in column three: in richer countries, workers sort more strongly across occupations, raising the average idiosyncratic skill draw and lowering the baseline h. Finally, column four shows that relative worker endowments operate in the opposite direction: richer countries have more skilled workers, lowering their marginal

Table 5: Elasticity of human-capital fixed effects, FE_s, with respect to GDP per worker

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

Notes. Each number represents, separately for each skill group, the estimated coefficient $\hat{\beta}_s^{FE}$ from the cross-country linear regression of the estimated skill group fixed effect FE_s from (22) on the log of non-agricultural GDP per worker. The estimated fixed effect varies by column and depends on the concept X, which is either skill quality h, the average wage, the selection effect, or the endowment effect, as described in the text.

product, which requires a higher inferred h to reconcile the model with observed wages and allocations in the countries in our sample.

4.2.2 Country-Embedded Productivity, A

We now turn to the cross-country behavior of the occupation-specific productivity terms A_j. As before, we run the regression

$$\log A_j^c = \alpha + \beta_j^A \log Y^c + \varepsilon_j^c,$$

where Y^c denotes output per worker.

The estimated elasticities $\widehat{\beta}_j^A$, reported in Table 6, indicate that richer countries exhibit higher productivity in nearly all occupations, with the exception of *service and sales occupations*. The magnitude of the elasticities rises with occupational complexity. Thus, richer countries not only have higher productivity levels, but their advantage is disproportionately concentrated in more complex, white-collar occupations.

Table 6: 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

Notes. Each number represents, separately for each occupation, the estimated coefficient $\hat{\beta}_j^A$ from the cross-country linear regression of the inferred productivity $\log A_j$ on the log of non-agricultural GDP per worker.

To interpret these results, we decompose A_j^c as in equation (19), yielding in log form:

$$\log A_j^c = \underbrace{\xi_j}_{\text{Constant}} + \underbrace{\log \overline{w}_{1j}^c}_{\substack{\text{Observed} \\ \text{wages}}} + \underbrace{\tfrac{1-\rho}{\theta_s} \log \pi_{1j}^c}_{\substack{\text{Observed} \\ \text{selection effect}}} + \underbrace{\tfrac{1}{\sigma-1} \log x_j^c + \tfrac{1}{\eta-1} \log x_{1j}^c}_{\substack{\text{G.E. demand} \\ \text{effect}}} + \underbrace{\tfrac{1}{\sigma-1} \left(\tfrac{\sigma-\gamma_j}{\gamma_j-1} \log \lambda_j^c + \log \lambda^c \right)}_{\substack{\text{G.E. capital} \\ \text{effect}}}. \tag{23}$$

Table 7 reports the elasticity of each component with respect to output per worker. The first row reproduces Table 6, while subsequent rows present the underlying drivers. The elasticity of average wages for the lowest skill group is somewhat higher in blue-collar than white-collar occupations. The selection-effect elasticity, by contrast, shows no systematic pattern.

The key result is that the increasing elasticity of A_j^c with occupational complexity is primarily driven by general-equilibrium forces. In particular, the elasticity of the GE occupational-share component rises steeply with complexity. Since occupations are substitutes ($\sigma > 1$), richer countries specialize more in white-collar work, requiring especially high productivity in those occupations. A similar mechanism is visible in the GE labor-income-share component: elasticities are highest for technicians, professionals, and managers. In these occupations, labor and capital are gross complements. Despite relatively cheap capital, labor shares are lower in richer countries, implying that productivity A_j^c must be particularly high.

Table 7: 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

Notes. Each number represents, separately for each occupation, the estimated coefficient $\hat{\beta}_j^X$ from the cross-country linear regression of each term X in (23) on the log of non-agricultural GDP per worker. The terms X are the inferred productivity A itself, the average wage, the selection effect, and each of the two general equilibrium effects, as described in the text.

In sum, while human-capital quality is higher in richer countries, their productivity advantage is further reinforced by systematically higher A_j, particularly in complex occupations. To understand how this interacts with technology choices, we next examine

the endogenous allocation of productivity across worker types, $B_{s,j}$.

4.2.3 Endogenous Technology, B

With A_j and $h_{s,j}$ in hand, we reconstruct the supply of human capital $H_{s,j}$ and, in turn, the endogenous technology choices $B_{s,j}$ from equation (15):

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

We set the short-run elasticity of substitution between low- and high-skilled workers to $\varepsilon = 1.49$, which implies a technological-menu elasticity $\nu = 2.15$.[20]

We then estimate

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

The elasticities $\widehat{\beta}_{s,j}^B$ are reported in Table 8. Two patterns emerge clearly. First, richer countries allocate more of their productivity A_j toward more educated and experienced workers. Second, across all occupations, lower-education and less-experienced workers operate relatively less productive technologies in richer economies.

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

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

Notes. Each number represents, separately for each skill group and occupation, the estimated coefficient $\hat{\beta}_{s,j}^B$ from the cross-country linear regression of the inferred endogenous productivity $\log B_{s,j}$ on the log of non-agricultural GDP per worker.

In short, country-embedded productivity A_j and endogenous technology $B_{s,j}$ work in tandem: the former rises steeply with occupational complexity, while the latter channels

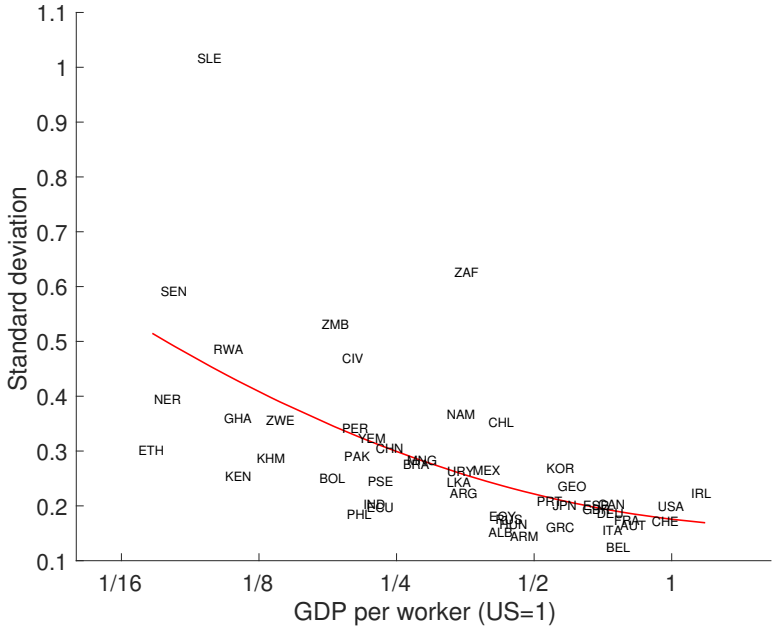
[20] At $\varepsilon = 1.49$, the quantitative elasticity of substitution for the US equals 1.5, consistent with Ciccone and Peri (2005). Recall that the long-run elasticity of substitution is $\eta = \frac{\nu-\varepsilon}{\nu(2-\varepsilon)-1}$, calibrated to 6.97, which allows us to infer ν.

productivity disproportionately toward more educated and experienced workers. Together, they amplify cross-country differences in effective skills.

4.2.4 Distortions, D

We now consider a final piece of the picture: the patter of occupational distortions, defined by $D^c_{s,j} = \frac{\overline{w}^c_{s,j}}{\overline{w}^c_{s,1}}$. Figure 3 plots the standard deviation of $\log D^c_{s,j}$ against output per worker. The relationship is clearly negative: within worker skill groups, occupational wedges are more dispersed in poorer countries, implying greater misallocation of human capital.

Figure 3: Dispersion of distortions



Notes: The y-axis plots the standard deviation of $\log D^c_{s,j}$. It is computed using as weights the labor income share $\frac{\overline{w}^c_{s,j} L^c_{s,j}}{\lambda^c Y^c}$ of each country's pair (s, j). The x-axis is non-agricultural GDP per worker, normalized to the US. The line of best fit is based on a regression with linear and quadratic terms.

Table 9 reports the elasticity of distortions with respect to output per worker. By construction, coefficients in the first row are zero due to the normalization $D^c_{s,1} = 1$. Relative to this baseline, coefficients are generally more negative for complex occupations, indicating that wedges discouraging entry into white-collar work decline with development. Since $D^c_{s,j} = \frac{\overline{w}^c_{s,j}}{\overline{w}^c_{s,1}}$, this implies that the white-collar wage premium, conditional on human capital, is higher in poorer countries—a pattern most 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 & inexp.	0.00	0.05	-0.04	-0.07	-0.19	-0.24	-0.24	-0.18
Primary & exp.	0.00	0.09	-0.09	-0.09	-0.35	-0.23	-0.25	-0.13
Low. sec. & inexp.	0.00	0.03	0.00	-0.02	-0.00	-0.15	-0.05	-0.06
Low. sec. & exp.	0.00	0.06	-0.03	-0.02	-0.10	-0.14	-0.05	-0.01
Up. sec. & inexp.	0.00	0.03	-0.00	0.05	-0.01	-0.11	-0.02	-0.05
Up. sec. & exp.	0.00	0.05	-0.03	0.04	-0.12	-0.11	-0.02	0.00
Tertiary & inexp.	0.00	-0.02	-0.03	0.05	-0.11	-0.09	-0.03	-0.10
Tertiary & exp.	0.00	-0.00	-0.06	0.04	-0.22	-0.09	-0.05	-0.07

Notes. Each number represents, separately for each skill group and occupation, the estimated coefficient $\hat{\beta}^{D}_{s,j}$ from the cross-country linear regression of the inferred endogenous productivity $\log D_{s,j}$ on the log of non-agricultural GDP per worker.

Overall, distortions are larger and more dispersed in poorer countries, particularly within white-collar occupations. This pattern reinforces the previous findings: while richer countries benefit from higher skill quality, stronger productivity, and more efficient technology allocation, poorer countries face the double burden of lower fundamentals and greater misallocation. In the next section, we formally explore how much these factors can account for the observed differences in output per worker.

5 Accounting for Cross-Country Differences

We now quantify the role of country-specific exogenous variables—human capital H, the relative price of equipment R, productivity A, and occupational distortions D—using the United States as benchmark.[21] Two counterfactuals are considered. In the first, each country is endowed with one US value at a time and the resulting equilibrium is compared to the country's baseline. In the second, the US baseline is compared to its counterfactual with another country's value. Identical changes can have different effects across countries because of complementarities among human capital, country-embedded productivity, distortions and the cost of physical capital.

We focus on three outcomes: output per worker, the white-collar employment share, and the white-to-blue-collar wage ratio. To illustrate our method, let $g_c = \log Y_c - \log Y_{US}$ denote the log output gap between country c and the US. In the first counterfactual, we

[21] Unless stated otherwise, H combines the composition of skills L and their quality h. This differs from the aggregator H in (17), which also depends on the endogenous π_{sj} through (12).

decompose this gap as

$$g_c = g_c(H) + g_c(R) + g_c(D) + g_c(A) + g_c(COV), \tag{24}$$

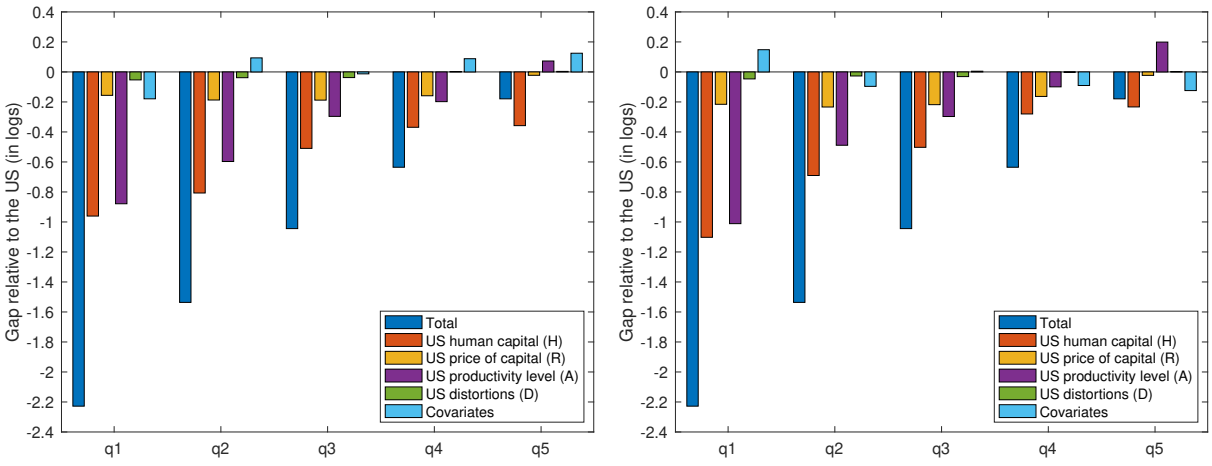
where, for instance, $g_c(H) = \log Y_c - \log Y_c(H_{US})$ is the log output gap between country c and the same country endowed with US human capital. The terms $g_c(R)$, $g_c(A)$, and $g_c(D)$ are defined analogously, and $g_c(COV)$ is the residual ensuring that (24) holds. In the second counterfactual, the decomposition is

$$g_c = \widetilde{g}_c(H) + \widetilde{g}_c(R) + \widetilde{g}_c(A) + \widetilde{g}_c(D) + \widetilde{g}_c(COV), \tag{25}$$

where, for example, $\widetilde{g}_c(H) = \log Y_{US}(H_c) - \log Y_{US}$ measures the effect of endowing the US with the human capital of country c.

5.1 Output per Worker

Figure 4: Output-per-worker gap relative to the US (logs)



(a) Counterfactual versus country baseline

(b) US baseline versus counterfactual

Notes: The bar "total" reports the arithmetic average logarithmic difference (i.e., gap) in output per worker between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining bars plot counterfactuals. In the left panel, the gaps are between country c and its counterfactual with one US endowment at a time. In the right panel, the gaps are between a counterfactual US with one country c endowment at a time and the US itself. The bar "covariates" captures all remaining differences between the empirical gap and the sum of counterfactual gaps, as described in (24) and (25).

Figure 4 reports the decomposition of output per worker, grouping countries into the same income quintiles used throughout the paper. In both counterfactual exercises, human capital explains the largest share of the gap. For the poorest quintile, productivity and human capital contribute in roughly equal measure, while in richer countries human

capital dominates. The relative price of equipment, R, and distortions, D, play a secondary role. The covariate term is typically positive in decomposition (24) and negative in (25).

Table 10: Contribution to output-per-worker 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	-2.23	-1.54	-1.04	-0.64	-0.18	-1.12	100	100	100	100	100	100
Human capital, H	-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
Productivity, A	-0.95	-0.54	-0.30	-0.15	0.14	-0.36	42	35	28	23	-76	32
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

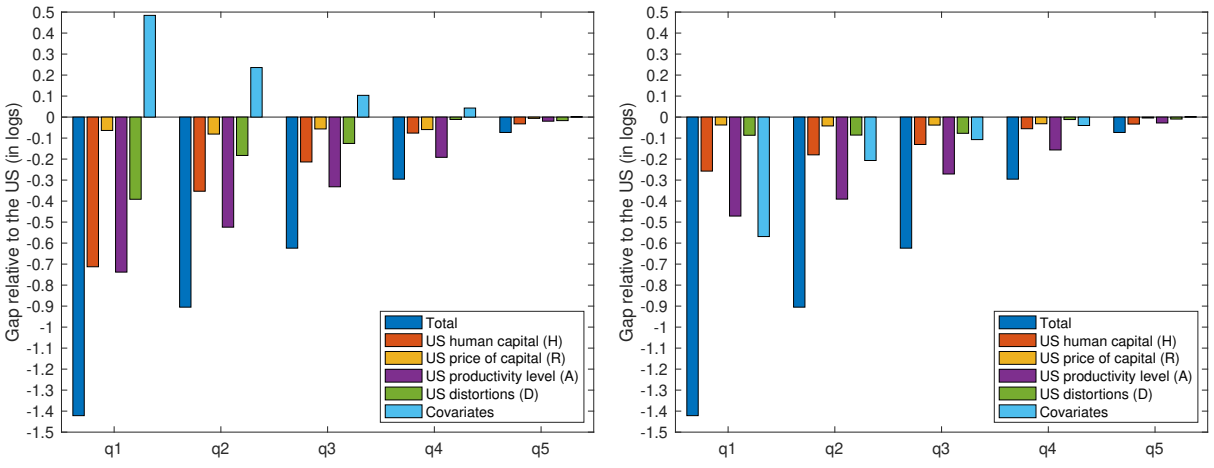
Notes. The line "total gap" in the left part of the table reports the arithmetic average logarithmic difference in output per worker between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining lines report counterfactuals. They represent the average between the two counterfactuals in the left and right panels of Figure 4. The right part of the table reports the contribution of each counterfactual as a percent share of the total gap, for each quintile separately as well as for all countries together. The counterfactuals (including the covariance term) sum to 100.

Table 10 summarizes the results. Averaging over the two decompositions, human capital accounts for 46 percent of the output gap in the poorest quintile and 52 percent across all quintiles. Productivity accounts for 32 percent on average, and is negative in the richest quintile, where productivity exceeds the US level. The price of equipment explains 8 percent of the gap in the poorest quintile but as much as 25 percent in the fourth quintile. Distortions contribute little, between 2 and 3 percent in the bottom three quintiles.

5.2 White-Collar Employment Share

Figure 5 shows that the decomposition for white-collar employment differs from that for output per worker. Table 11 averages across the two exercises. Productivity explains about half of the gap, while human capital accounts for one-third. This stands in contrast to the partial-equilibrium analysis in Figure 1 that suggested that much of the white-collar employment gap across countries was due to differences in the composition of skill groups. The general equilibrium dampens this channel: increases in human capital lower white-collar wages, offsetting part of the employment effect. Distortions account for roughly 15 percent of the gap, a non-negligible role.

