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DISCUSSION PAPER SERIES

IZA DP No. 16938

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ABSTRACT

Meritocracy across Countries*

Are labor markets in higher-income countries more meritocratic, in the sense that worker-job matching is based on skills rather than idiosyncratic attributes unrelated to productivity? If so, why? And what are the aggregate consequences? Using internationally comparable data on worker skills and job skill requirements of over 120,000 individuals across 28 countries, we document that workers' skills better match their jobs' skill requirements in higher-income countries. To quantify the role of worker-job matching in development accounting, we build an equilibrium matching model that allows for cross-country differences in three fundamentals: (i) the endowments of multidimensional worker skills and job skill requirements, which determine match feasibility; (ii) technology, which determines the returns to matching; and (iii) idiosyncratic matching frictions, which capture the role of nonproductive worker and job traits in the matching process. The estimated model delivers two key insights. First, improvements in worker-job matching due to reduced matching frictions account for only a small share of cross-country income differences. Second, however, improved worker-job matching is crucial for unlocking the gains from economic development generated by adopting frontier endowments and technology.

JEL Classification: C78, E24, J24, J31, O11, O12

Keywords: skills, sorting, matching, multidimensional heterogeneity, development accounting, wage inequality, gender, migration

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1 Introduction

Economic development goes hand in hand with a division of labor into increasingly specialized jobs. This process can lead to large productivity gains because it allows individuals to utilize their skills in jobs that require them. To realize these gains, the labor market must be meritocratic, in the sense that workers match with jobs based on skills to maximize output rather than based on idiosyncratic attributes unrelated to productivity.[1] The connection between meritocracy in the labor market and economic development prompts us to ask: Are workers better matched to jobs in higher-income countries? If so, why? And do differences in worker-job matching explain cross-country income differences?

To address these questions, we use microdata on worker skills and job skill requirements together with an equilibrium model to quantify the role of worker-job matching in economic development. Our approach integrates tools from the theory of matching (Becker, 1973; Choo and Siow, 2006) under multidimensional skill heterogeneity (Lindenlaub, 2017; Lindenlaub and Postel-Vinay, 2023) into a development accounting framework (Hall and Jones, 1999; Hsieh and Klenow, 2010). In doing so, we innovate on micro-level analyses of worker-job matching by assessing the aggregate consequences of mismatch across a large set of countries along the development spectrum. We also innovate on macro-level analyses of development accounting by modeling workers and jobs as heterogeneous production inputs whose sorting pattern affects output and wages.

Central to our analysis are internationally comparable microdata from the Programme for the International Assessment of Adult Competencies (PIAAC), a representative sample of over 120,000 working-age individuals across 28 middle- and high-income countries. A unique feature of these data is that they test worker skills and elicit job skill requirements along multiple dimensions, including numeracy and literacy. The former circumvents the long-standing issue of the incomparable quality of education in research on economic development (Barro and Lee, 2013; Martellini et al., 2023). The latter allows us to dispense with the assumption that different countries have the same job-level skill requirements (Atencio-De-Leon et al., 2023; Caunedo et al., 2023). We exploit this rich information to empirically study worker-job matching across countries and to inform an equilibrium model of the labor market, which we separately estimate for each of the 28 countries in our data. We use the estimated model for development accounting by linking worker-job matching patterns at the micro level to differences in countries' aggregate output and wage structure at the macro level.

Our analysis proceeds in three steps. In the first, we document several facts about worker-job matching across countries. Our central starting observation is that in high-income countries, there is more skill-based sorting along both the intensive margin—i.e., workers' skills are more aligned with their jobs' skill requirements—and the extensive margin—i.e., employed workers are more positively selected on skills. We focus on three mechanisms that underlie the relationship between

[1] The notion of meritocracy has an extensive tradition in political philosophy and the social sciences (Arrow et al., 2000; Sen, 2000). The idea of selecting the best men to run the State goes as far back as Confucius, circa 551 BC, in the East and Plato, circa 428 BC, in the West (Mulligan, 2023).

worker-job matching and economic development. The first mechanism focuses on endowments of worker skills and job skill requirements, which determine match feasibility. The similarity between two-sided endowments governs the potential share of matches in which worker skills are aligned with job skill requirements. The second mechanism pertains to technology—broadly defined to include not only machinery and equipment but also management practices and the organization of labor—which shapes the wage returns to worker-job matches. If technology features greater complementarities between certain worker skills and certain job skill requirements, there are stronger incentives to sort along these dimensions. The third mechanism relates to idiosyncratic matching frictions, which guide the relative importance of workers' and jobs' unproductive traits in the matching process. These include social networks, family ties and wealth, and attributes that are discriminated against at the hiring stage.[2] A key advantage of using comparable microdata from several countries is that we can use residual wage dispersion conditional on worker skills and job skill requirements to identify country-specific deviations from the law of one price and, thus, matching frictions. We find that all three mechanisms favor greater meritocracy in the form of skill-based sorting of workers across jobs in higher-income countries.

The empirical relation between worker-job matching and national income is an equilibrium outcome and causality may go in either direction. In the spirit of development accounting, we quantify the contribution of the three mechanisms that underlie this relation. To this end, in the second step of our analysis, we develop an equilibrium model of worker-job matching that allows us to bridge micro evidence with macro implications.

In the model, each country's labor market is characterized by three fundamentals: the endowments of worker skills and job skill requirements, technology, and idiosyncratic matching frictions. In a given country, workers who differ in multidimensional skills and gender match with jobs that differ in multidimensional skill requirements and firm size to produce output. Workers may choose to remain nonemployed and jobs may choose to remain idle. Worker-job matching maximizes total match surplus, which is competitively split into workers' wages and jobs' profits. Importantly, total match surplus consists of the sum of match output, determined by the productive attributes of workers and jobs, and idiosyncratic factors unrelated to productivity. We refer to the latter as "frictions" in the sense that they lead to deviations from the output-maximizing worker-job allocation, though we attach no normative meaning to them. The importance of these frictions is guided by a country-specific dispersion parameter of idiosyncratic matching wedges that enter total match surplus.

Our model allows us to formalize the notion of meritocracy as the degree to which workers with certain skills sort into jobs with certain skill requirements in an output-maximizing way. Accordingly, we define a country's *meritocracy index* as the ratio of actual to potential output, where the latter reflects a frictionless worker-job allocation. All three model fundamentals—endowments, technology, and idiosyncratic matching frictions—together determine a country's worker-job matching. The endowments of worker skills and job skill requirements determine

[2] See, for example, Bertrand and Schoar (2006), Beaman and Magruder (2012), and Spenkuch et al. (2023).

match feasibility. Technology determines the returns to a given worker-job match. Matching frictions guide the relative importance of workers' and jobs' idiosyncratic traits unrelated to productivity in the matching process. Through their effect on worker-job matching, these three fundamentals shape a country's aggregate outcomes, which includes their meritocracy index.

In the third step, we confront our model with the data to quantify the sources and consequences of cross-country differences in worker-job matching patterns. We start by pinning down the relative contributions of the three model fundamentals. To this end, we prove that all model parameters are identified based on the information contained in the PIAAC microdata. The main challenge is to separately identify a country's technology and matching frictions, since both affect the worker-job allocation and wages. Building on Salanié (2015), we solve this issue by showing that the extent of matching frictions in each country is identified based on residual wage dispersion conditional on worker skills and job skill requirements. Intuitively, through the lens of our model, this residual wage dispersion can be rationalized only through idiosyncratic matching frictions, which give rise to dispersion in total match surplus within a worker-job match type. Having pinned down the extent of matching frictions—and given that the distributions of workers' skills and jobs' skill requirements are directly identified based on the PIAAC microdata—a country's technology is then identified based on the observed sorting patterns between workers and jobs. To our knowledge, this is the first application to the labor market context that disentangles technology from matching frictions in this way.

We separately estimate the model for each of the 28 countries in our data by matching moments on worker-job sorting and residual wage dispersion that are informed by our identification argument. Our estimates suggest large cross-country differences in the three model fundamentals. Higher-income countries not only have more productive worker skills and job skill requirements but also better alignment between these two endowments. They also have stronger complementarities between worker skills and job skill requirements in production and, importantly, less severe matching frictions. The estimated model fits the data well in terms of targeted moments and accounts for a substantial share of the cross-country variation in untargeted features, including output per worker and wage inequality.

Based on the estimated model, we compute the meritocracy index—i.e., the ratio of actual to potential output—for each country to quantify the output losses from worker-job misallocation due to matching frictions. We find that matching frictions are important everywhere, in that the average country achieves roughly half its potential output. In line with our empirical evidence, the estimated model implies a positive relation between the meritocracy index and economic development. For instance, Norway—our sample's highest-income country—has a meritocracy index of 0.75, which is almost four times that of Ecuador—our lowest-income country. The empirical worker-job matching patterns, therefore, reflect greater misallocation in lower-income countries.

This observation leads us to ask: What are the sources of cross-country differences in worker-job misallocation, and what are the consequences for economic development? To provide answers, we use the estimated model for several counterfactuals, eliminating cross-country differences in one or more of the three fundamentals—endowments, technology, and matching frictions. We conduct a development accounting exercise that assesses how much a country's aggregate output and wage inequality would change if it had access to Norway's frontier fundamentals.

We find that differences in endowments and technology account for most of the variation in aggregate output across countries.[3] Giving all countries access to the same frontier technology reduces the cross-country variation in output per worker by 35 percent. In turn, if all countries had the same highly skilled workforce and jobs that demand those skills, the cross-country variation in output would be 25 percent lower. Jointly adopting the frontier endowments and technology explains the lion's share (i.e., 94 percent) of cross-country differences in output per worker, which suggests strong complementarities between different fundamentals in economic development. In contrast, idiosyncratic factors associated with deviations from the output-maximizing worker-job allocation play a relatively modest role. Assigning all countries the relatively low labor market frictions of the frontier country reduces cross-country income differences by only 6 percent. This reflects our first key finding: Improving the matching between workers and jobs by eliminating frictions yields limited benefits for lower-income countries where inferior skill endowments and technology constrain the returns to worker-job matching and potential output. Reducing frictions in these places merely shifts actual output closer to a *low* potential.

While these results show that differences in endowments and technology account for the bulk of economic development, this is not to say that improvements in worker-job matching—for example, due to more flexible labor laws or reduced nepotism in hiring—are unimportant. On the contrary, a large share (36 percent) of the gains from adopting frontier endowments and technology are realized through enhanced sorting. Improvements in worker-job matching thus constitute an important amplification channel for economic development, which is our second key finding. Altogether, our results suggest that meritocracy in the form of improved worker-job allocation is a consequence, rather than a source, of economic development. Our findings imply that policy interventions designed to increase the returns to skill-based sorting are more powerful than those designed to minimize idiosyncratic matching frictions in lower-income countries. Investments in technology may yield the highest payoffs, especially when including not only equipment and machinery but also management practices that affect firms' hiring strategies and human capital development (Bloom and Reenen, 2010; Aghion et al., 2021).

The estimated model also lends itself to accounting for differences in wage inequality across countries. Empirically, we find significantly higher wage inequality in lower-income countries. While counterfactual improvements in all three model fundamentals—endowments, technology, and matching frictions—tend to increase the meritocracy index everywhere, they each have very different effects on the distribution of wages within countries. Therefore, an increase in labor market meritocracy may or may not increase inequality, depending on its fundamental sources.

We end with two natural applications of our model. In the first one, we study the misallocation of worker skills by gender. Despite the universal increase in female labor force participation over

[3]While all three fundamentals might be jointly determined, we treat them as exogenous in our accounting exercise.

the past decades, there is still significant underutilization of women's skills, especially in low-income countries (Andrew et al., 2021; Ashraf et al., 2023). To study this issue, we counterfactually lower women's home production value—which captures supply- and demand-side factors that limit their participation—by setting it equal to that of men in each country. We find a large surge in female employment, particularly in less developed countries. However, because jobs are relatively scarce there, the rise in employment among women is offset by an almost one-for-one decline in employment among men. In contrast, if the number of jobs is allowed to adjust, we find large gains in overall employment rates and aggregate output.

In the second application, we study the effects of international labor market integration. The fact that income gains from migration can be large has been extensively documented (Borjas, 1999; Hendricks and Schoellman, 2018; Lagakos et al., 2018a; Dustmann and Preston, 2019). We complement these findings through equilibrium counterfactuals, in which we integrate the labor markets of countries in the same region or across the world. We find sizable gains in output per capita, ranging from 5 percent when allowing for regional migration to 11 percent when allowing for global migration. Importantly, these gains are entirely driven by improved worker-job allocation relative to our baseline with national labor markets.

To sum up, this paper advances our understanding of the role of matching workers to jobs in economic development. We study the micro sources and macro consequences of worker-job sorting in a set of countries with large income differences. To this end, we bring to development accounting a combination of rich microdata on worker skills and job skill requirements as well as tools from matching theory—which has predominantly been applied to advanced countries (Shimer, 2007; Lise et al., 2016; Bagger and Lentz, 2018; Hsieh et al., 2019; Lise and Postel-Vinay, 2020; Choné and Kramarz, 2024).[4] Previous accounts for cross-country income inequality have emphasized differences in human capital (Gennaioli et al., 2013; Jones, 2014; Lagakos et al., 2018b; Hendricks and Schoellman, 2018, 2023), physical capital (Young, 1995), and especially technology (Caselli and Coleman II, 2006; Caselli, 2017; Comin and Mestieri, 2018; Malmberg, 2022; Rossi, 2022; Bassi et al., 2022). We contribute to growing evidence on the role of factor misallocation in development, which is traditionally hidden in total factor productivity (TFP). Such studies have focused on whether some firms have too much or too little *homogeneous* labor and capital (Hsieh and Klenow, 2009; Buera et al., 2011; Midrigan and Xu, 2014; Gopinath et al., 2017; Bau and Matray, 2023). Since labor accounts for around two-thirds of national income, understanding how the matching of *heterogeneous* workers and jobs—and thus meritocracy in the labor market—affects aggregate outcomes across countries is of prime importance. This is the contribution of our paper.

[4] In turn, Roy-Fréchet models have been applied to the development context (Lagakos and Waugh, 2013; Young, 2013; Gottlieb et al., 2024; Lee, 2024). However, in contrast to us, they do not distinguish between endowments, technology, and matching frictions, given that worker skills and job skill requirements are unobserved in their contexts.

2 Data Description

2.1 The Survey of Adult Skills

Data Description. Our main data source is the Survey of Adult Skills of the PIAAC administered by the Organisation for Economic Co-operation and Development (OECD), which provides a representative sample of working-age adults across middle- and high-income countries surveyed between 2012 and 2018.[5] A unique feature of these data is their detailed account of both workers' skills and the skill requirements of their jobs—including multidimensional measures in the areas of numeracy and literacy—for a large set of countries. Importantly, skills are measured using standardized tests rather than being self-reported or inferred. The survey as a whole, including the assessment of skills and skill requirements, is designed to be comparable across countries. Using these harmonized skill measures, we do not need to rely on education-based metrics, such as years of schooling, which may not be comparable across countries. The PIAAC data span 38 countries, 28 of which have all of the information (e.g., continuous wages) required for our study; see Appendix A.1 for the complete list of countries.

Sample Selection. We restrict attention to individuals between the ages of 20 and 59 with nonmissing information for key variables (i.e., numeracy and literacy skill scores, gender, employment status, and sampling weight) who report a value for their wage when employed. We also drop the self-employed, for whom we do not have reliable wage information.[6]

2.2 Variable Definitions

Worker Skills. For each country, the PIAAC reports scores from numeracy and literacy skill tests on a scale from 0 to 500 for all—employed and nonemployed—workers.[7] Although we observe raw test scores, it is instructive to consider the meaning of their different ranges. The lowest range (scores below 176) on the numeracy test refers to the ability to do "simple processes such as counting, sorting, performing basic arithmetic operations, or understanding simple percentages." The modal range (scores from 226 to 275) reflects the ability to "identify and act on mathematical information embedded in common contexts." The highest range (scores from 376 to 500) covers the top 1 percent of the sample who can "understand complex representations and abstract and formal mathematical and statistical ideas, possibly embedded in complex text."