Figure 5: White-collar employment share gap relative to the US (logs)



(a) Counterfactual versus country baseline

(b) US baseline versus counterfactual

Notes: The bar "total" reports the arithmetic average logarithmic difference (i.e., gap) in the white-collar employment share between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining bars plot counterfactuals. In the left panel, the gaps are between country c and its counterfactual with one US endowment at a time. In the right panel, the gaps are between a counterfactual US with one country c endowment at a time and the US itself. The bar "covariates" captures all remaining differences between the empirical gap and the sum of counterfactual gaps, as described in (24) and (25).

Table 11: Contribution to white-collar employment 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
Human capital, H	-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
Productivity, A	-0.60	-0.46	-0.30	-0.17	-0.02	-0.31	43	51	48	59	32	47
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

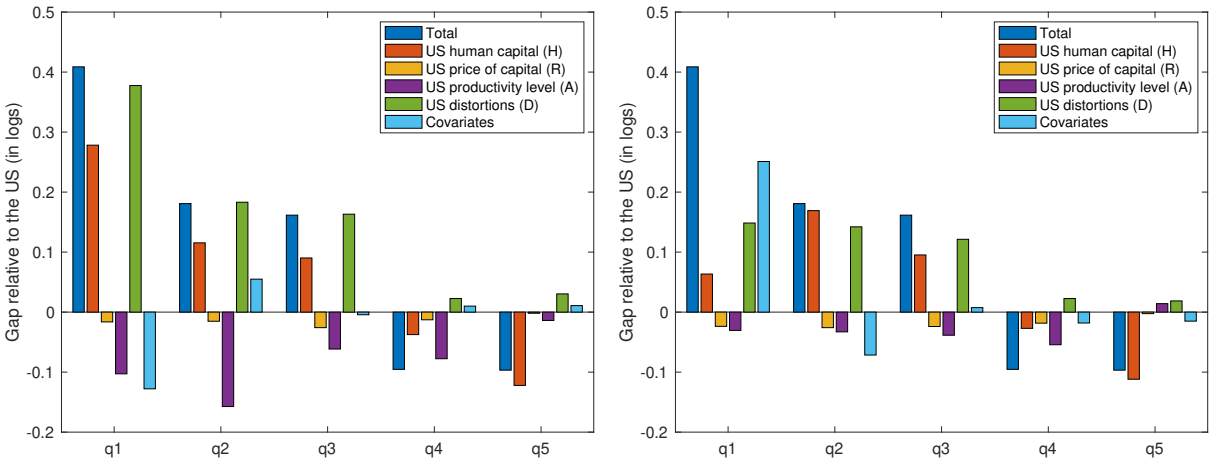
Notes. The line "total gap" in the left part of the table reports the arithmetic average logarithmic difference in the white-collar employment share between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining lines report counterfactuals. They represent the average between the two counterfactuals in the left and right panels of Figure 5. The right part of the table reports the contribution of each counterfactual as a percent share of the total gap, for each quintile separately as well as for all countries together. The counterfactuals (including the covariance term) sum to 100.

5.3 White- to Blue-Collar Wage Ratio

Figure 6 and Table 12 show that both human capital and distortions are key drivers of the white-collar wage premium relative to the US. Human capital accounts for about half of the premium, while distortions raise the premium across all quintiles by discouraging white-collar employment. Productivity differences, by contrast, reduce the relative wage of white-collar workers in poorer countries.

Appendix F.1 provides further details of the decomposition for each counterfactual separately, and Appendix F.2 reports country-level results.

Figure 6: White-to-blue-collar wage ratio gap relative to the US (logs)



(a) Counterfactual versus country baseline

(b) US baseline versus counterfactual

Notes: The bar "total" reports the arithmetic average logarithmic difference (i.e., gap) in the ratio of average white-collar to blue-collar average wages between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining bars plot counterfactuals. In the left panel, the gaps are between country c and its counterfactual with one US endowment at a time. In the right panel, the gaps are between a counterfactual US with one country c endowment at a time and the US itself. The bar "covariates" captures all remaining differences between the empirical gap and the sum of counterfactual gaps, as described in (24) and (25).

Table 12: Contribution to white-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
Human capital, H	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
Productivity, A	-0.07	-0.10	-0.05	-0.07	0.00	-0.06	-16	-53	-31	69	-0	-50
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

Notes. The line "total gap" in the left part of the table reports the arithmetic average logarithmic difference in the ratio of average white-collar to blue-collar average wages between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining lines report counterfactuals. They represent the average between the two counterfactuals in the left and right panels of Figure 6. The right part of the table reports the contribution of each counterfactual as a percent share of the total gap, for each quintile separately as well as for all countries together. The counterfactuals (including the covariance term) sum to 100.

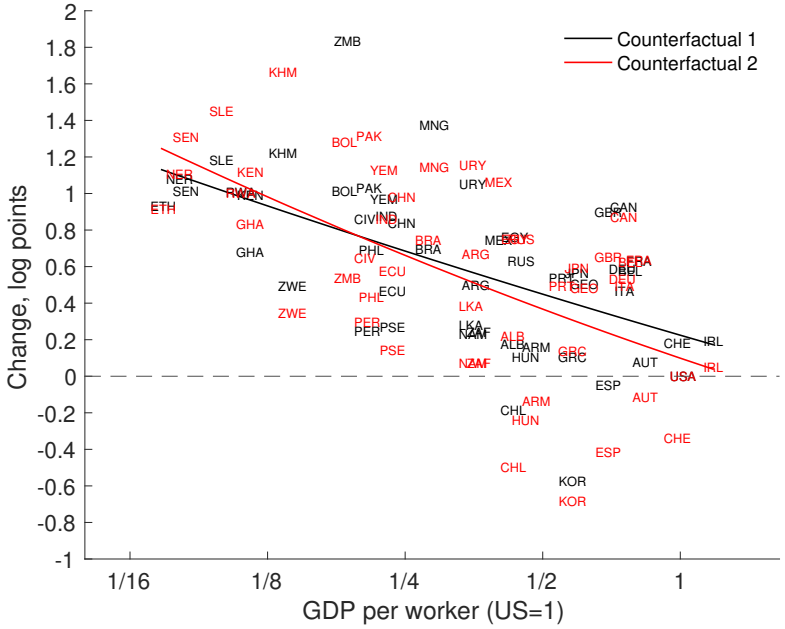
5.4 Human Capital and Output per Worker

We now decompose the channels through which human capital affects output per worker. We start by visualizing the baseline results in Figure 7 that shows the output change from endowing countries with US human capital. In counterfactual 1, output in the least-developed countries rises by 168%.[22] In counterfactual 2, the rise is 187%.

Next, in Figure 8, we separate the effects of the skill group composition, L, from

[22] A change of 0.99 log points, which is the fitted linear–quadratic evaluated at the average non-agricultural GDP per worker of the poorest quintile. This level is 10.7% of the US in 2019, approximately Rwanda in 2016.

Figure 7: GDP change after adoption of US human capital (quality and composition)



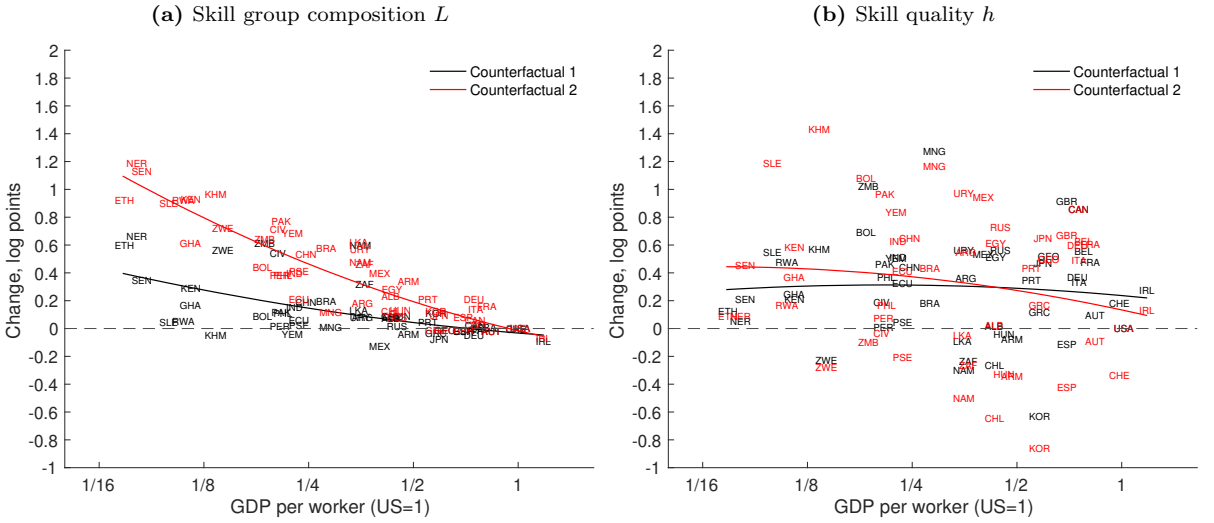
Notes: The y-axis plots the logarithmic difference in output between a counterfactual economy and the baseline. "Counterfactual 1" consists of country c endowed with US human capital (skill group composition and skill quality) relative to the empirical country c. "Counterfactual 2" consists of the empirical US relative to a US endowed with the human capital of country c. The x-axis is non-agricultural GDP per worker, normalized to the US. The line of best fit is based on a regression with linear and quadratic terms.

skill quality, h. Changing composition alone in the left panel yields relatively uniform gains, especially for poorer countries in counterfactual 1 (36% in the bottom quintile). From the US perspective (counterfactual 2), avoiding the composition of the poorest countries generates large gains (140%), reflecting complementarity with US endowments. Changing quality alone in the right panel produces more dispersion, as many countries already exceed US skill quality. On average, endowing countries with US skill quality (h) would raise the output for both poor and rich countries; for the poorest quintile the gain is 35% (counterfactual 1) and 55% for the US (counterfactual 2). In isolation, improving L or h raises GDP by roughly one-third in the poorest countries—far less than the combined 168%—highlighting strong complementarities between quality and composition.

Figure 9 refines the decomposition by education and age. Both panels change h. The left panel shifts the education composition to match the US within experience groups; the right panel shifts the experience composition within education groups.[23] Education dominates experience. Moving from least-developed to US educational composition changes

[23] Among inexperienced (experienced) workers, we impose the US educational distribution; analogously, among education groups, we impose the US experience distribution.

Figure 8: GDP change after adoption of either US skill quality or composition



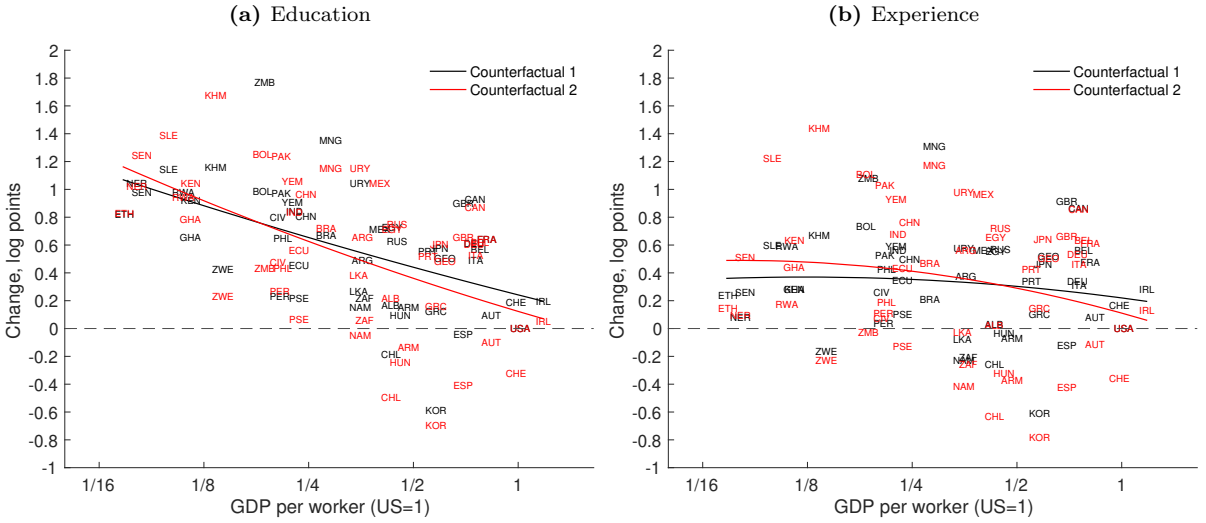
Notes: The y-axis plots the logarithmic difference in output between a counterfactual economy and the baseline. In the left panel, "Counterfactual 1" consists of country c endowed with the US skill group composition L relative to the empirical country c. "Counterfactual 2" consists of the empirical US relative to a US endowed with the skill group composition L of country c. In the right panel, the counterfactuals represent skill quality h instead of the skill group composition. The x-axis is non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a regression with linear and quadratic terms.

GDP by 154% (counterfactual 1) and 168% (counterfactual 2). For experience, the corresponding effects are 45% and 62%. The left panel nearly replicates the total H effect in Figure 7, while the right panel mirrors the h-only effect in Figure 8. Two forces explain education's dominance: larger cross-country dispersion in educational composition than in experience, and larger gaps in h across education than across experience. Appendix F.4 and Figure F.32 document this further by holding h constant.

We next assess the interaction of human capital with the endogenous technology responses, B. In the left panel of Figure 10, we change skill quality h while holding B fixed. Poor countries gain little from adopting US skill quality given their existing technology (counterfactual 1), whereas the US would lose substantially if it were endowed with poor-country skill quality given its existing technological choices B. The right panel changes composition L only, now holding skill quality h and technology B fixed: most poor countries would lose by adopting the US skill group composition L given their skill quality h and technology B. These results indicate that, conditional on h and B, countries' allocations across skill groups are close to efficient. Appendix F.5 documents how technology B itself adjusts when human capital changes.

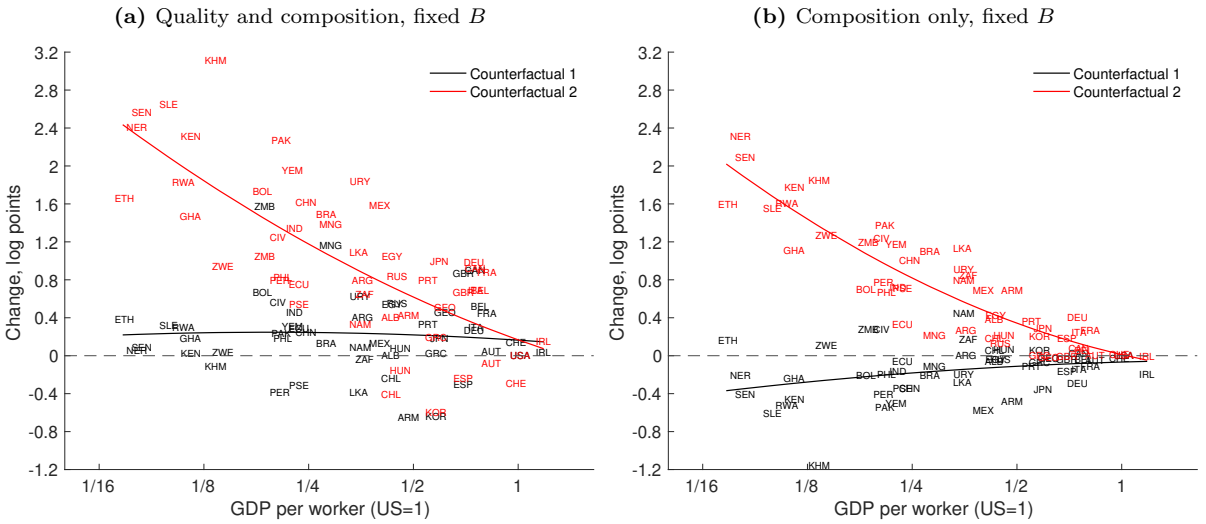
Table 13 summarizes Figures 7–10, reporting the contribution of human capital to the GDP gap under each scenario and counterfactual.

Figure 9: GDP change after adoption of US skill quality and (education or experience) composition



Notes: The y-axis plots the logarithmic difference in output between a counterfactual economy and the baseline. In the left panel, "Counterfactual 1" consists of country c endowed with US skill quality h and the US educational composition L_{edu} relative to the empirical country c. We construct this by imposing the US relative educational composition within each country's experience group. "Counterfactual 2" consists of the empirical US relative to a US endowed with the skill quality and the educational composition L_{edu} of country c. In the right panel, the counterfactuals are analogous only that we vary the experience composition while holding fixed the educational composition. The x-axis is non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a regression with linear and quadratic terms.

Figure 10: GDP change after adoption of US human capital, holding technology B fixed



Notes: The y-axis plots the logarithmic difference in output between a counterfactual economy and the baseline. In the left panel, "Counterfactual 1" consists of country c endowed with the US human capital (skill group composition and skill quality) relative to the empirical country c, with technology B remaining that of country c. "Counterfactual 2" consists of the empirical US relative to a US endowed with the human capital of country c and the technology B of the US. In the right panel, the counterfactuals only vary the skill group composition L while leaving skill quality h unchanged. The x-axis is non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a regression with linear and quadratic terms.

5.5 Robustness

We close this section by assessing the robustness of our results. For brevity, we focus on the output-per worker gains from adopting US human capital. To this end, we vary

Table 13: Contribution of human capital to GDP ratio gap: various scenarios

(a) Counterfactual 1

	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
Human capital, hL	-0.96	-0.81	-0.51	-0.37	-0.36	-0.60	43	53	49	58	200	53
Skill composition, L	-0.27	-0.18	-0.14	-0.02	0.02	-0.12	12	12	14	2	-9	11
Skill quality, h	-0.29	-0.39	-0.20	-0.27	-0.30	-0.29	13	25	20	42	169	26
Human capital: education comp.	-0.91	-0.76	-0.49	-0.37	-0.37	-0.58	41	50	47	58	205	52
Human capital: exp. comp.	-0.36	-0.44	-0.23	-0.28	-0.30	-0.32	16	29	22	43	165	28
Human capital, fixed B	-0.20	-0.32	-0.19	-0.18	-0.23	-0.22	9	21	18	28	131	20
Skill comp., fixed B	0.35	0.20	0.07	0.10	0.10	0.17	-16	-13	-7	-16	-56	-15

(b) Counterfactual 2

	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
Human capital, hL	-1.10	-0.69	-0.50	-0.28	-0.23	-0.56	49	45	48	44	130	50
Skill composition, L	-0.87	-0.51	-0.38	-0.12	-0.06	-0.39	39	33	36	19	32	35
Skill quality, h	-0.52	-0.34	-0.26	-0.22	-0.24	-0.32	23	22	25	35	136	28
Human capital: education comp.	-1.04	-0.63	-0.48	-0.28	-0.25	-0.54	47	41	46	44	138	48
Human capital: exp. comp.	-0.55	-0.40	-0.28	-0.23	-0.23	-0.34	25	26	27	36	131	30
Human capital, fixed B	-2.07	-1.24	-0.92	-0.47	-0.37	-1.01	93	81	88	74	207	90
Skill comp., fixed B	-1.59	-0.92	-0.65	-0.23	-0.12	-0.70	71	60	63	36	70	62

Notes. In both panels, the lines "total gap" report the arithmetic average logarithmic difference in output per worker between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining lines report counterfactuals. In panel (a), the gaps are between country c and its counterfactual with one US endowment at a time. In panel (b), the gaps are between a counterfactual US with one country c endowment at a time and the US itself. The second line in each panel reports the counterfactual gaps based on altering human capital (the composition of skill groups and skill quality). The third line changes only the composition of skill groups while the fourth line changes only skill quality, as described in Figure 8. The fifth and sixth lines change skill quality as well as either the educational or the experience composition, respectively, as described in Figure 9. The seventh line and eighth line leave technology unaltered while changing either human capital or only the skill group composition, as described in Figure 10. The right part of the table reports the contribution of each counterfactual as a percent share of the total gap, for each quintile separately as well as for all countries together.

one parameter at a time.[24] Results are in Table 15, whose first row lists the baseline by quintile and counterfactual.

We first vary the dependence parameter ρ around the calibrated value $\rho = 0.35$. This parameter governs the dispersion of idiosyncratic productivity within occupations and thus the elasticity of average idiosyncratic productivity with respect to occupational employment.[25] A higher ρ scales the Fréchet dispersion parameters θ_s up and reduces idiosyncratic variation. We report $\rho = 0$ (independent extreme-value draws) and $\rho = 0.7$.[26] As Table 15 shows, results are little affected. The reason is that cross-country differences in sorting π_{sj} are modest, so changes in ρ barely affect inferred differences in

[24] When re-solving, we recalibrate only the occupational equipment-intensity parameters α_j so that, in the US, each occupation's equipment income share equals the aggregate value of 0.193.

[25] From (11), $\overline{z}_{sj} = \Gamma_s \, \pi_{sj}^{-(1-\rho)/\theta_s}$.

[26] Note that $\rho = 1$ eliminates comparative advantage and yields no equilibrium.

Table 15: GDP change (percent) due to US human capital, parameter sensitivity

	Counterfactual 1					Counterfactual 2				
	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Baseline	161	124	66	45	43	201	99	65	32	26
No dependence between shocks (ρ=0)	168	122	62	43	52	196	90	56	23	27
High dependence between shocks (ρ=0.7)	155	126	71	47	35	199	106	73	41	24
Low long-run EoS of skill groups ($\eta = 4.0$)	448	299	138	57	64	457	210	118	26	28
High long-run ES of skill groups ($\eta = \infty$)	30	29	18	36	27	56	24	23	36	22
Low EoS of occupations ($\sigma = 1.6$)	148	115	62	41	40	209	104	68	35	28
High EoS of occupations ($\sigma = 2.0$)	174	132	70	48	46	195	96	63	30	25
Preference shocks (half)	168	128	71	46	40	200	100	68	35	25
Preference shocks (full)	177	138	82	51	30	205	116	83	49	22

Notes. The baseline reports the average percent change in GDP per worker by income quintile depending on the counterfactual. "Counterfactual 1" compares country c endowed with US human capital (skill group composition and skill quality) relative to the empirical country c. "Counterfactual 2" compares the empirical US relative to a US endowed with the human capital of country c. All income quintile averages are computed as average log differences and transformed to percent changes. The remaining lines report counterfactuals based on different parameter constellations, as described in the text.

$\overline{z}_{sj}$ and thus in skill quality h_{sj}. This can be see from (21), that we state again here:

$$\begin{aligned}\log h^c_{sj} \;=\; &\left(\log \overline{w}^c_{sj} - \log \overline{w}^c_{1j}\right) + \left(\log \Gamma_1 - \log \Gamma_s\right) + \frac{1-\rho}{\theta_s}\left(\log \pi^c_{sj} - \log \pi^c_{1j}\right) \\ &+ \frac{1}{\eta - 1}\left[\log\left(\overline{w}^c_{sj} L^c_{sj}\right) - \log\left(\overline{w}^c_{1j} L^c_{1j}\right)\right].\end{aligned} \tag{26}$$

Next we vary η, the elasticity of substitution across human-capital groups within occupations (baseline $\eta = 6.97$). With more complementarity ($\eta = 4$), cross-country differences in h_{sj} are amplified: rich countries typically have higher relative total earnings for high-skill groups, and a lower η maps these into larger quality gaps; output gains from adopting US H rise accordingly. In the limit $\eta \to \infty$, relative total earnings no longer inform h_{sj}, reducing inferred quality differences and lowering output gains.

We then vary the elasticity of substitution across occupations σ (baseline $\sigma = 1.81$). With more complementarity ($\sigma = 1.6$), output gains from US H shrink for poor countries but rise for the US; with more substitutability ($\sigma = 2$), the pattern reverses. Two forces are at play, as can be seen from the inferred A_j from (23):

$$\begin{aligned}\log A^c_j \;=\; &\xi_j + \log \overline{w}^c_{1j} + \frac{1-\rho}{\theta_s}\log \pi^c_{1j} + \frac{1}{\sigma - 1}\log x^c_j + \frac{1}{\eta - 1}\log x^c_{1j} \\ &+ \frac{1}{\sigma - 1}\left(\frac{\sigma - \gamma_j}{\gamma_j - 1}\log \lambda^c_j + \log \lambda^c\right).\end{aligned} \tag{27}$$

Richer countries have lower (higher) income shares x_j in less (more) complex occupations; lower σ compresses (expands) inferred productivity gaps accordingly. Second, additional

high-skill labor disproportionately augments complex occupations. With low σ, poor countries channel these additional skills into occupations where inferred the A_j is relatively low, dampening gains; for the US, the opposite holds.

Finally, we allow some workers to sort on preferences rather than productivity, as considered in Hsieh, Hurst, Jones, and Klenow (2019). Suppose a fraction δ sorts on preferences while $1-\delta$ sorts on productivity. Then

$$\overline{z}_{sj} = \Gamma_s \left[\delta + (1-\delta)\,\pi_{sj}^{-(1-\rho)/\theta_s}\right], \qquad D_{sj} = \frac{\overline{w}_{sj}}{\overline{w}_{s1}}\left[\delta\left(\frac{\pi_{sj}}{\pi_{s1}}\right)^{-(1-\rho)/\theta_s} + 1 - \delta\right].$$

For $\delta = 0.5$ and $\delta = 1$, the output impact of adopting US H remains close to baseline. As with ρ, limited cross-country variation in π_{sj} implies small changes in inferred h_{sj} and thus in aggregate effects.

All in all, our results are reliable as they are robust to parameter variations and the mode of selection of workers to occupations.

6 Conclusions

This paper develops and calibrates a framework to quantify the contribution of human capital, country-embedded productivity, technology choices, and distortions to cross-country differences in output per worker. By inverting the equilibrium system and utilizing detailed data on wages and employment shares across skill groups and occupations, we have provided an impact decomposition that isolates the role of human capital and other margins for a sample of 50 countries spanning the entire development spectrum.

Our results show that both the composition and quality of human capital rise systematically with development. In turn, human capital, on average, accounts for more than 1/2 of the GDP gap between the US and poorer countries. The contribution of productivity is lower, about 1/3. We also find that country-embedded productivity and technology choices play complementary roles in shaping cross-country gaps. Richer countries not only employ workers with higher human-capital quality, but also deploy technologies that make more efficient use of their skills. Distortions, by contrast, dampen the extent to which these potential advantages are realized, particularly in poorer economies.

Human capital also accounts for approximately 1/3 of the white-collar employment

gap relative to the US and about 1/2 of the white-collar to blue-collar wage ratio gap. Occupational distortions, although more pronounced in developing countries, depress white-collar employment and contribute substantially to a higher white-collar wage premium, yet ultimately have a modest impact on aggregate output. Taken together, our findings suggest that differences in output per worker reflect not only the supply of human capital but also the institutional and technological environment in which it is employed. Our results suggest that expanding access to schooling and improve the quality of education are likely to generate large gains for developing countries. Such gains will be fully realized in environments where superior workers' skill are coupled with complementing technologies. Similarly, institutions that reduce distortions may amplify the returns to investments in human capital.

Naturally, our analysis has limitations. We have abstracted from sectoral linkages, international trade, and dynamic considerations of human-capital accumulation, each of which may interact with the margins we study. Future work that integrates these elements within a comparable framework could provide a richer account of development differences. Nevertheless, the evidence presented here underscores the central role of human capital —both in composition and quality— for the output differences of countries that would likely be found in those richer settings.

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Online Appendix for: "From Skills to Occupations: Comparative Advantage and Cross-Country Income Differences"

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A Harmonization of surveys

A.1 Survey and sample selection

We use nationally representative household and labor force surveys. A full list of surveys can be found in Table A.1. 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).

A.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 to 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.

A.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.

A.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.

A.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).

B Construction of employment shares and wages

Our goal is to construct, for each country c, employment shares $L^c_{s,j}$ and average wages $\overline{w}^c_{s,j}$ where s is one of the eight skill 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 (s, j) often showing up as empty.[27] Instead, we propose to estimate $L^c_{s,j}$ via multinomial logistic regressions and $\overline{w}^c_{s,j}$ via wage regressions. We do this for each country-year-survey separately.

B.1 Shares

We start with the construction of employment shares. Let

$$y_{ij} = const_j + X_i\beta_j + \varepsilon_{ij}$$

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 relevant 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

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

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

$$L_{s,j} = \sum_{i \in s} \widehat{\pi}_{ij}\omega_i \tag{28}$$

where s is one of the final eight skill groups. Note that the multinomial logistic regression forces the

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

Table A.1: 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 sixth column reports total sample size of the dataset across all years.

aggregate occupational share to coincide exactly with the raw data moment,

$$L_j = \sum_s L_{s,j} = L_j^{raw} \text{ where } L_j^{raw} \equiv \sum_i \mathbb{I}_{ij}\omega_i. \tag{29}$$

Also, note that the aggregate share of worker skill groups equals the raw data,

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

B.2 Wages

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

$$\ln w_i = \sum_j \mathbb{I}_{ij} \left(\gamma_j + X_i \beta_j \right) + \varepsilon_i \tag{30}$$

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 weighted least squares using weights ω_i. We predict the wage of individual i in any occupation j, $\widehat{w}_{ij}$, which we then use to construct the predicted average wage of skill group s in occupation j as

$$\overline{w}_{s,j} = \zeta_j \frac{\sum_{i \in s} \widehat{w}_{ij} \widehat{\pi}_{ij} \omega_i}{\sum_{i \in s} \widehat{\pi}_{ij} \omega_i}. \tag{31}$$

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,

$$\overline{w}_j = \frac{\sum_s \overline{w}_{s,j} L_{s,j}}{\sum_s L_{s,j}} = \overline{w}_j^{raw} \quad \text{where} \quad \overline{w}_j^{raw} \equiv \frac{\sum_i \mathbb{I}_{ij} w_i \omega_i}{\sum_i \mathbb{I}_{ij} \omega_i}. \tag{32}$$

This adjustment is necessary given that the average predictions obtained from wage regression (30) 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 wage for each *skill group* necessarily coincides with the raw data moment,

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

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 two in any skill group s. This again 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 skill 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 Namibia).[28] 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 skill group 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.

[28] 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.

C Aggregate data

C.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 in 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 indexes all non-agricultural sectors. 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. 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 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.[29]

The left panel of Figure C.1 plots the cross-country relationship between our measure of non-agricultural GDP per worker (on the x-axis) and the standard aggregate GDP per worker (on the y-axis). Both are normalized to the US non-agricultural GDP per non-agricultural worker.

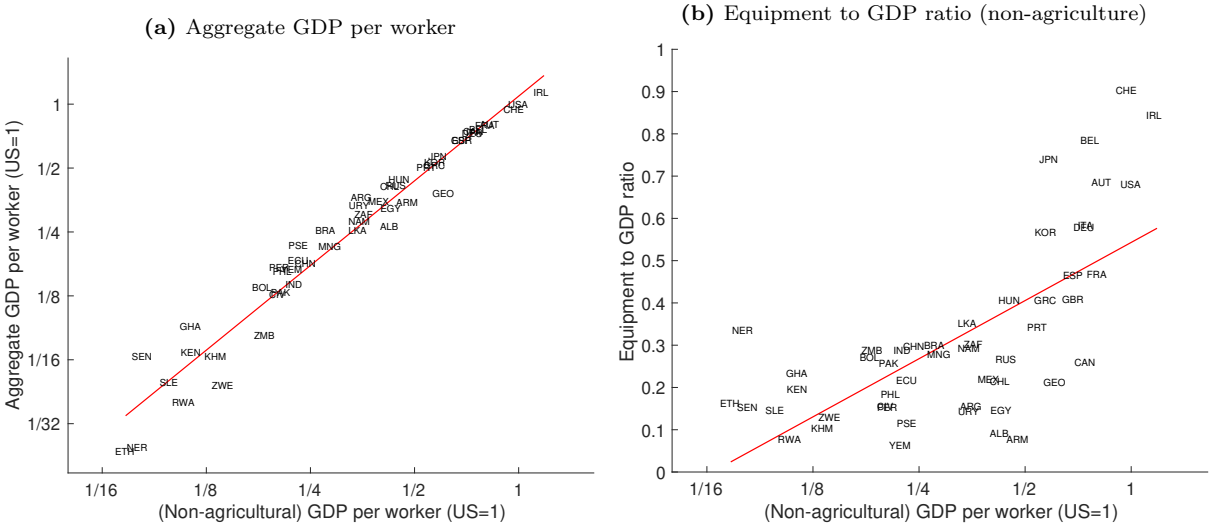
C.2 Non-agricultural equipment

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 $\widetilde{V}_{i,ct}^{S}$ and $\widetilde{V}_{n,ct}^{S}$ 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 $\widetilde{V}_{i,ct}^{K}$ for investment and $\widetilde{V}_{n,ct}^{K}$ for the net capital stock, respectively. Also, define the share of the equipment value as $s_{i,ct} \equiv \frac{\widetilde{V}_{i,ct}^{K}}{\widetilde{V}_{i,ct}^{S}+\widetilde{V}_{i,ct}^{K}}$ and $s_{n,ct} \equiv \frac{\widetilde{V}_{n,ct}^{K}}{\widetilde{V}_{n,ct}^{S}+\widetilde{V}_{n,ct}^{K}}$. The tilde notation defines aggregate values as opposed to non-agricultural ones (without the tilde).

[29] 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."

Figure C.1



Notes: The left panel plots aggregate GDP per worker, normalized to the US, against non-agricultural GDP per worker, normalized to the US. The right panel plots the ratio equipment to non-agricultural GDP, against non-agricultural GDP per worker. The lines of best fit are based on a linear and quadratic regression.

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.[30] 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.[31] 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 C.1.

C.3 Income share of equipment

We calibrate the parameters $\alpha_j, \forall j \in \{1, 2, ..., J\}$, 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, $\frac{RK_j}{p_j Y_j} = \frac{RK}{Y}, \forall j$.[32] Second, we assume that the equipment capital income share in non-agriculture is

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

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

[32] 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.

identical to that of the aggregate economy. The next step is to separate the aggregate capital income share into equipment and structures: $\frac{RK}{Y} = \frac{RK}{RK+R_S S}\widetilde{\alpha} = \frac{RK/(R_S S)}{RK/(R_S S)+1}\widetilde{\alpha}$ where $R_S S$ 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 $\frac{RK}{R_S S}$. We deduce it as follows from a neoclassical growth model with two types of capital.

Suppose that the representative household's budget constraint is

$$C + P_K K' + P_S S' = (1-\delta_K) P_K K + R_K K + (1-\delta_S) P_S S + R_S S$$

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

$$\frac{RK}{R_S S} = \left(\frac{1-\beta(1-\delta_K)}{1-\beta(1-\delta_S)}\right)\frac{P_K K}{P_S S} = \left(\frac{r+\delta_K}{r+\delta_S}\right)\frac{P_K K}{P_S S}$$

where $r = \frac{1-\beta}{\beta}$ is the the steady-state interest rate. The Capital Detail of PWT 10.01 provides data on $\frac{P_K K}{P_S S}$. In addition, we determine δ_i from the steady-state relationships $\delta_K = \frac{P_K I_K}{P_K K}$ and $\delta_S = \frac{P_S I_S}{P_S S}$ where $P_K I_K$ and $P_K I_K$ denote investment for which data is also available in the Capital Detail of PWT 10.01.[33]

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.

D Conditional employment shares and wages

Table 1 reports unconditional employment shares and average wages. As a complement, Table D.2 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.

Analogously, Table D.3 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.

E Inferred productivity, skill quality, and distortions

Figure E.2 portrays the inferred productivity terms, A, for each occupation. Figures E.3-E.10 plot the inferred skill quality terms, h, for each skill group, conditional on each occupation. Figures E.19-E.26

[33] These data are described in the previous subsection where the notation is $P_K K = \widetilde{V}_n^K$, $P_S S = \widetilde{V}_n^S$, $P_K I_K = \widetilde{V}_i^K$, and $P_S I_S = \widetilde{V}_i^S$.