In most of our analyses, we use a discretized version of the skill distributions to ensure similar treatment in the data and in the model. Appendix B demonstrates the robustness of our results to

[5] For earlier uses of the PIAAC data in different contexts, see Autor (2014), Cooper and Liu (2019), Hoxby (2021), Cervantes and Cooper (2022), Lewandowski et al. (2022), and Caunedo et al. (2023).

[6] In the top-left panel of Figure A5 in Appendix A.5, we demonstrate that in all countries in our sample, self-employment is much less common than in the lowest-income countries in the world. Importantly, we keep informally employed workers who make up a substantial part of lower-income countries' labor (LaPorta and Shleifer, 2008, 2014).

[7] A subset of countries report problem-solving or Information and Communications Technology skills, which we explore in Appendix B.4. Here, we focus on numeracy and literacy skills because these are available for most countries.

this discretization. To deal with the fact that skills and skill requirements are measured in different units but need to be comparable to analyze worker-job sorting, we construct what we refer to as *global quintiles* in each dimension of worker skills and job skill requirements. To construct these global quintiles in a given skill dimension, we first order all individuals pooled across countries and assign each of them a number between 0 and 1 that reflects their rank in the global distribution of that skill dimension. We then take the mean over the global ranks across those workers that are in the same country- and skill-specific quintile. This yields discrete distributions of numeracy and literacy skills for each country, with each taking values between 0 and 1 while preserving differences in skill levels across countries.[8]

A key advantage of the skill measures on the PIAAC compared with using education as a proxy for skills is that the tests were designed to be comparable across countries, whereas differences in the unobservable quality of education render international comparisons difficult (Barro and Lee, 2013; Martellini et al., 2023). To highlight the difference between education and PIAAC's skill measures, Figure A2 in Appendix A.4 shows that educational attainment explains only a small share of the variation in skills, especially in lower-income countries.

Job Skill Requirements. To measure skill requirements for a given job, defined by 4-digit International Standard Classification of Occupations (ISCO-08) codes, we consider all workers in a country who are employed in that occupation.[9] For each skill area, the survey asks workers whether they perform a number of related tasks. For instance, for numeracy, they are asked about operating a calculator, using algebra, creating budgets, and so on. We sum the number of tasks a worker completes in each skill dimension—i.e., numeracy and literacy—and weigh them by their difficulty; see Appendix A.2 for more details. We then take the average of this measure across all workers in a given occupation in each country to arrive at a set of country-specific numeracy and literacy skill requirements for each job.[10] Figure A3 shows the constructed numeracy and literacy skill requirements for different occupations. Reassuringly, the skill requirements for high-skilled occupations such as managers and professionals are higher on average than the skill requirements for low-skilled occupations such as plant and machine operators. To render the units of job skill requirements comparable to those of worker skills, we again transform them into global quintiles, as we did above for worker skills. As a result, job skill requirements also take values between 0 and 1—while at the same time, their levels differ across countries as reflected by the raw data.

Worker-Job Matching. In a meritocratic labor market, worker-job matching is based on merit related to skills rather than idiosyncratic attributes unrelated to productivity. Here, we define

[8]We use global quintiles to balance two objectives. On the one hand, we want the cells of the discretized distributions to be sufficiently populated, which is why we create quintiles *within* each country. On the other hand, we attach *global* ranks to these country-specific quintiles to preserve cross-country differences in the skill distributions.

[9]The United States and Ireland only report 2-digit ISCO-08 codes, whereas Estonia and Finland only report 1-digit codes. For those countries, we use 2- and 1-digit codes, respectively. We use 4-digit codes for all other countries.

[10]As skill requirements are based on survey responses, there may be measurement error correlated with GDP per capita. We can show, however, that the variation of skill requirements within an occupation is similar across countries.

two summary measures of worker-job matching that reflect this notion:[11] one that differentiates skills vertically, by ranking levels of a given skill, and one that differentiates them horizontally, by distinguishing between different skill dimensions. The first measure is a categorical variable that splits the worker-job pairs into three categories according to the proximity of a worker's skills and their job's skill requirements. The second measure is a continuous variable equal to the distance between a worker's skills and their job's skill requirements.

To build the first measure of worker-job matching, we first assign each worker skill and each job skill requirement to quintiles of their respective distributions within each country. As a result, each worker (job) is characterized by a two-dimensional vector of numeracy and literacy skills (skill requirements), with each vector entry taking on values 1 to 5. Thus, there are 25 possible worker types and 25 possible job types. We define a match as "perfect" when the worker's skill vector and the job's skill requirement vector are exactly equal, "good" when each of the worker's skills and the job's skill requirements are at most one quintile away from each other, and "poor" otherwise. The advantage of the categorical measure is that it is simple to interpret. The price of simplicity is coarseness, since this measure does not take into account the cardinal distance between worker skills and their jobs' skill requirements.

Therefore, we build a second measure of worker-job matching with a cardinal interpretation. Based on the global quintiles of worker skills and job skill requirements above, we compute the average Euclidean distance between a worker's skill vector and their job's skill requirement vector, both contained in the unit square. For each individual worker and their job, this measure takes value 0 when the worker's skills perfectly match their job's skill requirements and $\sqrt{2} \approx 1.414$ when the worker's skills are at a maximum distance from their job's skill requirements.

Beyond the matching pattern between employed workers and jobs, we will also be interested in which individuals select into paid employment in the first place. We capture this extensive margin by measuring the skill gap between employed versus nonemployed individuals on the PIAAC, computed as the percentage difference in mean skill levels between the two groups.

2.3 Summary Statistics

Our sample comprises 120,448 observations that represent over 718.2 million individuals in 28 countries. Table 1 presents some key summary statistics.[12] Panel A shows general country characteristics. The data cover middle- to high-income countries and span a substantial part of the development spectrum, with GDP per capita ranging from Ecuador at 11,424 dollars (2017 PPP) to Norway at 62,399 dollars (2017 PPP)—a ratio of around 5.5. Regarding population size, our sample ranges from Estonia, with 0.7 million covered individuals, to the United States, with 285 million covered individuals. Women's population share and age are relatively homogeneous across countries. Hourly wages show a range similar to that of GDP per capita, with a factor of 5.2 between the

[11] What constitutes meritocratic worker-job matching, of course, depends on the available endowments, which determine the feasibility of matches, and the production function, which determines the returns to matching worker skills to job skill requirements. We formally introduce these fundamentals in our equilibrium model in Section 4.

[12] Appendix A.4 presents additional summary statistics separately by country.

lowest- and highest-wage countries. Finally, the dataset contains an average of 4,302 observations per country, which is sizable but also imposes practical limits on data splitting in our analysis.

Panel B shows labor supply characteristics. There are marked cross-country differences in worker skills. The average respondent scores just above half of the correct answers on each of the skill tests. In the top panels of Figure A1 in Appendix A.4, we show the distributions of skills within each country, and highlight the two lowest-income countries (Ecuador and Mexico) and the two highest-income countries (the United States and Norway). Average skills are greater in higher-income countries, but there is significant dispersion. Finally, years of schooling and employment shares vary widely across countries, and the latter especially among women.

Panel C shows labor demand characteristics. In the bottom panels of Figure A1 in Appendix A.4, we show the distributions of skill requirements within each country, again highlighting the two lowest-income and highest-income countries. Like worker skills, job skill requirements are also greater in higher-income countries but with significant dispersion. Another notable fact is the scarcity of large firms in some countries, which—as expected—are those with lower income.

Table 1: Summary Statistics across Countries

	Mean	Min	P25	P50	P75	Max
Panel A: Country Characteristics						
GDP per Capita (2017 $, PPP)	37,000	11,424	26,957	35,950	47,082	62,399
Population (Millions)	25.65	0.67	2.57	6.97	26.05	284.42
Share of Women	0.53	0.50	0.51	0.52	0.54	0.56
Age	39.00	35.92	38.71	39.13	39.88	40.81
Hourly Wage	14.33	4.79	8.96	15.05	19.07	24.76
Number of Observations	4,302	2,854	3,680	4,008	4,620	7,159
Panel B: Labor Supply						
Numeracy Skill	260.41	186.22	252.98	264.97	276.66	293.67
Literacy Skill	265.45	195.39	256.08	272.10	276.93	302.88
Years of Schooling	12.79	10.50	12.23	12.92	13.44	14.90
Share of the Employed	0.70	0.45	0.64	0.72	0.78	0.82
Share of the Employed among Women	0.66	0.49	0.60	0.63	0.76	0.78
Panel C: Labor Demand						
Numerical Skill Requirement	1.00	0.84	0.95	1.00	1.04	1.25
Literacy Skill Requirement	1.27	1.03	1.18	1.25	1.39	1.50
Share of Firms with $>$ 50 Workers	0.29	0.10	0.25	0.29	0.35	0.42

Notes: This table shows summary statistics for the PIAAC data across the 28 countries included in our analysis. Panel A shows basic country characteristics. Panel B shows labor supply statistics. Panel C shows labor demand statistics. Columns represent the mean, minimum, 25th percentile, median, 75th percentile, and maximum of each variable at the country level. *Source:* PIAAC.

2.4 Context and Data Validation

To provide context for our study and validate PIAAC survey data, we draw on four additional data sources for worker skills, job skill requirements, and broad labor market outcomes.

A unique aspect of the PIAAC is that it directly tests various dimensions of skills among the working-age population. To validate these measures, Figure A7 in Appendix A.6 shows strong positive correlations between the skill scores of working-age respondents on the PIAAC and the corresponding skill scores of 15-year-old students on the Program for International Student Assessment (PISA) along multiple skill dimensions. This suggests that, first, the skill measures on the PIAAC are meaningful, and second, the skills tested by the PIAAC are persistent across time and age, which motivates our assumption of treating them as fixed factors in our model below.

Another distinct feature of the PIAAC is its information on the country-specific skill requirements of jobs. An alternative to these country-specific skill requirement measures could be the commonly used job task contents from the Occupational Information Network (O*NET) developed in the United States. However, our country-specific measures are preferable in that different countries may use different technologies to produce the same goods, which implies that the skill requirements of a given job are not necessarily the same everywhere. As a result, worker-job matches may be misclassified if skill requirements from the United States were universally applied to all countries (Atencio-De-Leon et al., 2023; Caunedo et al., 2023). Figure A4 in Appendix A.4 plots the R^2 from a regression of skill requirements from PIAAC on corresponding O*NET measures for each job. Reassuringly, for the United States, the job skill requirements from PIAAC and O*NET are highly correlated. However, in any other country, O*NET explains only around 20–60 percent of the variation in numeracy requirements and around 40–70 percent of the variation in literacy requirements, with the R^2 being greater in higher-income countries.

To inspect the coverage and representativeness of PIAAC data, we compare the PIAAC, in which participation is incentivized, along important dimensions with nationally representative data from the Jobs of the World Database (JWD) and the Luxembourg Income Study (LIS), both within and across countries, with two main findings.[13] First, we confirm the representativeness of PIAAC data within countries for important labor market outcomes such as the share of workers in paid jobs, education, labor force participation rates and hourly wages (Figure A5 in Appendix A.5), as well as the occupational composition (Figure A6 in Appendix A.5). Second, we compare the sample of countries on the PIAAC with a wider range of countries across the development spectrum. We find that the subset of PIAAC countries falls in the upper tercile of all countries ranked by GDP per capita, as do their shares of workers in salaried jobs, average years of education, the ratio of the female to male labor force participation, and average hourly wages.

[13] The JWD harmonizes census data from the International Integrated Public Use Microdata Series (IPUMS-International) and the Demographic and Health Surveys (DHS).

3 Worker-Job Matching across Countries

We think of a meritocratic labor market as one in which individuals sort into positions based on merit related to skills rather than idiosyncratic attributes unrelated to productivity. With this in mind, we first document how worker-job matching patterns differ across countries. We then investigate three mechanisms behind worker-job matching in the data. The first mechanism comprises the endowments of worker skills and job skill requirements, which determine match feasibility. The second mechanism pertains to technology—which is broadly defined to include not only differences in machinery and equipment but also in management practices and the organization of labor—which shapes the returns to the productive attributes of workers and jobs and, thus, the incentives to sort. The third mechanism consists of matching frictions, which guide the relative importance of idiosyncratic as opposed to productive attributes in the matching process. Such frictions may reflect both the formal institutions (e.g., regulatory weaknesses or lack of enforcement of antidiscrimination laws) and informal institutions (e.g., corruption or social norms) that enable agents' nonproductive attributes to affect their labor market outcomes.[14] In what follows, we document several facts suggestive of meritocracy with the primary purpose of informing our equilibrium model, through the lens of which we will interpret the data.

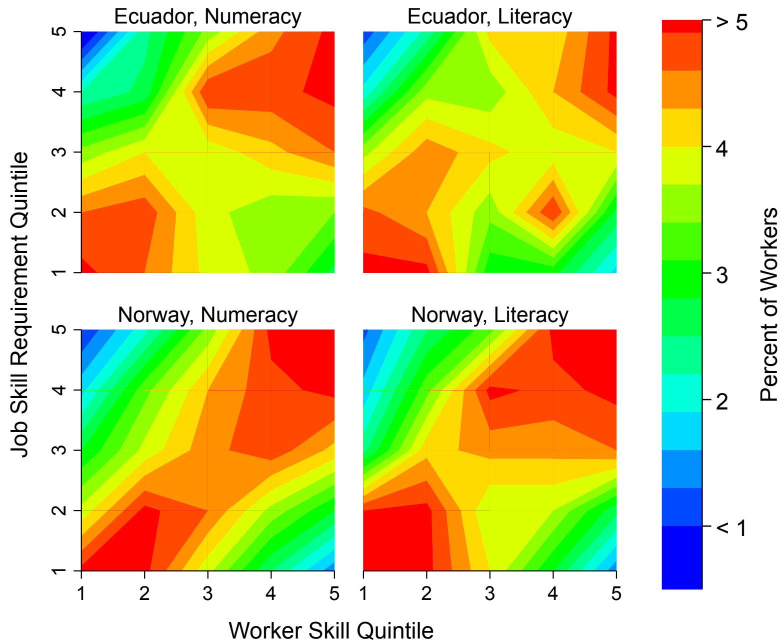
3.1 Are Workers Better Matched to Jobs in Higher-Income Countries?

Intensive-Margin Matching. We first illustrate the matching of workers with different skills to jobs with different skill requirements across countries in the raw data. Figure 1 plots a heatmap of worker skills and the skill requirements of their jobs for numeracy and literacy in Ecuador and Norway, the poorest and richest countries in our sample. In each country, we first order workers (jobs) by skills (skill requirements), separately for numeracy and literacy, and then plot the population shares across cells defined as the intersection of a worker skill quintile and a job skill requirement quintile. Warmer colors all the way up to red indicate higher population shares. Perfectly assortative matching would result in a red stripe along the diagonal and blue everywhere else. In contrast, the figure shows that empirical matches occur in all combinations of skills and skill requirements. Importantly, however, comparing the two countries, we see more mass along the diagonal—suggesting that sorting is more assortative—in Norway compared to Ecuador.

To summarize these multidimensional matching patterns and analyze how they vary by country income, Figure 2 shows the country-specific shares of perfect and good matches between worker skills and job skill requirements, defined in Section 2.2. The share of perfect worker-job matches (left panel) ranges from 7 percent to 16 percent across countries. The more generous definition of good worker-job matches is higher, between 35 percent and 60 percent. Importantly, the shares of perfect and good matches are both increasing in GDP per capita. Figure 3 underscores this finding based on our continuous measure of worker-job mismatch—namely, the average Eu-

[14] While the endowments of worker skills and job skill requirements, as well as technology, reflect past investments in human and physical capital that are affected by meritocracy in the labor market, we treat these as given.