Table D.2: Employment shares and wages conditional on education

	Employment shares					Relative wages				
All occupations	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Elementary occ., LS	20	21	24	19	18	1.00	1.00	1.00	1.00	1.00
Service & sales, 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 & trade, 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 occ., HS	5	7	7	5	4	1.00	1.00	1.00	1.00	1.00
Service & sales, 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 & trade, 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

Notes. The left part of the table reports average employment hour shares per occupation conditional on broad skill groups across income quintiles of countries (by non-agricultural GDP per worker). The upper part of the table conditions on low-skilled workers (primary school and lower secondary school workers), the lower part conditions on high-skilled workers (upper secondary school workers and tertiary school workers). Employment shares are expressed in percentages and sum up to 100 in the columns of each sub-table. The right part of the table reports average hourly wage premia across countries in each quintile. The wage premium in each occupation and broad skill group is expressed relative to elementary occupations among either low-skilled or high-skilled workers.

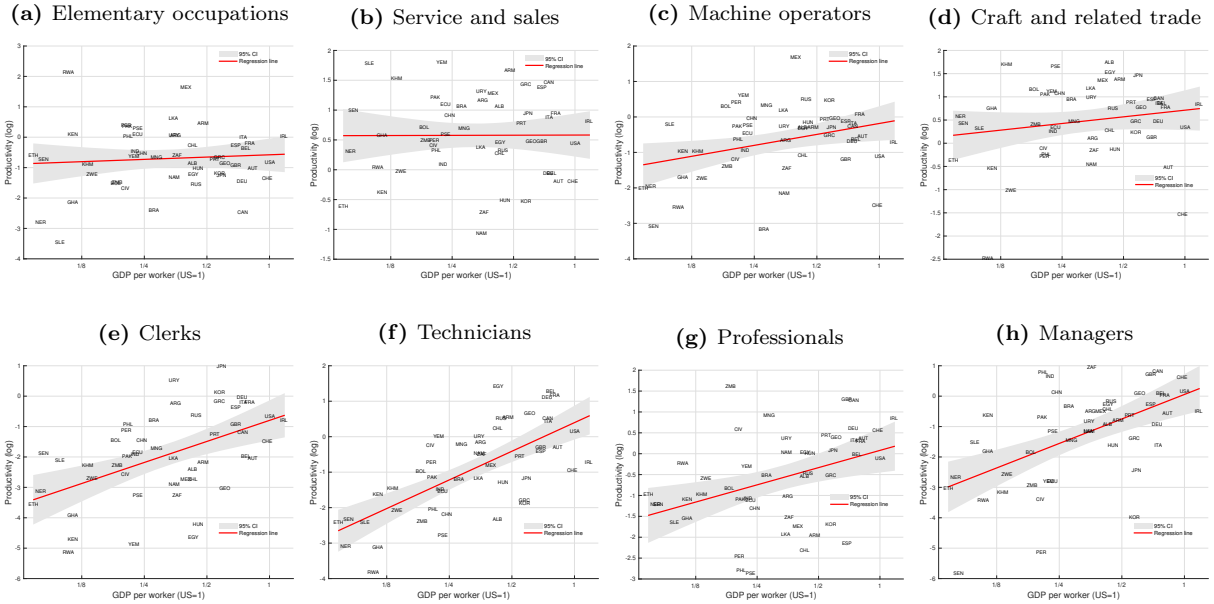
depict the inferred distortions, D, for each occupation, conditional on each skill group.

Table D.3: Employment shares and wages conditional on occupation

	Employment shares					Relative wages				
All skill groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Primary, inexperienced, BC	44	27	13	4	3	1.00	1.00	1.00	1.00	1.00
Primary, experienced, BC	23	19	18	9	7	1.18	1.21	1.12	1.03	1.17
Lower secondary, inexperienced, BC	15	19	20	10	10	1.30	1.15	1.13	1.05	1.03
Lower secondary, experienced, BC	6	10	13	15	17	1.66	1.45	1.32	1.10	1.29
Upper secondary, inexperienced, BC	9	13	17	23	23	1.61	1.32	1.29	1.10	1.15
Upper secondary, experienced, BC	3	5	14	23	25	2.03	1.68	1.51	1.20	1.38
Tertiary, inexperienced, BC	1	5	4	8	8	2.48	1.67	1.71	1.27	1.26
Tertiary, experienced, BC	0	2	2	7	7	3.11	2.06	1.98	1.39	1.48
Main skill 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 skill groups	q1	q2	q3	q4	q5	q1	q2	q3	q4	q5
Primary, inexperienced, WC	9	5	2	0	0	1.00	1.00	1.00	1.00	1.00
Primary, experienced, WC	9	6	4	2	1	1.40	1.46	1.25	1.14	1.35
Lower secondary, inexperienced, WC	12	8	8	3	2	1.07	1.00	1.10	1.01	1.09
Lower secondary, experienced, WC	7	6	6	5	6	1.61	1.46	1.48	1.17	1.54
Upper secondary, inexperienced, WC	19	16	18	16	13	1.39	1.25	1.39	1.15	1.32
Upper secondary, experienced, WC	10	9	16	17	21	2.02	1.88	1.85	1.36	1.79
Tertiary, inexperienced, WC	21	29	25	28	24	2.22	1.93	2.17	1.53	1.71
Tertiary, experienced, WC	15	19	20	30	32	3.22	2.89	2.78	1.91	2.28
Main skill 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

Notes. The left part of the table reports average employment hour shares per skill group conditional on the broad occupations across income quintiles of countries (by non-agricultural GDP per worker). The upper part of the table conditions on blue-collar workers, the lower part conditions on white-collar workers. Employment shares are expressed in percentages and sum up to 100 in the columns of each sub-table. The right part of the table reports average hourly wage premia across countries in each quintile. The wage premium in each skill group and broad occupation is expressed relative to inexperienced (young) workers with primary education or less among either blue-collar or white-collar workers.

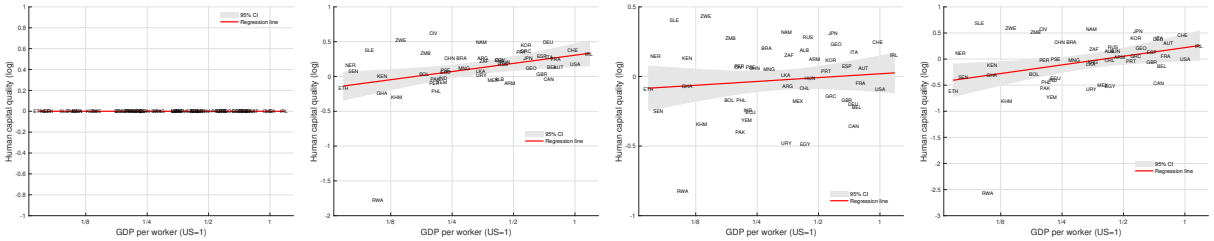
Figure E.2: Productivity, A



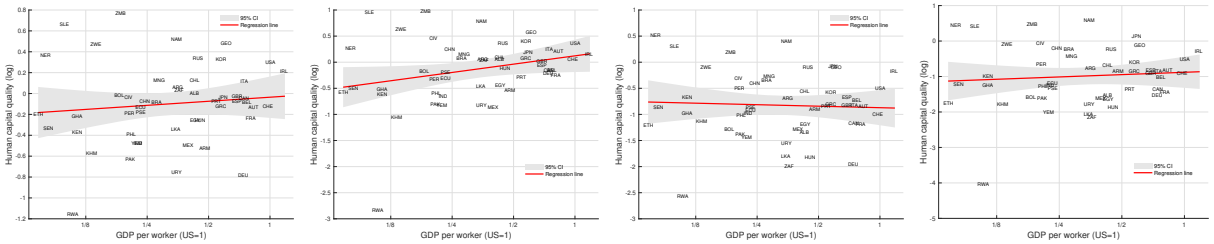
Notes: Each panel represents the logarithm of inferred productivity A_j^c for country c in occupation j against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.3: Skill quality, h: elementary occupations

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.



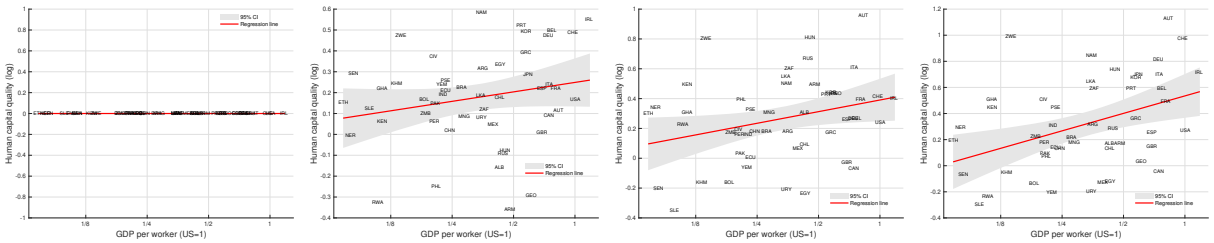
(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



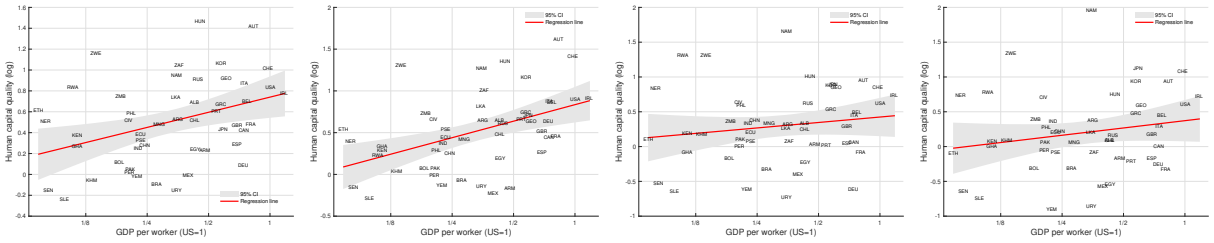
Notes: Each panel represents the logarithm of inferred skill quality $h^c_{s,j}$ for country c in skill group s and occupation j = *elementary occupations* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.4: Skill quality, h: service and sales occupations

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.



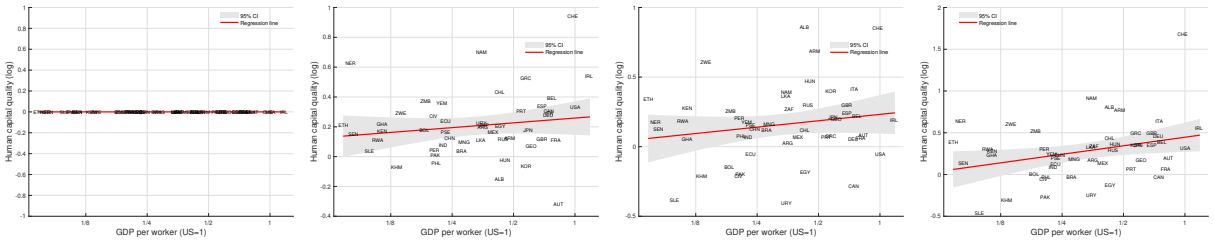
(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



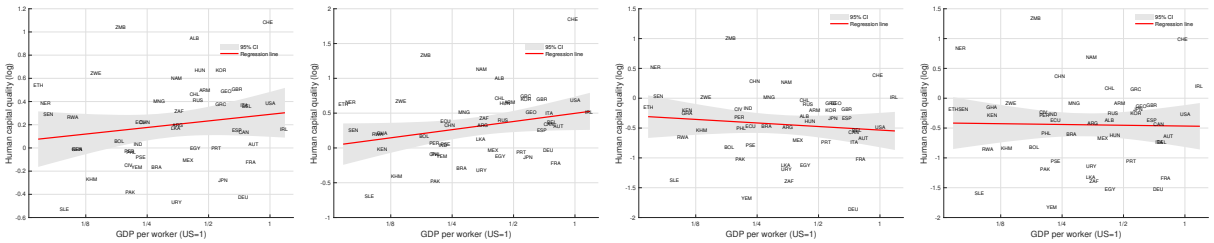
Notes: Each panel represents the logarithm of inferred skill quality $h^c_{s,j}$ for country c in skill group s and occupation j = *service and sales occupations* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.5: Skill quality, h: machine and plant operators

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.



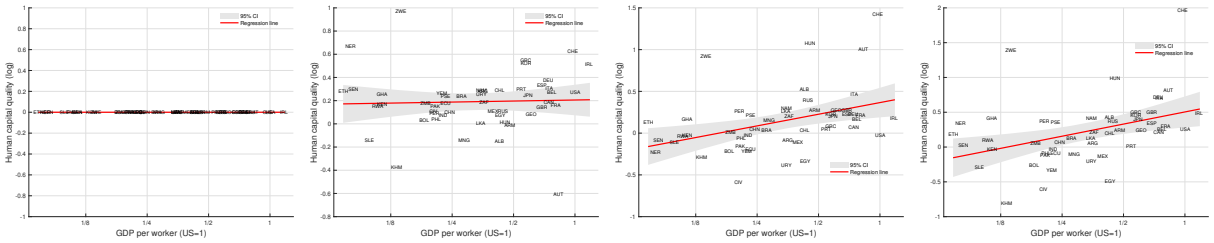
(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



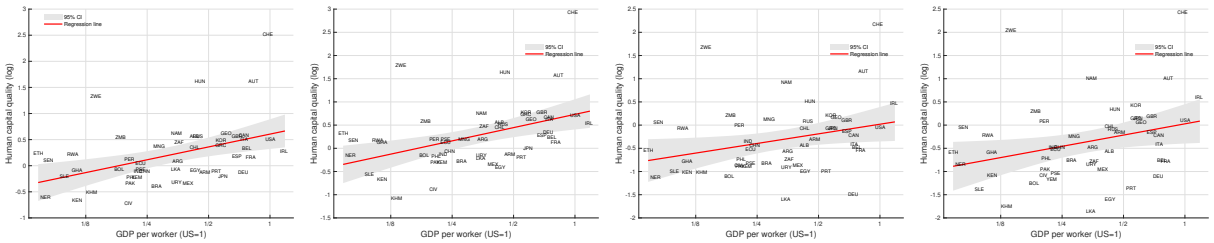
Notes: Each panel represents the logarithm of inferred skill quality $h^c_{s,j}$ for country c in skill group s and occupation j = *machine and plant operators* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.6: Skill quality, h: craft and related trade

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.

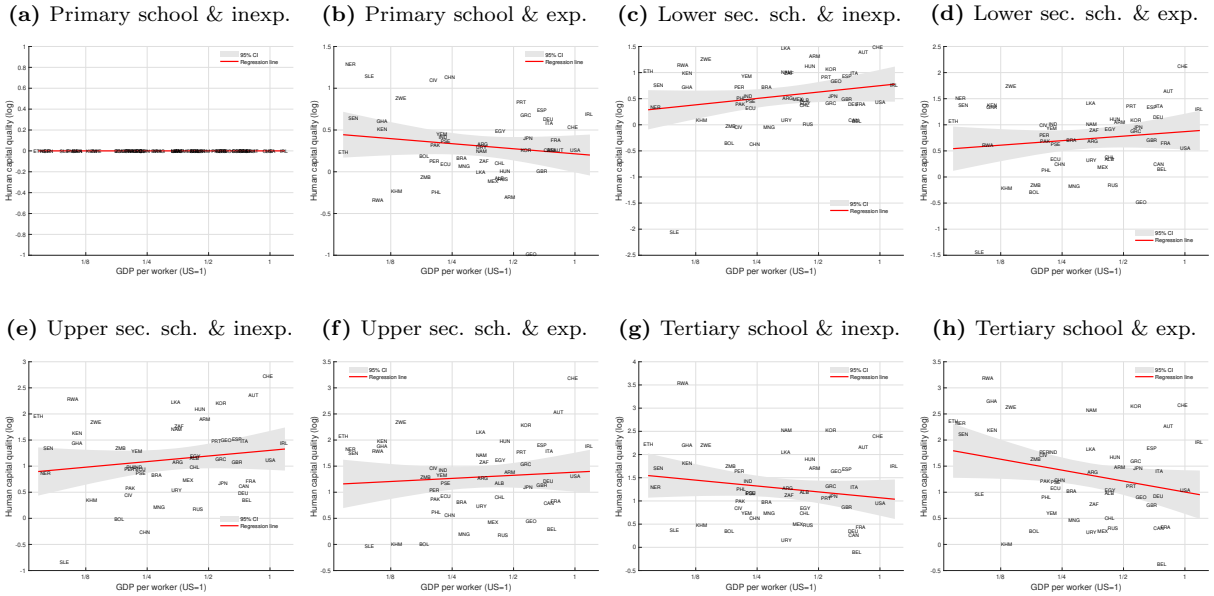


(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



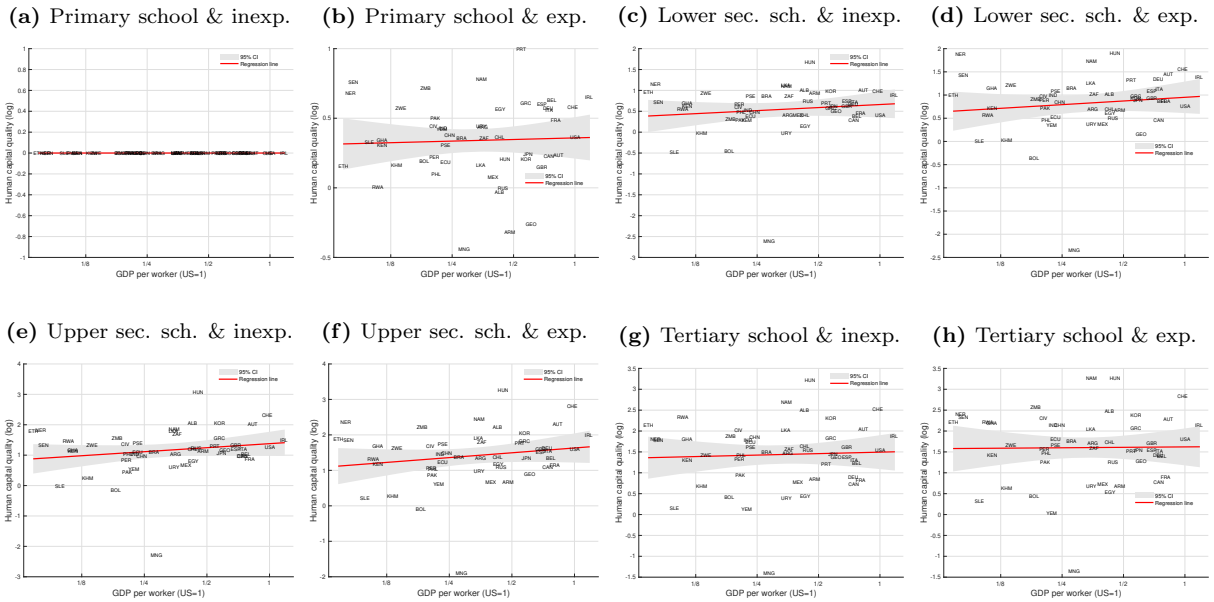
Notes: Each panel represents the logarithm of inferred skill quality $h^c_{s,j}$ for country c in skill group s and occupation j = *craft and related trade* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.7: Skill quality, h: clerks