Figure 1: Joint Distribution of Worker Skills and Job Skill Requirements by Skill Dimension



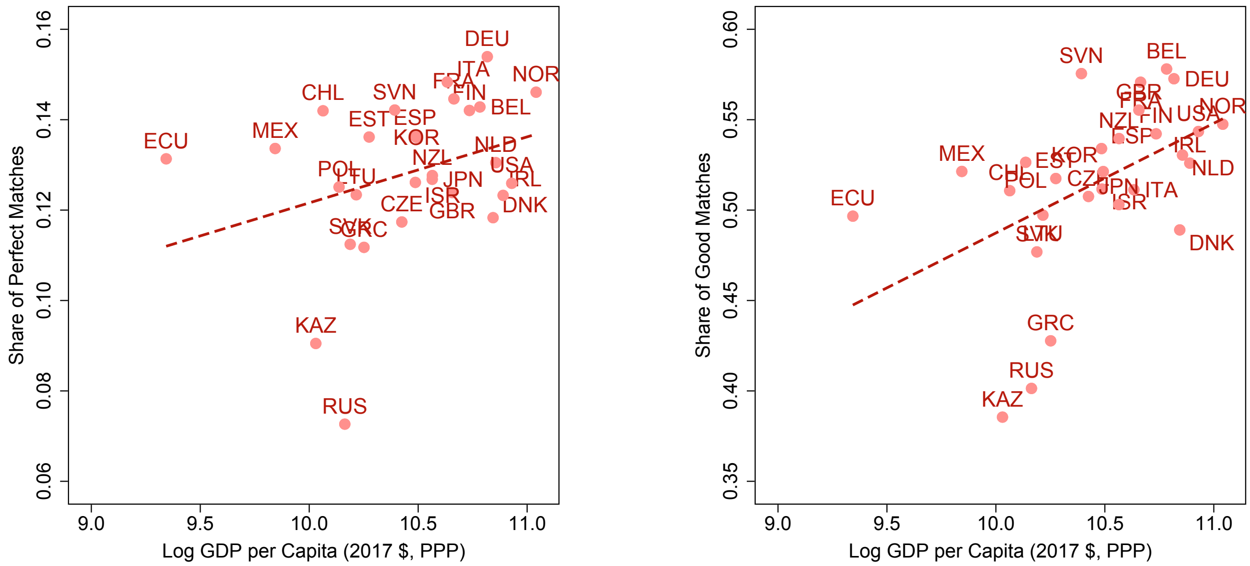
Notes: Each panel shows the joint distribution of worker skills and job skill requirements in a given country (i.e., Ecuador in the top panels and Norway in the bottom panels) for a given skill dimension (i.e., numeracy in the left panels and literacy in the right panels). Colors represent percentages of workers, ranging from low in blue to high in red. *Source:* PIAAC.

clidean distance between a worker's skills and their job's skill requirements, defined in Section 2.2. We find that this distance varies significantly across countries and is decreasing in GDP per capita.[15] This shows that there are large cross-country differences in skill-based sorting and that higher-income countries have better worker-job matches, in the sense that workers' skills are better aligned with their jobs' skill requirements. These facts suggest that higher-income countries have more meritocratic labor markets along the intensive margin.

Extensive-Margin Matching. So far, our analysis has been conditioned on employment. However, nonemployment rates are substantial, especially in lower-income countries. Thus, we are also interested in individuals' selection into employment based on skills. Figure 4 shows the skill gap between employed and nonemployed individuals across countries, measured by the ratio of their skills. Focusing on the overall population in the left panel, two observations emerge. First, the skill gap is positive in all countries, which reflects positive skill-based selection into employment. Second, there is a positive correlation between the skill gap and GDP per capita, with the skill ratio increasing from 1.1 to around 1.2 across the development spectrum.[16] Computing the skill gap separately by gender reveals that women are more positively selected on average but that the selection of men is more steeply increasing with economic development. Both facts are consistent with evidence that women face substantial barriers to labor market participation, espe-

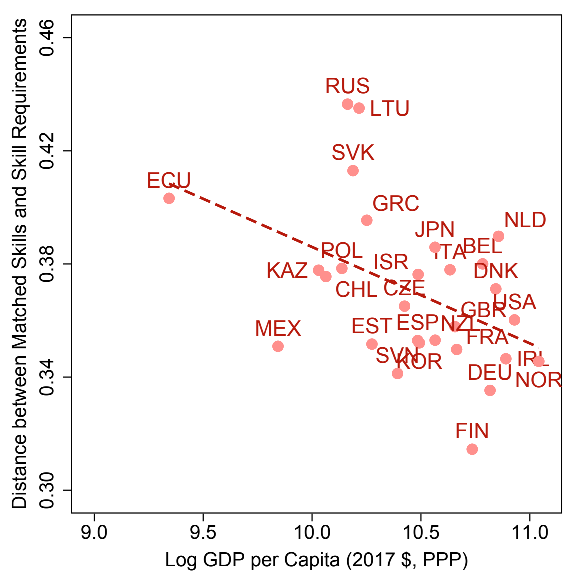
[15] Figure B4 in Appendix B.2 shows robustness to using raw skills and skill requirements instead of global quintiles.
[16] Figure B5 Appendix B.2 shows that these patterns are robust to using raw skills and skill requirements.

Figure 2: Intensive Margin: More Perfect and Good Worker-Job Matches in Higher-Income Countries



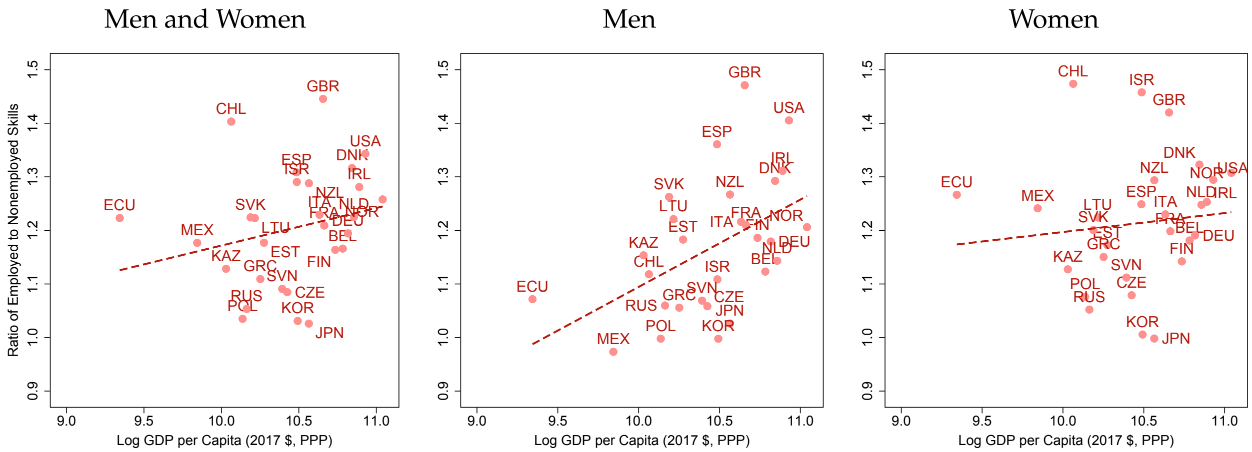
Notes: The left panel shows the share of "perfect" worker-job matches, defined as matches in which the worker's skill quintiles equal their job's skill requirement quintiles in each of the two skill dimensions. The right panel shows the share of "good" worker-job matches, defined as matches in which the worker's skill quintiles are no more than one quintile away from their job's skill requirement quintiles in each of the two skill dimensions. *Source:* PIAAC.

Figure 3: Intensive Margin: More Skill-Based Worker-Job Matching in Higher-Income Countries



Notes: This figure plots the mean distance between workers' skills and the skill requirements of their jobs by country. This distance is computed as the average Euclidean distance between the vector containing the global quintiles of each worker's numeracy and literacy skills and the vector containing the global quintiles of their job's numeracy and literacy skill requirements. *Source:* PIAAC.

Figure 4: Extensive Margin: Greater Skill-Based Selection into Employment in Higher-Income Countries



Notes: This figure plots the ratio of employed-to-nonemployed skills against GDP per capita across countries. For each individual, we average their global quintiles of numeracy and literacy skills and then compute the ratio of average skill quintiles of the employed and the nonemployed. *Source:* PIAAC.

cially in lower-income countries. Such obstacles mean that only the most skilled women engage in paid labor, thereby increasing the skill gap relative to that of men (Ashraf et al., 2023). These facts suggest that higher-income countries are also more meritocratic along the extensive margin.