Notes: Each panel represents the logarithm of inferred skill quality $h^c_{s,j}$ for country c in skill group s and occupation j = *clerks* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

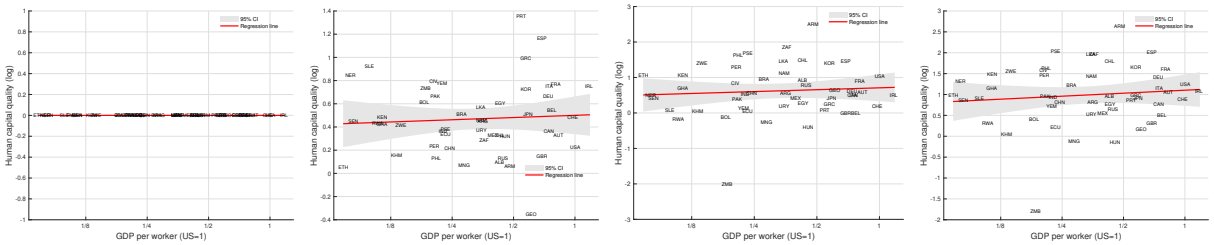
Figure E.8: Skill quality, h: technicians and associate professionals



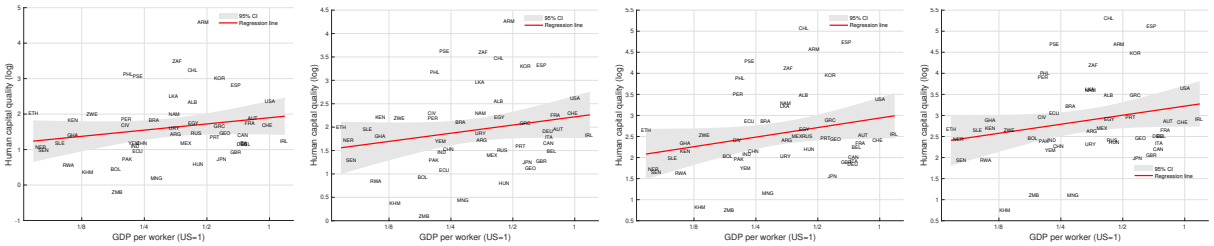
Notes: Each panel represents the logarithm of inferred skill quality $h^c_{s,j}$ for country c in skill group s and occupation j = *technicians and associate professionals* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.9: Skill quality, h: professionals

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.



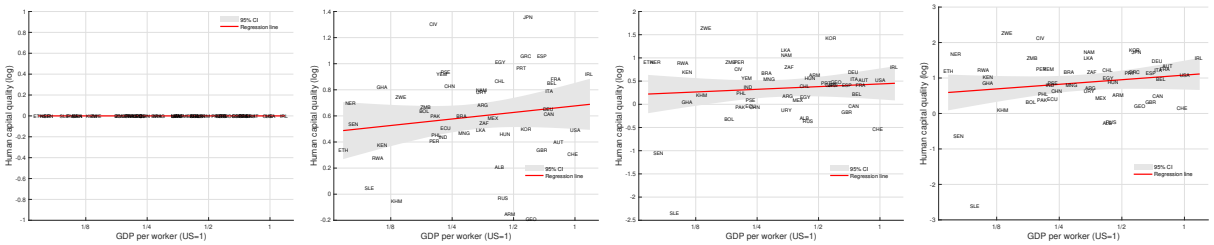
(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



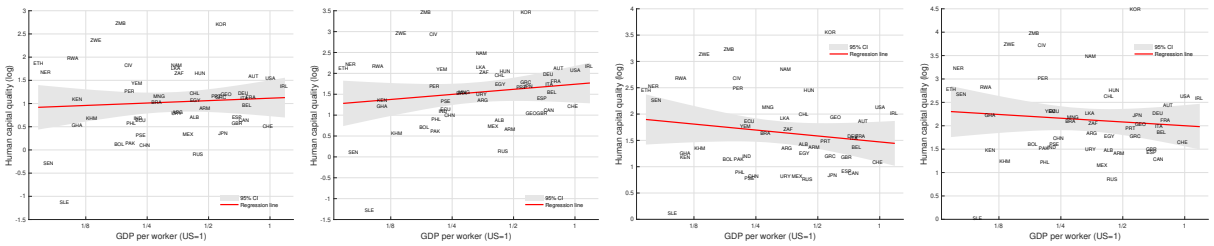
Notes: Each panel represents the logarithm of inferred skill quality $h^c_{s,j}$ for country c in skill group s and occupation j = *professionals* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.10: Skill quality, h: managers

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.

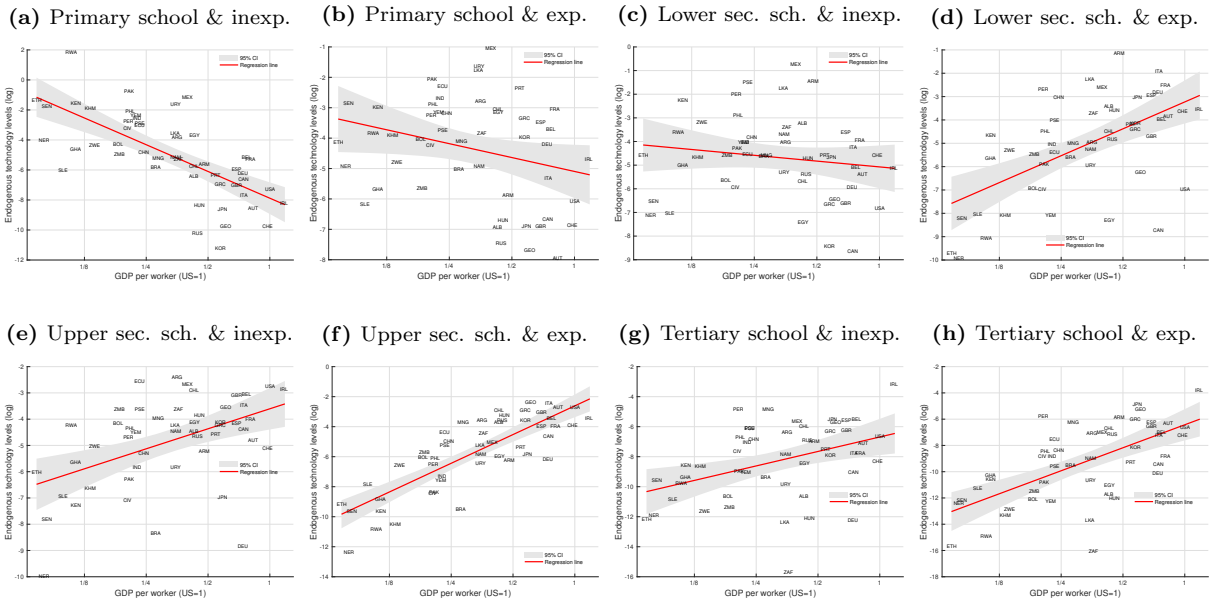


(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



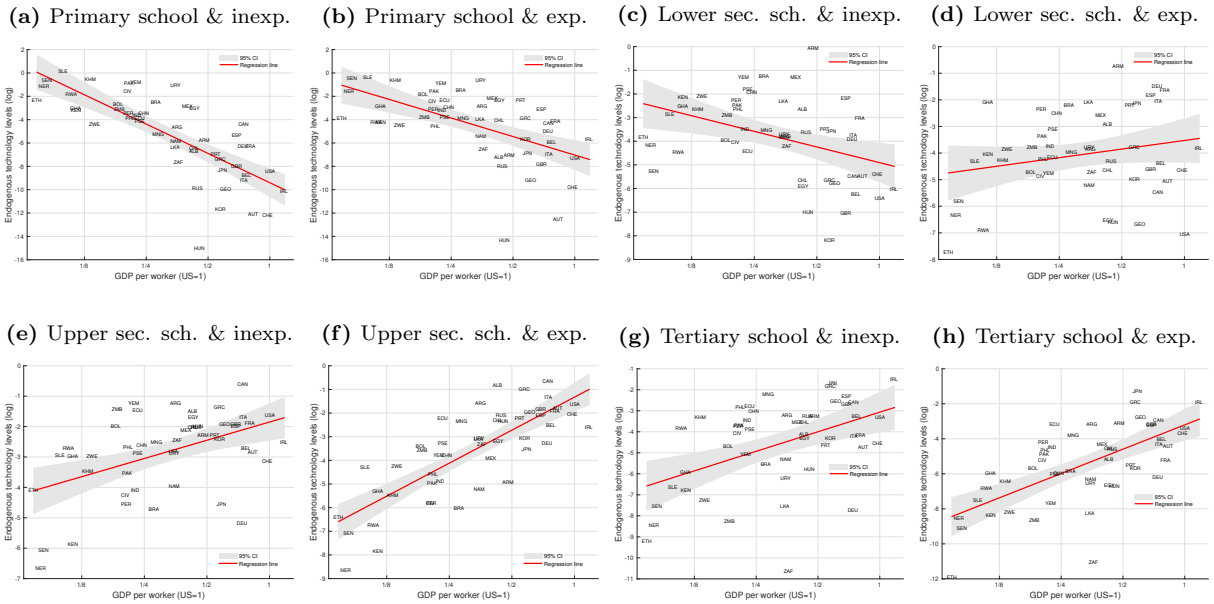
Notes: Each panel represents the logarithm of inferred skill quality $h^c_{s,j}$ for country c in skill group s and occupation j = *managers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.11: Endogenous productivity, B: elementary occupations



Notes: Each panel represents the logarithm of inferred endogenous technology $B^c_{s,j}$ for country c in skill group s and occupation j = *elementary occupations* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.12: Endogenous productivity, B: service and sales occupations

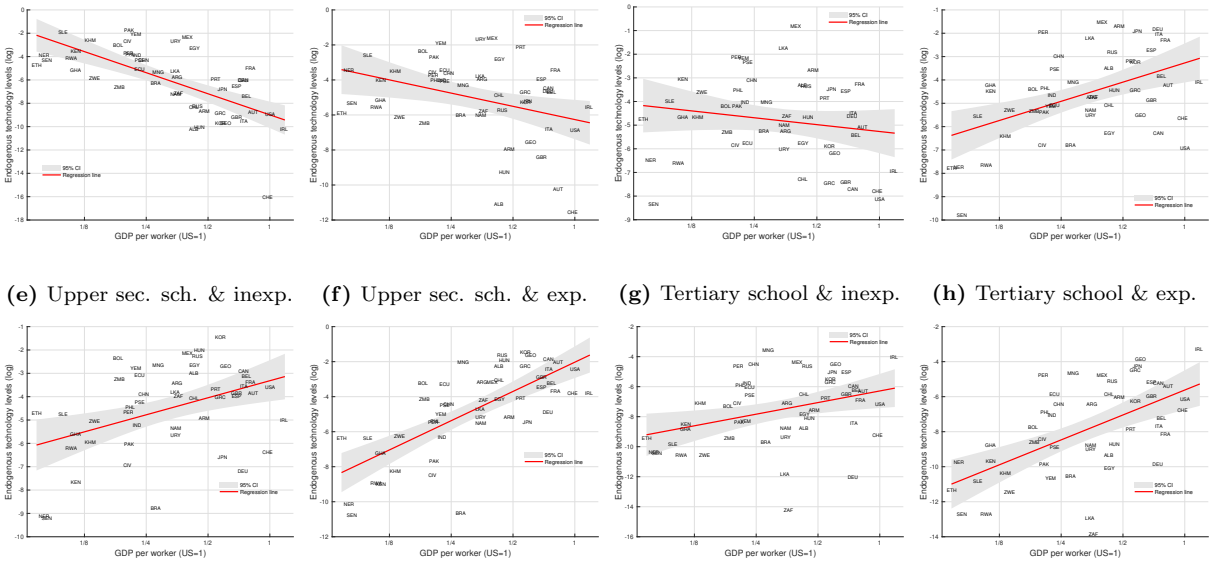


Notes: Each panel represents the logarithm of inferred endogenous technology $B^c_{s,j}$ for country c in skill group s and occupation j = *service and sales occupations* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.13: Endogenous productivity, B: machine and plant operators

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.

(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.

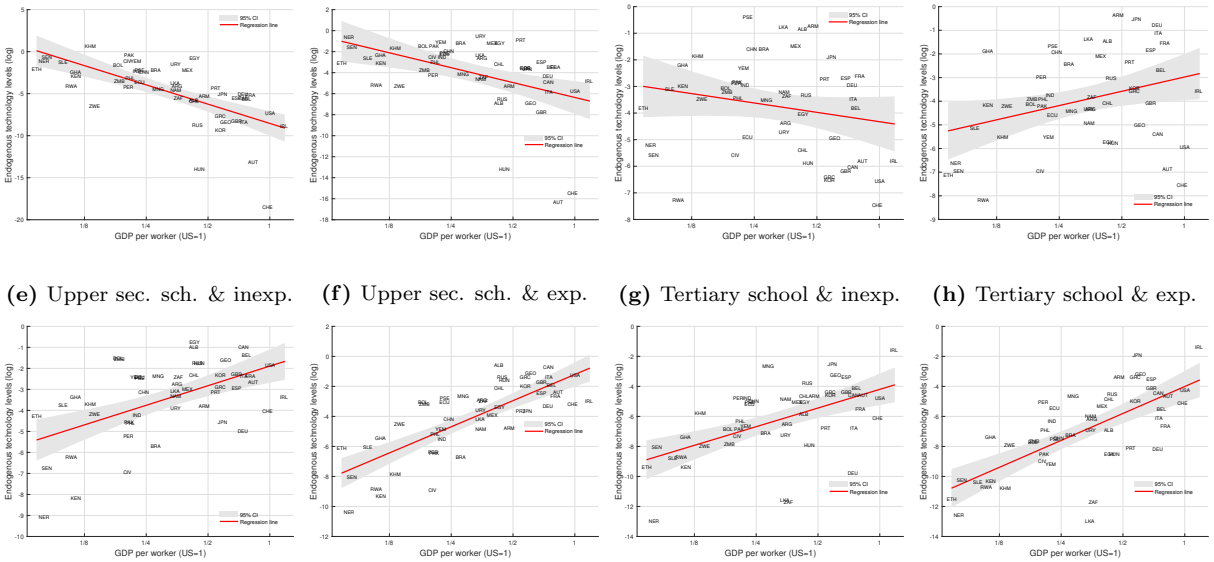


Notes: Each panel represents the logarithm of inferred endogenous technology $B^c_{s,j}$ for country c in skill group s and occupation j = *machine and plant operators* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.14: Endogenous productivity, B: craft and related trade

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.

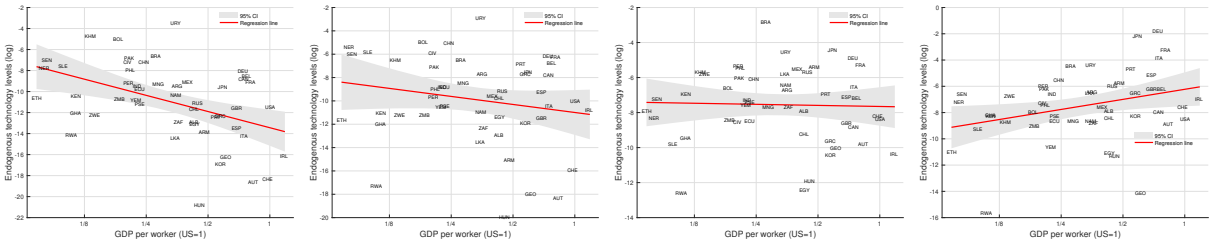
(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



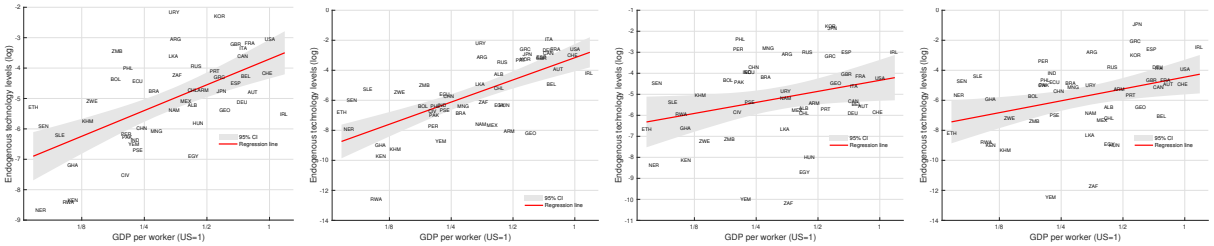
Notes: Each panel represents the logarithm of inferred endogenous technology $B^c_{s,j}$ for country c in skill group s and occupation j = *craft and related trade* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.15: Endogenous productivity, B: clerks

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.