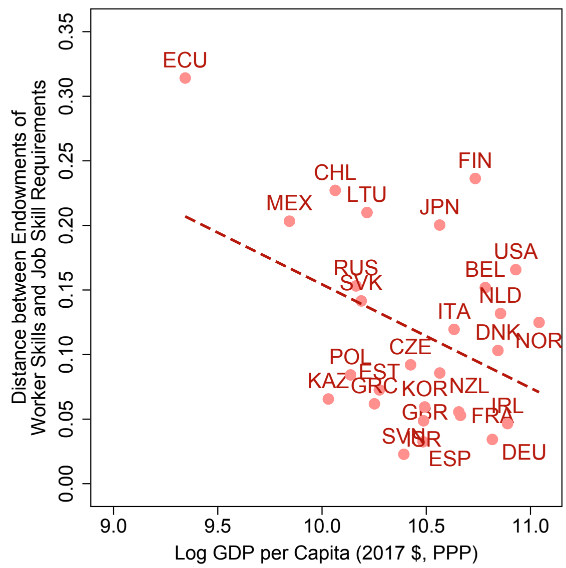
3.2 Three Mechanisms Behind Worker-Job Matching

We now present evidence on three mechanisms that potentially underlie the documented worker-job matching patterns and how they vary across countries.

Mechanism 1: Endowments of Worker Skills and Job Skill Requirements. The extent to which an economy's endowment of worker skills overlaps with that of job skill requirements determines the feasibility of worker-job matches. We measure the alignment between a country's endowments of worker skills and job skill requirements using a simple distance metric.[17] Specifically, we compute the average Euclidean distance between the intersections of global quintiles of worker skills and job skill requirements available in the economy. This distance is minimized (i.e., 0) when, for each worker with a particular skill vector, there exists a job with those exact skill requirements. Conversely, it is maximized (i.e., $\sqrt{2} \approx 1.414$) when the economy's skill requirements are maximally misaligned with its skills. Importantly, this distance metric does not depend on actual worker-job matches, since it compares all available worker skills and job skill requirements in a country. Figure 5 plots this measure against GDP per capita across countries. We find a smaller distance, which reflects more aligned endowments of worker skills and job skill requirements, in

[17] We explore alternative measures of the overlap between skill supply and demand in Appendix B.1. Figure B2 shows detailed differences between the endowments of multidimensional skills and skill requirements in each country. Figure B3 summarizes this information and shows that the share of potential perfect matches is increasing in GDP.

Figure 5: Endowments: More Aligned Worker Skills and Job Skill Requirements in Higher-Income Countries



Notes: This figure shows the distance between the distributions of worker skills and job skill requirements against GDP per capita across countries. Unlike in the analysis of worker-job matches in Figure 3, here we do not restrict the skill distribution to only employed individuals. In each country, the distance is computed as the weighted average Euclidean distance between the vector of global quintiles of all workers' numeracy and literacy skills (i.e., irrespective of workers' employment status) and the vector of the global quintiles of all jobs' numeracy and literacy skill requirements. These differences are weighted by the combined probability mass of workers and jobs in each cell that is defined by the intersection of skills and skill requirement quintiles. *Source:* PIAAC.

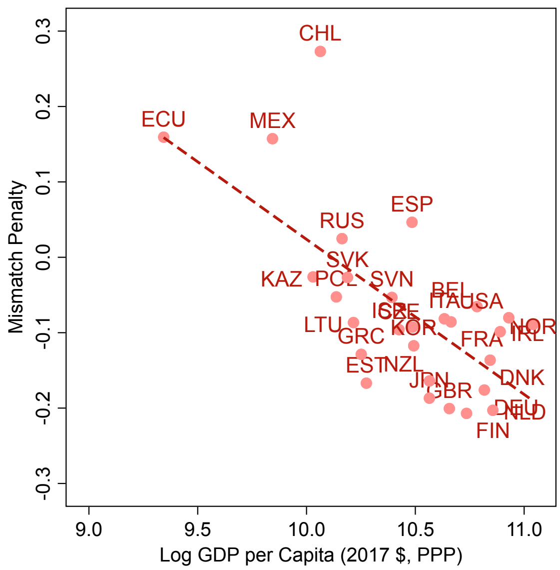
higher-income countries. Intuitively, one expects that greater overlap in worker and job endowments in higher-income countries facilitates meritocracy in the form of better worker-job matches.

Mechanism 2: Technology. A country's production technology determines match payoffs across combinations of worker skills and job skill requirements. Thus, technological differences may be behind greater skill-based sorting in higher-income countries if they produce higher-quality products, use more sophisticated machines, or organize firms with deeper hierarchies in ways that strengthen worker-job complementarities. While technology is not directly observed, in a decentralized market economy it will be reflected in wages that induce workers to choose jobs based on their relative returns. To capture technological differences across countries, Figure 6 plots the wage penalty for worker-job skill mismatch, which we estimate as the coefficient on the Euclidean distance between worker skills and their jobs' skill requirements in a Mincerian wage regression.[18] We find a negative relationship between the estimated mismatch penalty and GDP per capita, which suggests that technological returns to worker-job sorting are greater in higher-income countries, which potentially pushes them toward greater meritocracy in the labor market.

Mechanism 3: Idiosyncratic Matching Frictions. The third mechanism that shapes a country's labor market sorting pertains to frictions that constrain matching based on skills alone. In a fric-

[18]Figure B6 in Appendix B.3 shows that this fact is robust to omitting Mincerian controls from the wage regression.

Figure 6: Technology: Greater Penalty for Worker-Job Skill Mismatch in Higher-Income Countries



Notes: We plot the estimates of the coefficient β from the following regression, run within each country, against GDP per capita: $\ln(w_i) = \alpha + \beta \text{Dist}_i + \gamma X_i + \varepsilon_i$, where Dist_i is computed as the average Euclidean distance between the vector containing the global quintiles of a worker's numeracy and literacy skills and the vector containing the global quintiles of their job's numeracy and literacy skill requirements. X_i is a vector of Mincerian controls for education, experience, and the square of experience. *Source:* PIAAC.

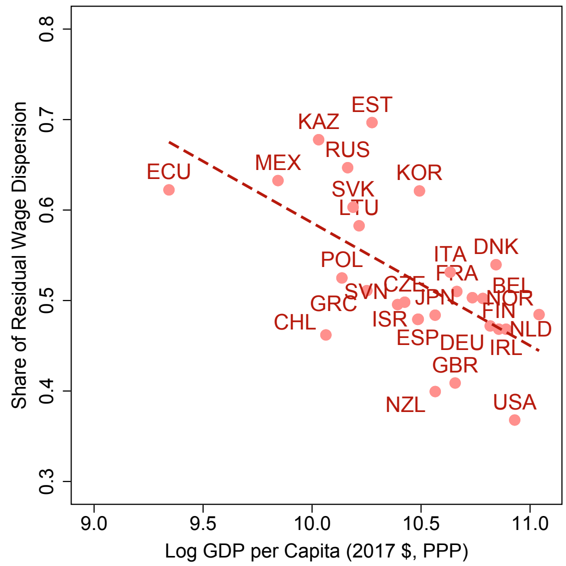
tionless labor market, the law of one price requires that individuals with the same skills in jobs with the same skill requirements earn the same wage. Any residual wage dispersion therefore suggests the presence of idiosyncratic, rather than skill-related, matching reasons—including social connections, family wealth, corruption, and discrimination at the hiring stage. While there is no reason to believe, a priori, that the distribution of these traits varies systematically across countries, the extent to which they affect the matching process might do. For example, the enforcement of anti-discrimination laws might be weaker and corruption might be more tolerated in less developed countries. If such frictions are more important in lower-income countries, they could lead to less skill-based matching there. To gauge the relative importance of idiosyncratic matching reasons in the data, Figure 7 plots each country's share of unexplained wage variation after flexibly residualizing log wages by the interacted worker skills and job skill requirements plus Mincerian controls. We find a negative relationship between residual wage dispersion and GDP per capita across countries.[19] This suggests that higher-income countries have a lower degree of matching frictions, consistent with a more meritocratic worker-job assignment.

3.3 Interpreting the Empirical Evidence

We started with the central observation that in higher-income countries, workers' skills are better aligned with their jobs' skill requirements, and individuals are more positively selected into employment. We interpreted this as evidence that meritocracy in the labor market is positively

[19]This pattern is robust to (i) alternative discretizations of skills and skill requirements, (ii) the omission of Mincerian controls, and (iii) adding or dropping some of the skill measures; see Figures B7, B8, and B9 in Appendix B.4.

Figure 7: Matching Frictions: Lower Residual Wage Dispersion in Higher-Income Countries



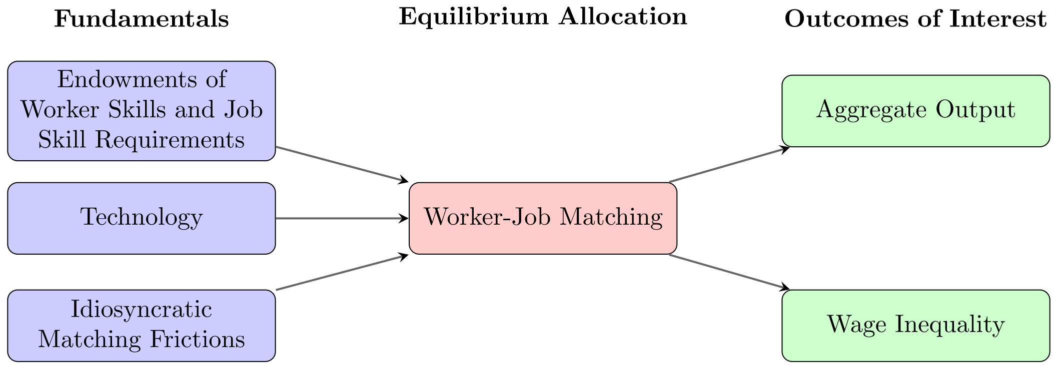
Notes: This figure plots the share of wage dispersion not explained by the interaction between worker skills and job skill requirements. Each employed worker i is assigned to country-specific cells formed by the intersection of their numeracy and literacy skill quintiles, $Num_i, Lit_i \in \{1, \ldots, 5\}$ and skill requirement quintiles $NumReq_i, LitReq_i \in \{1, \ldots, 5\}$. We then compute the share of within-cell wage dispersion based on the following regression: $\ln(w_i) = \sum_{k,k',k'',k'''} \beta_{k,k',k'',k'''} \mathbb{1}[(Num_i, Lit_i, NumReq_i, LitReq_i) = (k, k', k'', k''')] + \gamma X_i + \varepsilon_i$, where $\mathbb{1}[(Num_i, Lit_i, NumReq_i, LitReq_i) = (k, k', k'', k''')]$ is an indicator for worker i being in numeracy skill quintile k, literacy skill quintile k', numeracy skill-requirement quintile k'', and literacy skill-requirement quintile k'''. Here, X_i is a vector of Mincerian controls for education, experience, and the square of experience. *Source:* PIAAC.

correlated with economic development. We inspected three potential mechanisms behind this pattern. The first was closer alignment of the distributions of available worker skills and job skill requirements in higher-income countries. In our model in Section 4, this reflects cross-country differences in worker and job endowments that guide match feasibility. The second was greater returns to matching between worker skills and job skill requirements in higher-income countries. Our model rationalizes this through differences in technology that determine the economic rewards from matching certain bundles of worker skills with bundles of job skill requirements. The third mechanism was a lower share of residual wage dispersion in higher-income countries. In our model, this corresponds to differences in idiosyncratic matching frictions that affect worker-job sorting. Together, these facts inform our equilibrium model, in which countries can differ in their endowments, technology, and idiosyncratic matching frictions, which jointly shape worker-job matching—and thus meritocracy—in the labor market.

4 An Equilibrium Model of Meritocracy in the Labor Market

Motivated by the empirical facts documented above, we now study the sources and consequences of meritocracy in worker-job matching. To this end, we develop an equilibrium model that incorporates multidimensional heterogeneity (Lindenlaub, 2017; Lindenlaub and Postel-Vinay, 2023) in the seminal matching framework of Choo and Siow (2006) to study the matching between work-

Figure 8: Model Overview of Each Country's Economy



ers and jobs, which is determined by three country-specific fundamentals. First, the *endowments* of worker skills and job skill requirements guide match feasibility. Second, *technology* determines the returns to worker-job matching. Third, *idiosyncratic matching frictions*, whose strength is guided by a country-specific scale parameter, impede the output-maximizing worker-job allocation. We are interested in how these three factors shape worker-job matching and, thereby, aggregate output and wage inequality across countries. Figure 8 provides a schematic model overview.

4.1 Environment

The world consists of N^C countries, each with its own labor market. Each country is fully characterized by its endowments, technology, and idiosyncratic matching frictions, which we discuss below. In what follows, we describe the model economy of a single country. A discrete number of heterogeneous workers match with a discrete number of heterogeneous jobs in a static and competitive labor market. This process results in a number of worker-job matches on the one hand and some nonemployed workers, as well as idle jobs, on the other.[20] We assume transferable utility, so worker-job matches maximize total match surplus, which consists of the sum of systematic match surplus and idiosyncratic match surplus. The former represents systematic gains from trade between a certain type of worker and a certain type of job. The latter reflects idiosyncratic reasons for matching unrelated to productivity. The total match surplus is then split into wages and profits.

Endowments. On the labor supply side, there is a discrete number N^W of risk-neutral workers, indexed by i, characterized by their numeracy skill $x_n \in \mathbb{R}^+$, literacy skill $x_\ell \in \mathbb{R}^+$, and gender $x_g \in \{\text{female}, \text{male}\}$. Worker types $x = (x_n, x_\ell, x_g) \in \mathcal{X}$ follow a cumulative distribution $G(\cdot)$ with associated probability mass function (pmf) $g(\cdot)$ and normalized measure $m^W = 1$. On the labor demand side, there is a discrete number N^J of risk-neutral jobs, indexed by k, characterized by numeracy skill requirements $y_n \in \mathbb{R}^+$, literacy skill requirements $y_\ell \in \mathbb{R}^+$, and firm size $y_s \in \mathbb{R}^+$, which we take as a proxy for the job's productivity. Job types $y = (y_n, y_\ell, y_s) \in \mathcal{Y}$ follow a cumulative distribution $H(\cdot)$ with associated pmf $h(\cdot)$ and relative measure $m^J \in \mathbb{R}^+$.

[20]Motivated by the fluidity between unemployment and out-of-labor-force status in many countries (Donovan et al., 2023) and given our static model, we here distinguish only between employment versus nonemployment.

Technology. Each worker-job match produces output $f(x, y)$ that depends on worker attributes x and job attributes y. The payoff of an unmatched worker of type x is $f_{x\emptyset}(x)$, where the subscript $y = \emptyset$ indicates the worker's choice to remain nonemployed. Similarly, the payoff of an unmatched job of type y is $f_{\emptyset y}(y)$, where the subscript $x = \emptyset$ indicates the job's choice to remain idle. Workers' outside options depend on both skills and gender, which allows for gender-specific comparative advantage in home production. From here on, we assume $f_{\emptyset y}(y) = 0$.[21]

Idiosyncratic Matching Frictions. Idiosyncratic matching frictions lead to deviations from the output-maximizing worker-job allocation, along both the intensive margin (i.e., which worker matches with which job) and along the extensive margin (i.e., selection into employment). Specifically, matching is guided not only by systematic reasons relating to output but also by matching frictions, which we model as wedges that enter individual workers' and jobs' match payoffs. We denote by δ_{iy} the preference of worker $i \in \{1, ..., N^W\}$ for job type $y \in \mathcal{Y} \cup \emptyset$ and, similarly, by δ_{xk} the preference of job $k \in \{1, ..., N^J\}$ for worker type $x \in \mathcal{X} \cup \emptyset$. We assume that these idiosyncratic matching wedges follow an Extreme Value (EV) Type I, or Gumbel maximum, distribution:[22]

$$\delta_{iy} \sim \text{EV Type I}(0, \sigma), \quad \forall i \text{ over all } y \in \mathcal{Y} \cup \emptyset,$$
$$\delta_{xk} \sim \text{EV Type I}(0, \sigma), \quad \forall k \text{ over all } x \in \mathcal{X} \cup \emptyset,$$

where the scale parameter $\sigma \in \mathbb{R}^+$ determines the extent of idiosyncratic matching frictions: $\sigma \to 0$ results in the output-maximizing matching guided by the relative strengths of worker-job complementarities in production, and $\sigma \to \infty$ results in random matching.