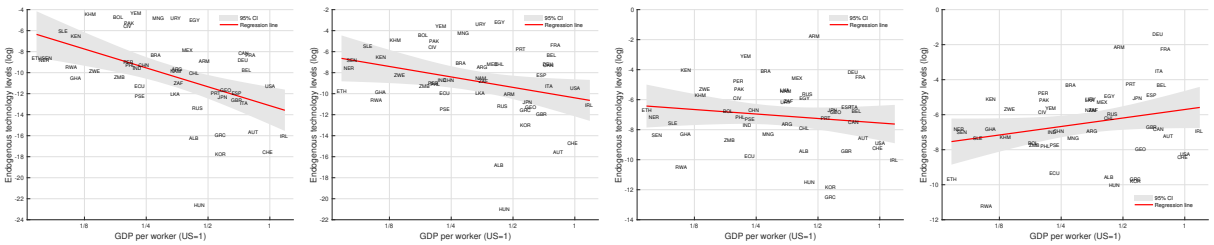
(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



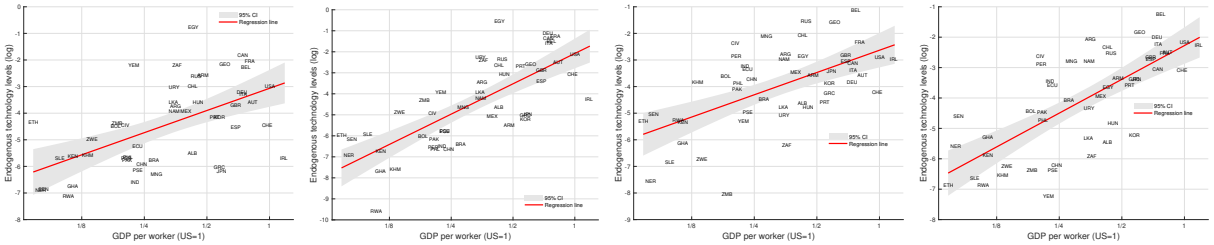
Notes: Each panel represents the logarithm of inferred endogenous technology $B^c_{s,j}$ for country c in skill group s and occupation j = *clerks* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.16: Endogenous productivity, B: technicians and associate professionals

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.



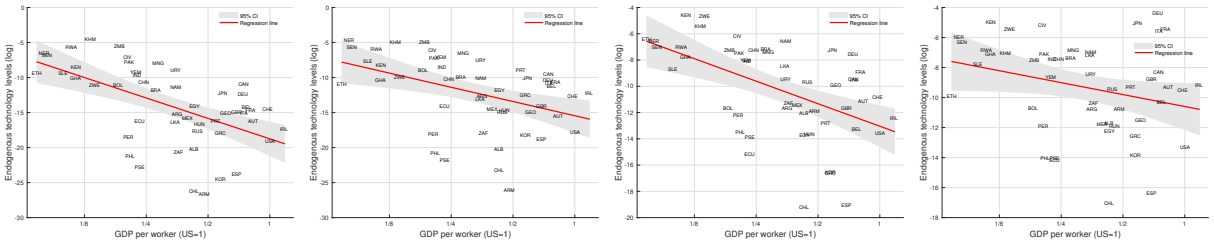
(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



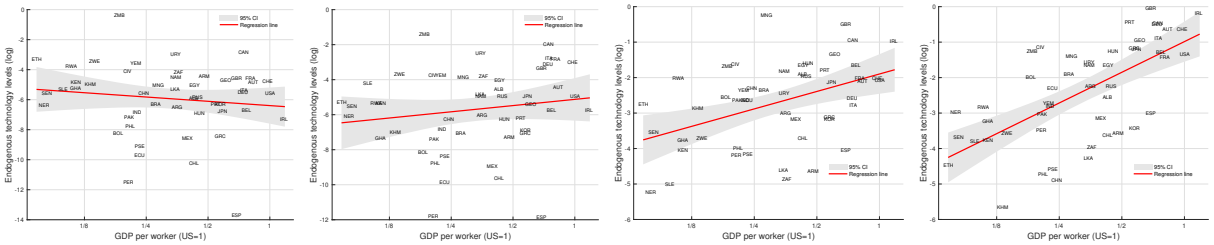
Notes: Each panel represents the logarithm of inferred endogenous technology $B^c_{s,j}$ for country c in skill group s and occupation j = *technicians and associate professionals* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.17: Endogenous productivity, B: professionals

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.



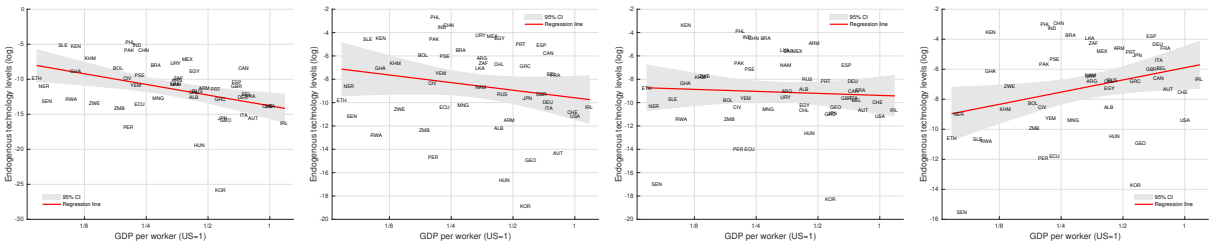
(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



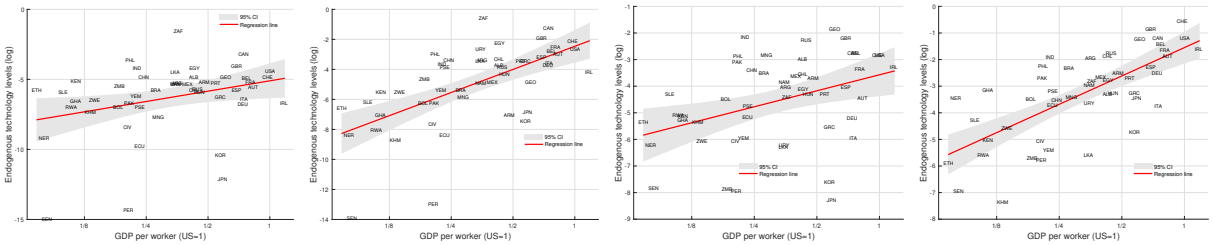
Notes: Each panel represents the logarithm of inferred endogenous technology $B^c_{s,j}$ for country c in skill group s and occupation j = *professionals* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.18: Endogenous productivity, B: managers

(a) Primary school & inexp. **(b)** Primary school & exp. **(c)** Lower sec. sch. & inexp. **(d)** Lower sec. sch. & exp.



(e) Upper sec. sch. & inexp. **(f)** Upper sec. sch. & exp. **(g)** Tertiary school & inexp. **(h)** Tertiary school & exp.



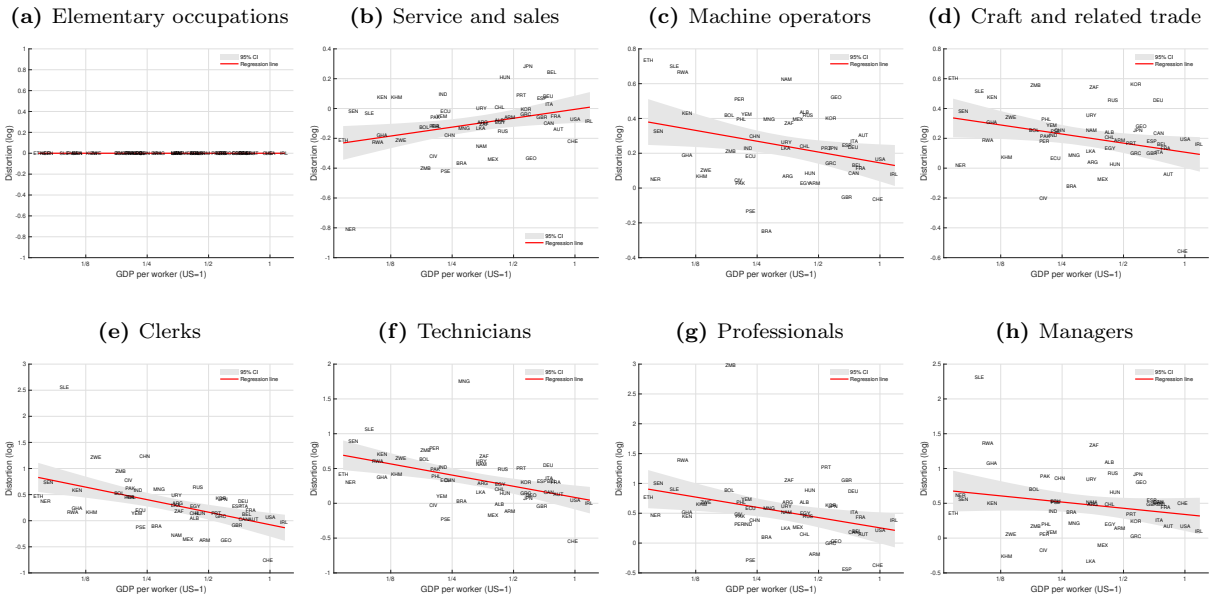
Notes: Each panel represents the logarithm of inferred endogenous technology $B^c_{s,j}$ for country c in skill group s and occupation j = *managers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.19: Distortions, D: primary school and inexperienced



Notes: Each panel represents the logarithm of inferred distortion $D^c_{s,j}$ for country c in occupation j and skill group s = *primary school and inexperienced workers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

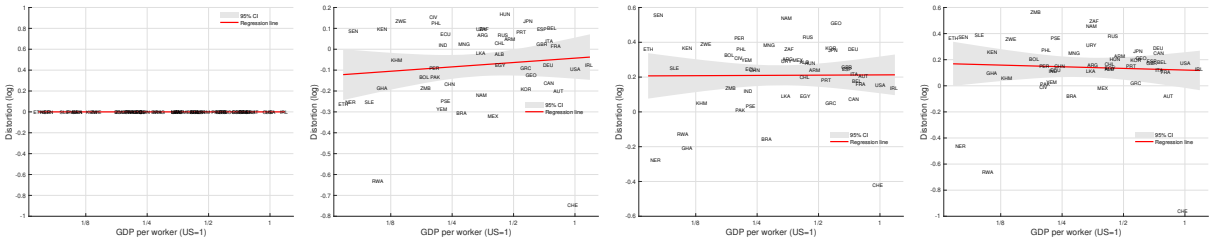
Figure E.20: Distortions, D: primary school and experienced



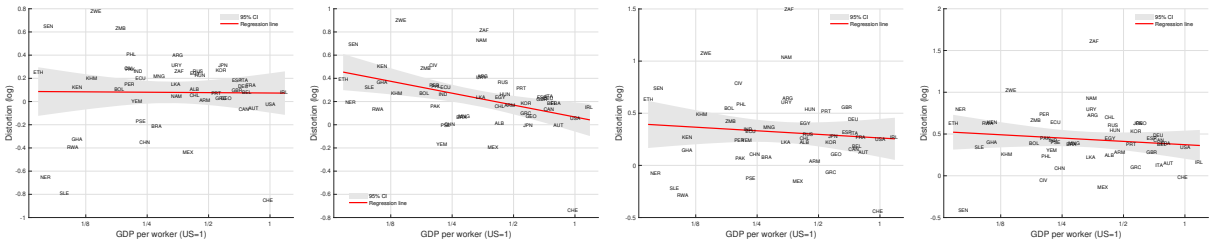
Notes: Each panel represents the logarithm of inferred distortion $D^c_{s,j}$ for country c in occupation j and skill group s = *primary school and experienced workers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.21: Distortions, D: lower secondary school and inexperienced

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



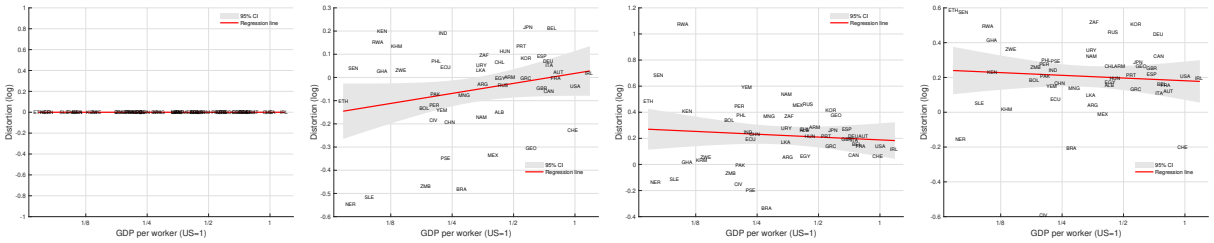
(e) Clerks **(f)** Technicians **(g)** Professionals **(h)** Managers



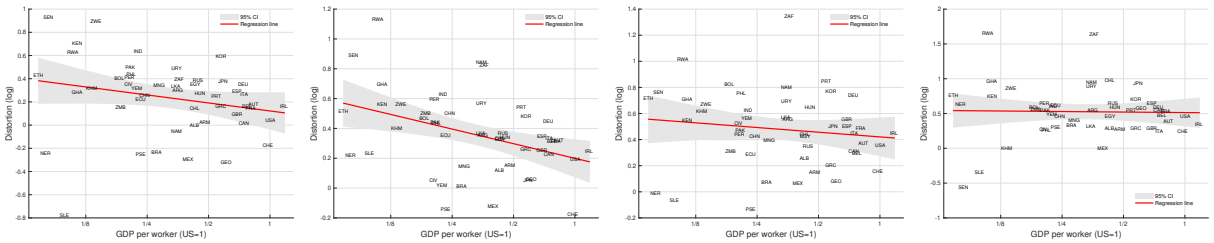
Notes: Each panel represents the logarithm of inferred distortion $D^c_{s,j}$ for country c in occupation j and skill group s = *lower secondary school and inexperienced workers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.22: Distortions, D: lower secondary school and experienced

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



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



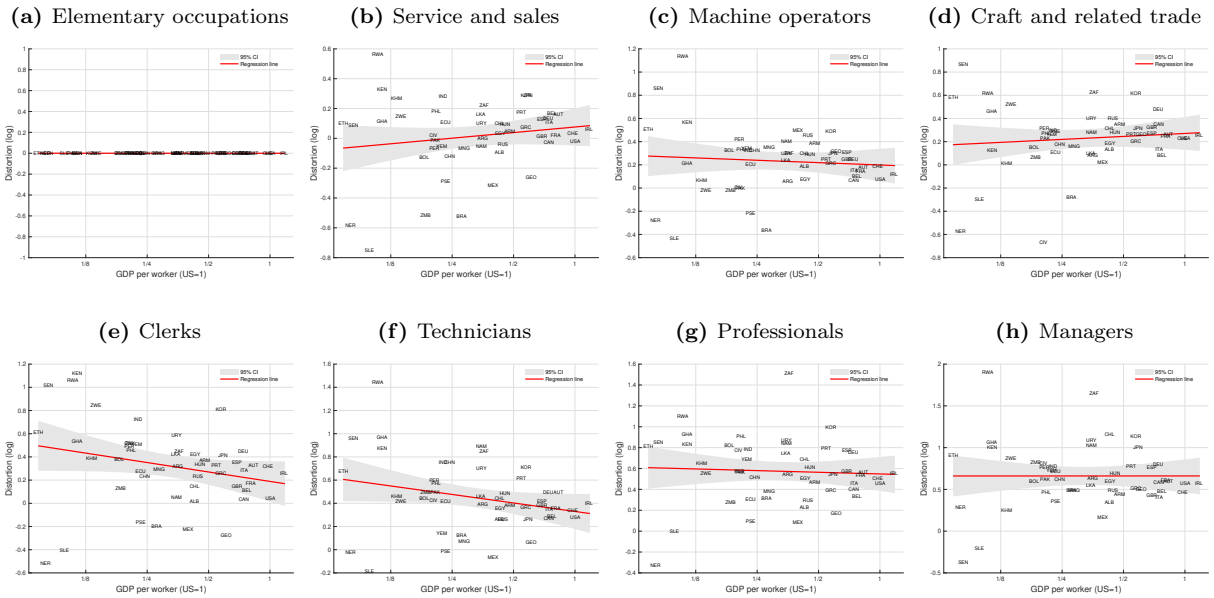
Notes: Each panel represents the logarithm of inferred distortion $D^c_{s,j}$ for country c in occupation j and skill group s = *lower secondary school and experienced workers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.23: Distortions, D: upper secondary school and inexperienced



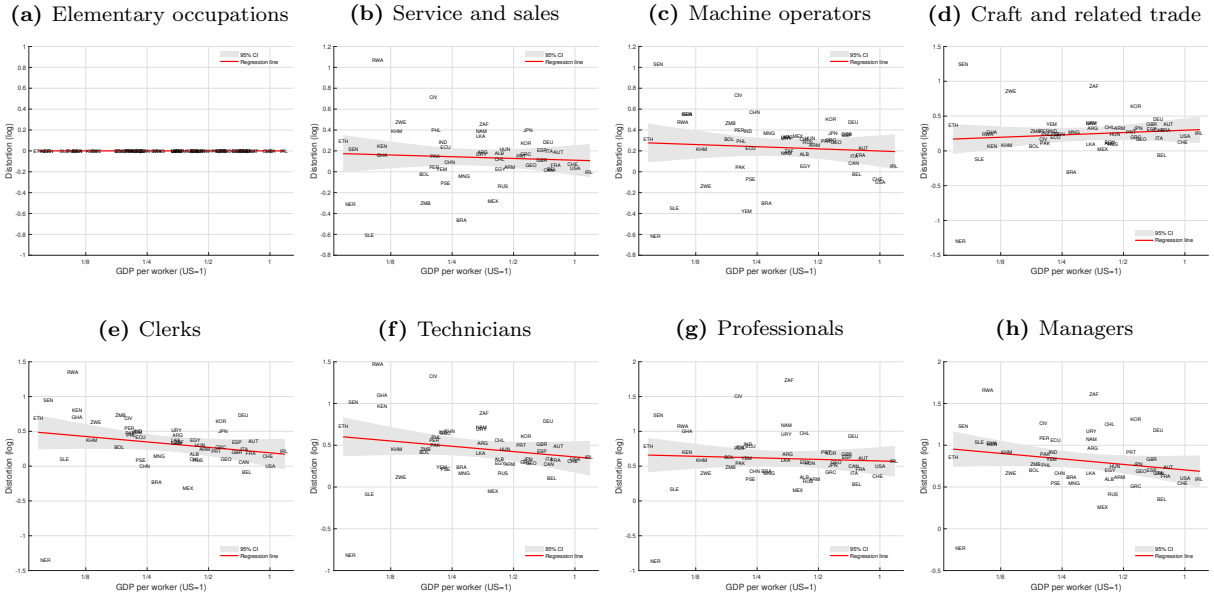
Notes: Each panel represents the logarithm of inferred distortion $D^c_{s,j}$ for country c in occupation j and skill group s = *upper secondary school and inexperienced workers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.24: Distortions, D: upper secondary school and experienced



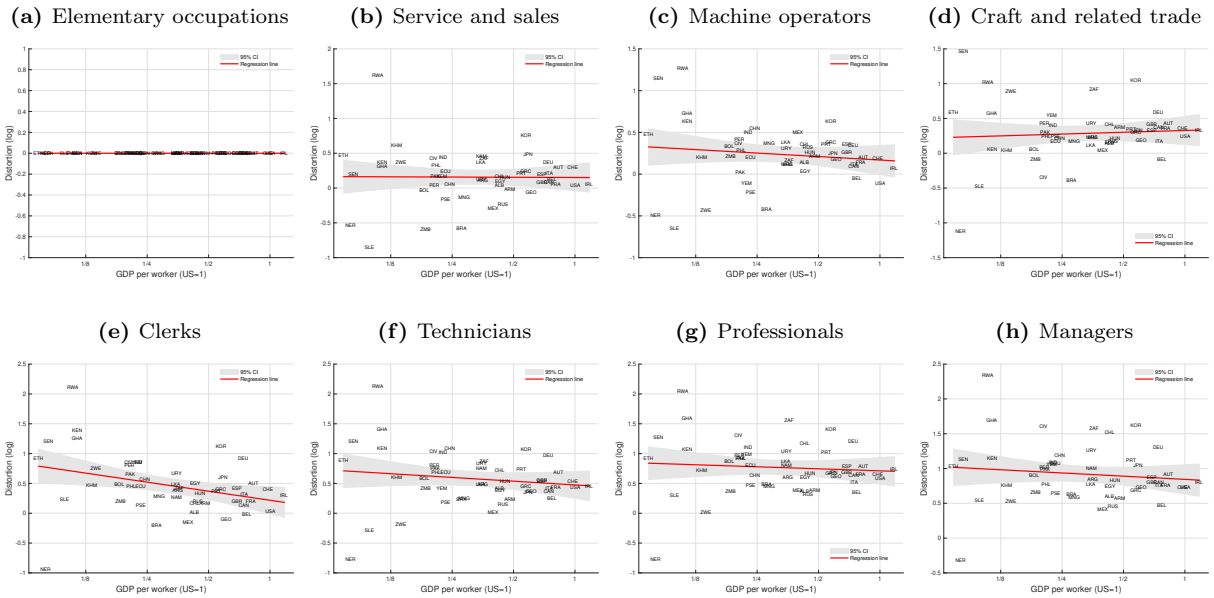
Notes: Each panel represents the logarithm of inferred distortion $D^c_{s,j}$ for country c in occupation j and skill group s = *upper secondary school and experienced workers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.25: Distortions, D: tertiary school and inexperienced



Notes: Each panel represents the logarithm of inferred distortion $D^c_{s,j}$ for country c in occupation j and skill group s = *tertiary school and inexperienced workers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

Figure E.26: Distortions, D: tertiary school and experienced



Notes: Each panel represents the logarithm of inferred distortion $D^c_{s,j}$ for country c in occupation j and skill group s = *tertiary school and experienced workers* against non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a linear regression. The grey area represents 95% confidence intervals.

F Additional counterfactual results

F.1 Decomposition of aggregate statistics by counterfactual type

Tables F.4-F.8 complement Tables 10-12 in the main text by reporting, for each counterfactual separately, the contribution of the various endowments to differences in GDP, white-collar employment, and the relative wage of white-collar to blue-collar workers.

Table F.4: Contribution to output-per-worker gap relative to the US

(a) Counterfactual 1

	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
Human capital, H	-0.96	-0.81	-0.51	-0.37	-0.36	-0.60	43	53	49	58	200	53
Price of capital, R	-0.16	-0.19	-0.19	-0.16	-0.02	-0.14	7	12	18	25	13	13
Productivity, A	-0.88	-0.60	-0.30	-0.20	0.07	-0.38	39	39	28	31	-41	34
Distortions, D	-0.05	-0.04	-0.04	0.00	0.00	-0.02	2	3	4	-0	-2	2
Covariance	-0.18	0.09	-0.01	0.09	0.12	0.02	8	-6	1	-14	-70	-2

(b) Counterfactual 2

	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
Human capital, H	-1.10	-0.69	-0.50	-0.28	-0.23	-0.56	49	45	48	44	130	50
Price of capital, R	-0.22	-0.23	-0.22	-0.16	-0.02	-0.17	10	15	21	26	13	15
Productivity, A	-1.01	-0.49	-0.30	-0.10	0.20	-0.34	45	32	28	16	-111	30
Distortions, D	-0.05	-0.03	-0.03	-0.00	0.00	-0.02	2	2	3	0	-1	2
Covariance	0.15	-0.10	0.00	-0.09	-0.12	-0.03	-7	6	-0	14	69	3

Notes. The lines "total gap" in both panels of the table report the arithmetic average logarithmic difference in output per worker between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining lines report counterfactuals. In panel (a), the gaps are between country c and its counterfactual with one US endowment at a time. In panel (b), the gaps are between a counterfactual US with one country c endowment at a time and the US itself. The bar "covariates" captures all remaining differences between the empirical gap and the sum of counterfactual gaps, as described in (24) and (25). The right part of the table reports the contribution of each counterfactual as a percent share of the total gap, for each quintile separately as well as for all countries together. The counterfactuals (including the covariance term) sum to 100 in each panel.

F.2 Counterfactual impact by individual countries

In this section we depict, for each country, the counterfactuals for all aggregate statistics of interest. Figure F.27 shows the change in GDP associated with shifting to US endowments. Panel (a) replicates Figure 7 in the main text whereas the other panels portray changes associated with adopting US prices of equipment, productivity, and distortions, respectively. Changes in productivity and human capital produce similar cross-country patterns and magnitudes. A shift to US distortions in panel (d) also produces a similar pattern, but at much smaller magnitudes: the GDP increase for the poorest countries is about 6% (counterfactual 1). Adopting the US price of equipment, on the other hand, produces a hump-shape pattern: countries in the middle of the distribution stand most to gain from lowering their price of equipment.

Figures F.28-F.29 reports changes in the white-collar employment share as well as in the average wage of white-collar to blue-collar workers associated with adopting US endowments. We focus the discussion on human capital and distortions. Adopting US human capital leads to a 17-percentage points increase in white-collar employment in the poorest countries (counterfactual 1). Endowing the poorest countries with US human capital also leads to a drop of 26% in the white-collar relative wage. Higher levels of human capital prompt a shift toward white-collar employment, which subsequently dampens the wage

Table F.6: Contribution to white-collar employment gap relative to the US

(a) Counterfactual 1

	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
Human capital, H	-0.71	-0.35	-0.21	-0.08	-0.03	-0.28	50	39	34	26	44	42
Price of capital, R	-0.06	-0.08	-0.06	-0.06	-0.01	-0.05	4	9	9	20	8	8
Productivity, A	-0.74	-0.52	-0.33	-0.19	-0.02	-0.36	52	58	53	65	27	54
Distortions, D	-0.39	-0.18	-0.13	-0.01	-0.02	-0.15	28	20	20	4	23	22
Covariance	0.48	0.24	0.10	0.04	0.00	0.17	-34	-26	-17	-15	-2	-26

(b) Counterfactual 2

	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
Human capital, H	-0.26	-0.18	-0.13	-0.06	-0.03	-0.13	18	20	21	19	45	20
Price of capital, R	-0.04	-0.04	-0.04	-0.03	-0.00	-0.03	3	5	6	11	6	5
Productivity, A	-0.47	-0.39	-0.27	-0.16	-0.03	-0.26	33	43	43	53	38	40
Distortions, D	-0.09	-0.09	-0.08	-0.01	-0.01	-0.05	6	9	12	4	13	8
Covariance	-0.57	-0.21	-0.11	-0.04	0.00	-0.18	40	23	17	14	-2	28

Notes. The lines "total gap" in both panels of the table report the arithmetic average logarithmic difference in the white-collar employment share between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining lines report counterfactuals. In panel (a), the gaps are between country c and its counterfactual with one US endowment at a time. In panel (b), the gaps are between a counterfactual US with one country c endowment at a time and the US itself. The bar "covariates" captures all remaining differences between the empirical gap and the sum of counterfactual gaps, as described in (24) and (25). The right part of the table reports the contribution of each counterfactual as a percent share of the total gap, for each quintile separately as well as for all countries together. The counterfactuals (including the covariance term) sum to 100 in each panel.

Table F.8: Contribution to white-to-blue-collar wage ratio gap relative to the US

(a) Counterfactual 1

	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
Human capital, H	0.28	0.12	0.09	-0.04	-0.12	0.06	68	64	56	39	126	58
Price of capital, R	-0.02	-0.02	-0.03	-0.01	-0.00	-0.01	-4	-8	-16	13	2	-13
Productivity, A	-0.10	-0.16	-0.06	-0.08	-0.01	-0.08	-25	-87	-38	81	14	-74
Distortions, D	0.38	0.18	0.16	0.02	0.03	0.16	92	101	101	-24	-31	139
Covariance	-0.13	0.05	-0.00	0.01	0.01	-0.01	-31	30	-3	-10	-11	-10

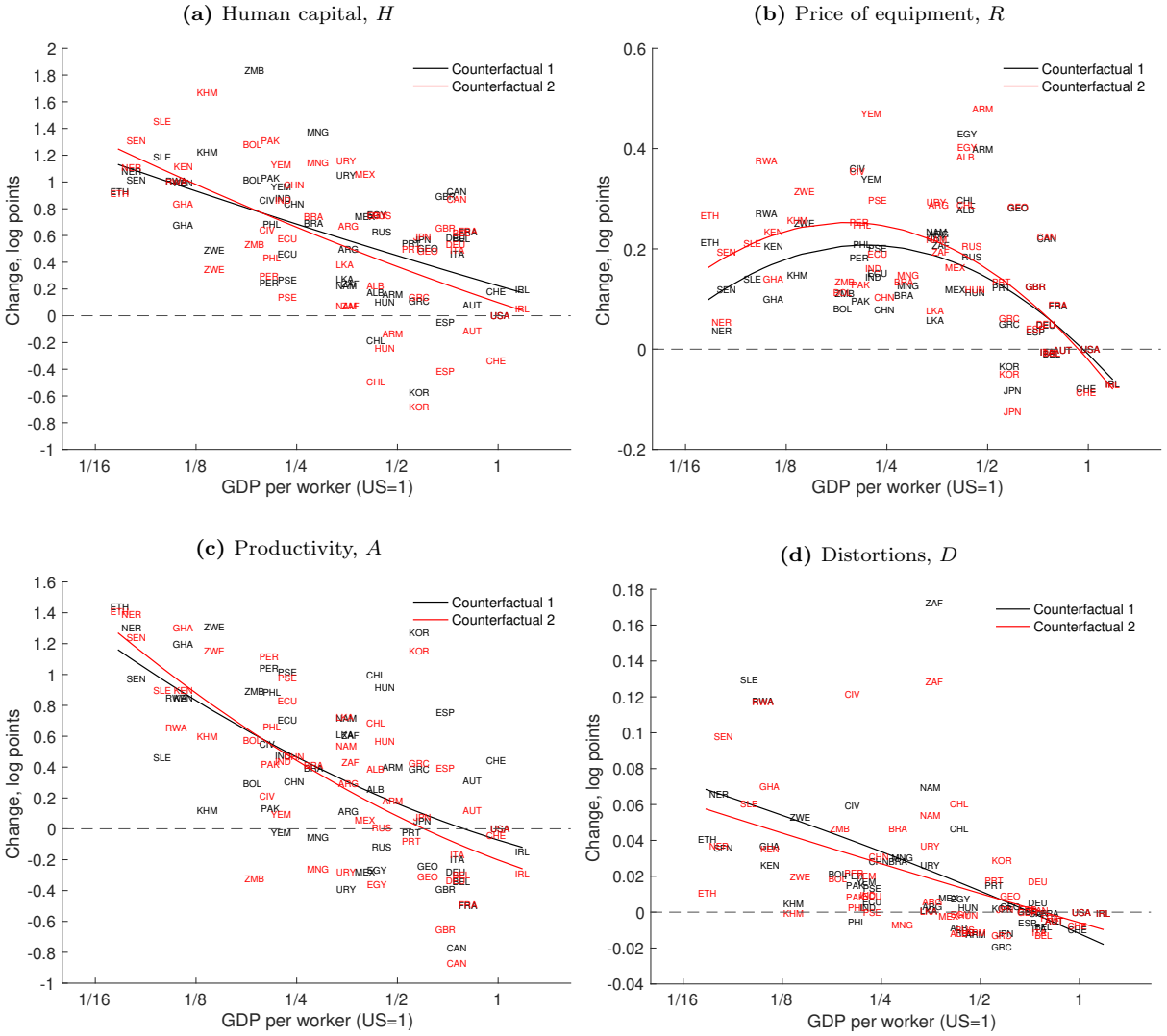
(b) Counterfactual 2

	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
Human capital, H	0.06	0.17	0.10	-0.03	-0.11	0.04	16	94	59	28	116	34
Price of capital, R	-0.02	-0.03	-0.02	-0.02	-0.00	-0.02	-6	-14	-15	19	3	-17
Productivity, A	-0.03	-0.03	-0.04	-0.05	0.01	-0.03	-7	-18	-24	57	-15	-25
Distortions, D	0.15	0.14	0.12	0.02	0.02	0.09	36	79	75	-24	-19	81
Covariance	0.25	-0.07	0.01	-0.02	-0.02	0.03	61	-40	5	19	16	27

Notes. The lines "total gap" in both panels of the table report the arithmetic average logarithmic difference in the ratio of average white-collar to blue-collar average wages between countries in various income quintiles, ordered by non-agricultural GDP per worker, and the US. The remaining lines report counterfactuals. In panel (a), the gaps are between country c and its counterfactual with one US endowment at a time. In panel (b), the gaps are between a counterfactual US with one country c endowment at a time and the US itself. The bar "covariates" captures all remaining differences between the empirical gap and the sum of counterfactual gaps, as described in (24) and (25). The right part of the table reports the contribution of each counterfactual as a percent share of the total gap, for each quintile separately as well as for all countries together. The counterfactuals (including the covariance term) sum to 100 in each panel.

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 decline is smaller,

Figure F.27: GDP change after adoption of US endowment

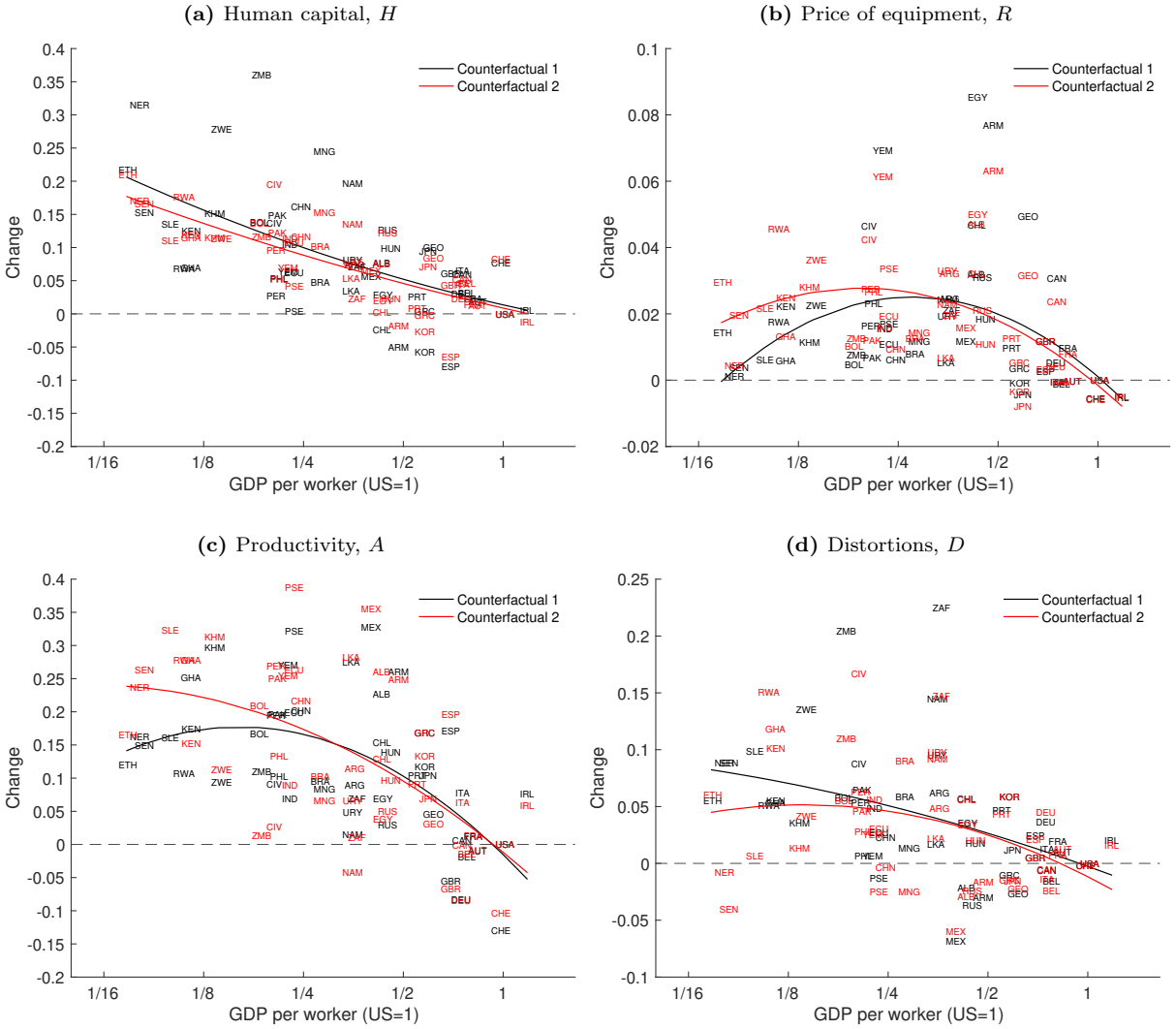


Notes: In panel (a), the y-axis plots the logarithmic difference in output between a counterfactual economy and the baseline. "Counterfactual 1" consists of country c endowed with US human capital (skill group composition and skill quality) relative to the empirical country c. "Counterfactual 2" consists of the empirical US relative to a US endowed with the human capital of country c. The x-axis is non-agricultural GDP per worker, normalized to the US. The line of best fit is based on a regression with linear and quadratic terms. Panels (b)-(d) are analogous while varying different endowments: the price of capital R, the vector of productivity A, and the matrix of distortions, D, respectively.

12%.

We also see that distortions play a prominent role in shaping white-collar employment and relative wages. Most countries feature distortions that lower white-collar employment relative to the US. The distortion-driven difference in white-collar employment between the US and the poorest countries ranges between 8 (counterfactual 1) and 5 (counterfactual 2) percentage points. Occupational distortions also have a particularly large impact on the cross-country variation in the white-collar wage premium. Endowing the poorest countries with US distortions decreases the white-collar relative wage by 31%, as seen from the first counterfactual in panel (d) of Figure F.29. For the US itself, switching away from low-income distortions decreases the relative white-collar wage by 14%. 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 those occupations.

Figure F.28: White-collar employment share change after adoption of US endowment



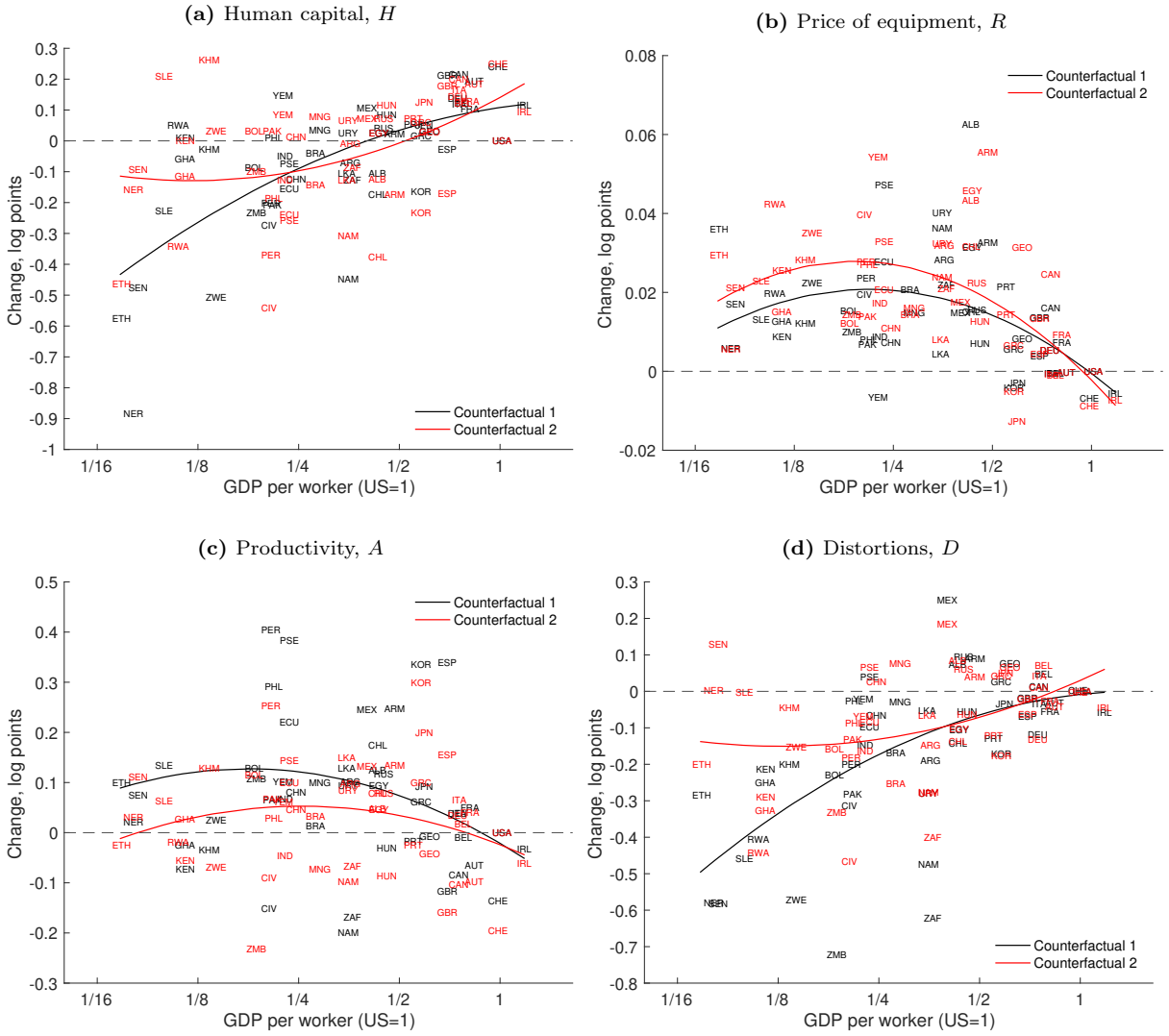
Notes: In panel (a), the y-axis plots the logarithmic difference in the white-collar employment share between a counterfactual economy and the baseline. "Counterfactual 1" consists of country c endowed with US human capital (skill group composition and skill quality) relative to the empirical country c. "Counterfactual 2" consists of the empirical US relative to a US endowed with the human capital of country c. The x-axis is non-agricultural GDP per worker, normalized to the US. The line of best fit is based on a regression with linear and quadratic terms. Panels (b)-(d) are analogous while varying different endowments: the price of capital R, the vector of productivity A, and the matrix of distortions, D, respectively.

F.3 Impact of human capital on employment shares and wages

We complement the findings in the previous section by reporting more detailed changes in employment shares and wages associated with adopting US human capital. For concision, we group countries by quintiles according to non-agricultural GDP per worker. The left panel of Figure F.30 shows the change in the 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 F.30. In all country groups, employment shifts from blue-collar to white-collar work. Among blue-collar occupations, there is a particularly strong decline in Services & Sales as well as in Craft & Trade. Among white-collar occupations, the increase is strongest amongst Professionals.

Next, Figure F.31 portrays the change in average wages by human capital group (left panel) and by occupation (right panel). All country income groups see wages increase in all categories. For the

Figure F.29: White-collar to blue-collar average wage change after adoption of US endowment



Notes: In panel (a), the y-axis plots the logarithmic difference in the ratio of average white-collar to blue-collar wages between a counterfactual economy and the baseline. "Counterfactual 1" consists of country c endowed with US human capital (skill group composition and skill quality) relative to the empirical country c. "Counterfactual 2" consists of the empirical US relative to a US endowed with the human capital of country c. The x-axis is non-agricultural GDP per worker, normalized to the US. The line of best fit is based on a regression with linear and quadratic terms. Panels (b)-(d) are analogous while varying different endowments: the price of capital R, the vector of productivity A, and the matrix of distortions, D, respectively.

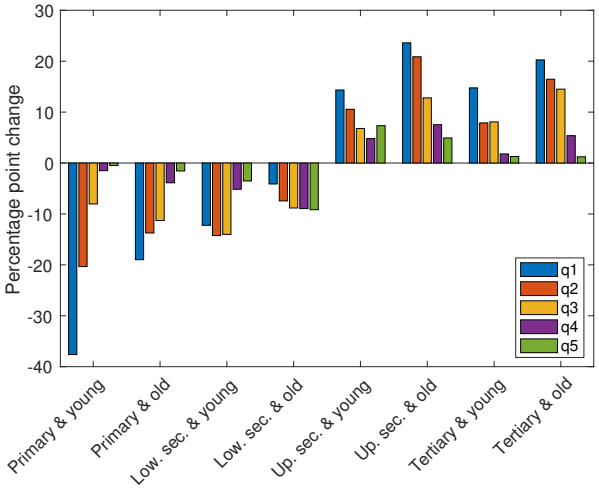
poorest countries, wages increase most strongly for primary-school educated workers and for Service & Sales occupations.

F.4 Composition of skill groups

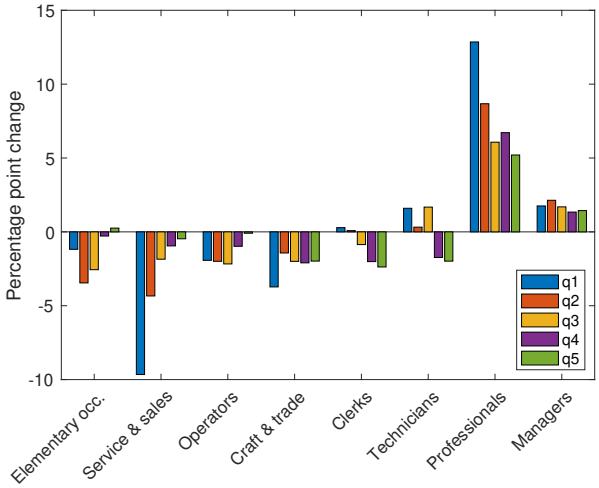
In Figure F.32 we focus only on the skill group composition and keep skill quality unaltered. The left panel shows experiments of endowing countries with the US education composition while keeping the experience composition constant. Analogously, in the right panel we vary the age composition while keeping that of education constant. Clearly, education matters substantially more than experience. For the poorest countries, counterfactual 1 reveals that adopting only the US educational composition raises output by 31% while adopting only the US experience composition raises output by 4%.

Figure F.30

(a) Change in skill group composition



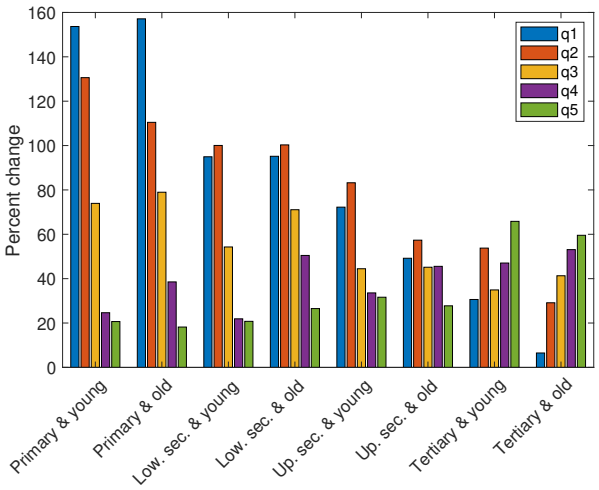
(b) Change in occupational composition



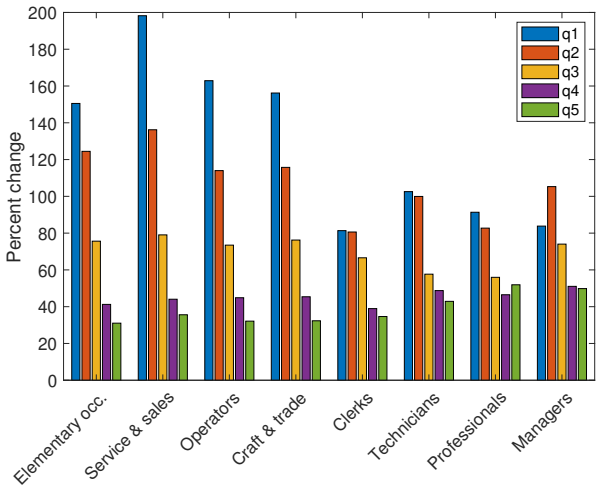
Notes: Each bar represents the arithmetic average percentage point change over quintiles of countries, ordered by non-agricultural GDP per worker. The left panel shows the change in the hourly employment share of skill groups between the US and various countries. The right panel shows the change in the hourly employment share of occupations between counterfactual countries with US human capital and the countries themselves.

Figure F.31

(a) Change in average wages by human capital



(b) Change in average wages by occupation

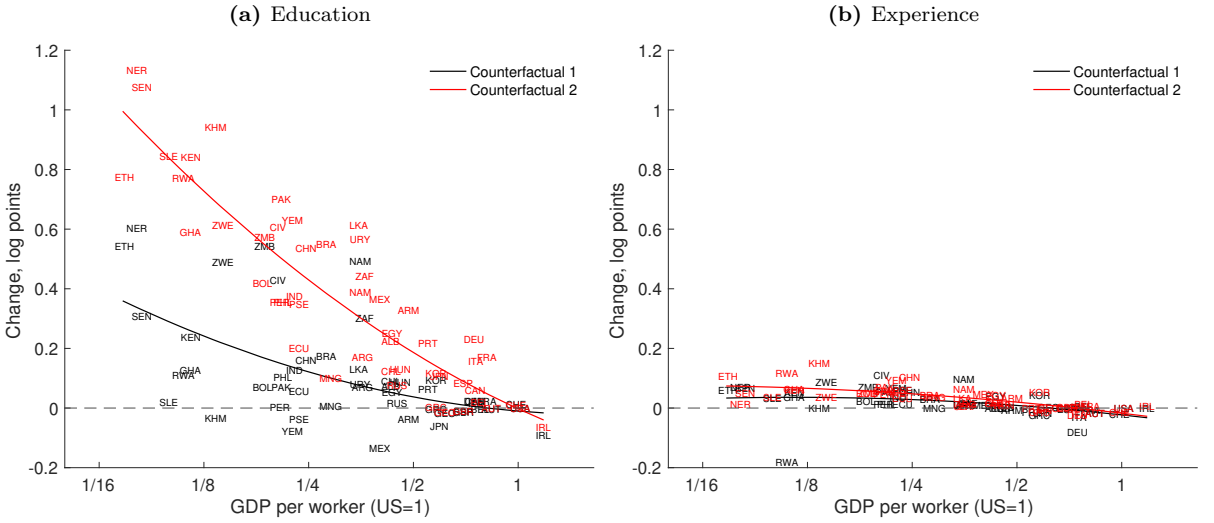


Notes: Each bar represents the average percent change over quintiles of countries, ordered by non-agricultural GDP per worker. The left panel shows the change in the hourly average wage of skill groups between counterfactual countries with US human capital and the countries themselves. The right panel is analogous and shows the change in the hourly average wage of occupations. In both cases, we first compute the average logarithmic change for each country by (skill or occupation) group, and then compute the arithmetic average of the logarithmic differences over quintiles of countries.

F.5 Counterfactual human capital and endogenous technology

Here we recompute the endogenous technology terms B_{sj} under the two counterfactuals of either (i) endowing all countries with the US human capital or (ii) endowing the US with the human capital of other countries. We then regress the resulting endogenous technology B_{sj} on GDP per worker and present the elasticities in Table F.10.

Figure F.32: GDP change after adoption of either US education or experience composition



Notes: The y-axis plots the logarithmic difference in output between a counterfactual economy and the baseline. In the left panel, "Counterfactual 1" consists of country c endowed with the US educational composition L_{edu} relative to the empirical country c. We construct this by imposing the US relative educational composition within each country's experience group. "Counterfactual 2" consists of the empirical US relative to a US endowed with the educational composition L_{edu} of country c. In the right panel, the counterfactuals are analogous only that we vary the experience composition while holding fixed the educational composition. The x-axis is non-agricultural GDP per worker, normalized to the US. The lines of best fit are based on a regression with linear and quadratic terms.

Consider first the upper part of Table F.10 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 the lower part of F.10 to the original Table 8. We see that when all countries are identical in all endowments *except* for human capital, the specialization pattern becomes even starker. In that scenario, economies with a higher share of educated and experienced workers would specialize technology even more toward those groups.

Table F.10: Elasticity of endogenous technology, B, with respect to GDP

(a) Counterfactual 1

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

(b) Counterfactual 2

	Elem.	Services	Operators	Craft	Clerks	Techn.	Profess.	Managers
Primary & inexp.	-2.74	-3.53	-3.16	-3.14	-4.02	-4.28	-5.24	-4.84
Primary & exp.	-1.34	-2.11	-1.75	-1.74	-2.60	-2.85	-3.79	-3.40
Lower secondary & inexp.	-0.32	-1.08	-0.72	-0.70	-1.55	-1.80	-2.73	-2.34
Lower secondary & exp.	1.03	0.30	0.64	0.66	-0.16	-0.41	-1.30	-0.93
Upper secondary & inexp.	1.41	0.65	1.01	1.02	0.17	-0.08	-1.00	-0.62
Upper secondary & exp.	2.44	1.69	2.04	2.06	1.22	0.98	0.07	0.45
Tertiary & inexp.	2.22	1.50	1.84	1.85	1.04	0.80	-0.08	0.28
Tertiary & exp.	2.76	2.04	2.38	2.4	1.60	1.36	0.49	0.85

Notes. In both sub-tables, each number represents, separately for each skill group and occupation, the estimated coefficient $\hat{\beta}^B_{s,j}$ from the cross-country linear regression of the inferred counterfactual endogenous productivity $\log B_{s,j}$ on the log of non-agricultural GDP per worker. The first counterfactual in the upper part is based on endowing all countries the US human capital. The second counterfactual in the lower part is based on endowing all countries with all US endowments except for its human capital.