While we refer to the idiosyncratic matching wedges δ_{iy} and δ_{xk} as "frictions," we think of them as a reduced form for any reason that prevents the output-maximizing matching pattern, with no normative meaning attached. This may reflect malignant reasons for mismatch, such as corruption (Weaver, 2021) or nepotism (Akcigit et al., 2021), but they may also reflect benign reasons, such as nonwage job aspects (Morchio and Moser, 2023) or individuals' valuations of living close to their parents (Chan and Ermisch, 2015). Regardless of their specific interpretation, matching wedges are separate from skill-related reasons for worker-job sorting. Our interest lies in the distribution of matching wedges, guided by scale parameter σ, that rationalizes observed worker-job matching patterns in a given country. In this sense, we conduct a positive accounting exercise within an equilibrium model, in the spirit of the literature on distortionary wedges in other areas of macroeconomics (Chari et al., 2007; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Hopenhayn, 2014; Hsieh et al., 2019; Birinci et al., 2024).

[21] This assumption is motivated by the free entry of jobs, which drives the value of an idle job to zero and circumvents the need to identify $f_{\emptyset y}(y)$, which we further discuss in Section 6.1.

[22] As in Caldwell and Danieli (2024), we tractably model preference heterogeneity in lieu of search frictions (e.g., Mortensen, 2003), which is the natural choice given our cross-sectional data.

4.2 Matching

Labor market matching results from a process in which workers choose either which job to work in or to remain nonemployed, and jobs choose which worker to hire or to remain idle.

Workers' Decisions. Given workers' idiosyncratic matching wedges $\{\delta_{iy}\}_{y\in\mathcal{Y}\cup\emptyset}$, each worker i of type x chooses to match with a job type y or to remain nonemployed to maximize their payoff:

$$\max\left\{\max_{y\in\mathcal{Y}}\{w(x,y)+\delta_{iy}\},\ f_{x\emptyset}(x)+\delta_{i\emptyset}\right\},$$

where $w(x,y)$ is the systematic wage of a worker of type x that matches with a job of type y. Based on well-known results from discrete-choice models with EV shocks (e.g., McFadden, 1973), the conditional choice probabilities associated with optimizing behavior of worker type x are

$$\mu_{y|x} := \frac{\mu^W(x,y)}{h(x)m^W} = \frac{\exp(w(x,y)/\sigma)}{\exp(f_{x\emptyset}(x)/\sigma)+\sum_{\tilde{y}\in\mathcal{Y}}\exp(w(x,\tilde{y})/\sigma)}, \tag{1}$$

$$\mu_{\emptyset|x} := \frac{\mu^W(x,\emptyset)}{h(x)m^W} = \frac{\exp(f_{x\emptyset}(x)/\sigma)}{\exp(f_{x\emptyset}(x)/\sigma)+\sum_{\tilde{y}\in\mathcal{Y}}\exp(w(x,\tilde{y})/\sigma)}, \tag{2}$$

where $\mu^W(x,y)$ and $\mu^W(x,\emptyset)$ are the frequencies of type x workers who choose job type y and nonemployment, respectively.

Jobs' Decisions. Similarly, given jobs' idiosyncratic matching wedges $\{\delta_{xk}\}_{x\in\mathcal{X}\cup\emptyset}$, each job k of type y chooses a worker type x to match with or to remain idle in order to maximize their payoff:

$$\max\left\{\max_{x\in\mathcal{X}}\{\nu(x,y)+\delta_{xk}\},\ f_{\emptyset y}+\delta_{\emptyset k}\right\},$$

where $\nu(x,y) := f(x,y)-w(x,y)$ is the systematic profit of a type-y job in a match with a type-x worker. Given optimizing behavior, the conditional choice probabilities for job type y are

$$\mu_{x|y} := \frac{\mu^J(x,y)}{g(y)m^J} = \frac{\exp((f(x,y)-w(x,y))/\sigma)}{\exp(f_{\emptyset y}(y)/\sigma)+\sum_{\tilde{x}\in\mathcal{X}}\exp((f(\tilde{x},y)-w(\tilde{x},y))/\sigma)}, \tag{3}$$

$$\mu_{\emptyset|y} := \frac{\mu^J(\emptyset,y)}{g(y)m^J} = \frac{\exp(f_{\emptyset y}(y)/\sigma)}{\exp(f_{\emptyset y}(y)/\sigma)+\sum_{\tilde{x}\in\mathcal{X}}\exp((f(\tilde{x},y)-w(\tilde{x},y))/\sigma)}, \tag{4}$$

where $\mu^J(x,y)$ and $\mu^J(\emptyset,y)$ are the frequencies of type y jobs that choose worker type x and idleness, respectively.

4.3 Equilibrium Definition and Properties

In equilibrium, workers and jobs choose their payoff-maximizing matches in such a way that demand and supply for each type of match balance. That is, labor market clearing requires that the equilibrium frequency of type (x, y) matches is

$$\mu(x,y) := \mu^J(x,y) = \mu^W(x,y), \quad \forall (x,y) \in \mathcal{X} \times \mathcal{Y}. \tag{5}$$

Let $\mu(x, \emptyset) := \mu^W(x, \emptyset)$ and $\mu(\emptyset, y) := \mu^J(\emptyset, y)$ denote the equilibrium frequencies of unmatched workers and firms, respectively. We can now define equilibrium.

Definition 1 (Equilibrium)**.** *An equilibrium consists of matching frequencies* $(\mu(x,y), \mu(x,\emptyset), \mu(\emptyset,y))$, *wages* $w(x,y)$, *and profits* $v(x,y)$ *for all* $(x,y) \in \mathcal{X} \times \mathcal{Y}$ *such that*

- *jobs and workers maximize their respective payoffs, which results in conditional choice probabilities* (1)–(2) *for workers and* (3)–(4) *for jobs, and*
- *labor market clearing* (5) *is satisfied.*

Equilibrium total match surplus is the sum of systematic match surplus, which consists of match output $f(x,y)$ net of both agents' outside options $f_{x\emptyset}(x)$ and $f_{\emptyset y}(y)$, and idiosyncratic match surplus, which equals the sum of both agents' idiosyncratic matching wedges δ_{xk} and δ_{iy}:

$$f(x,y) - f_{x\emptyset}(x) - f_{\emptyset y}(y) + \delta_{xk} + \delta_{iy}. \tag{6}$$

Due to the assumption of transferable utility, agents in the decentralized economy will choose an allocation that maximizes total match surplus (6) across worker-job matches.

We now state some useful equilibrium properties; see Appendix C for all derivations. Combining the relative choice probabilities $\mu^J(x,y)/\mu^J(\emptyset,y)$ for jobs of type y, and $\mu^W(x,y)/\mu^W(x,\emptyset)$ for workers of type x with labor market clearing (5), we obtain the following expression for the systematic match surplus of match (x,y):

$$s(x,y) := f(x,y) - f_{x\emptyset}(x) - f_{\emptyset y}(y) = \sigma \log\left(\frac{\mu(x,y)^2}{\mu(x,\emptyset)\mu(\emptyset,y)}\right). \tag{7}$$

We call $s(x,y)$ "systematic" because it captures output net of agents' outside options, both of which depend only on worker and job types. Systematic match surplus does not include the idiosyncratic matching wedges, which differ across agents of the same type. Clearly, $s(x,y)$ is positively related to the frequency of (x,y)-type matches, $\mu(x,y)$.

In equilibrium, systematic wages $w(x,y)$ are derived using workers' relative choice probabilities $\mu(x,y)/\mu(x,\emptyset)$, market clearing, and matching frequencies $\mu(x,y)$ from (7):

$$w(x,y) = \frac{\sigma}{2}\log\left(\frac{\mu(\emptyset,y)}{\mu(x,\emptyset)}\right) + \frac{f(x,y) + f_{x\emptyset}(x) - f_{\emptyset y}(y)}{2}. \tag{8}$$

This equilibrium relationship sheds light on the model determinants of wages. The transfer from jobs of type y to workers of type x in any match (x,y) positively depends on their systematic match output, the worker's outside option, and the availability of type y jobs relative to that of type x workers, captured by the ratio of idle jobs relative to nonemployed workers, $\mu(\emptyset,y)/\mu(x,\emptyset)$.

Conversely, job type y matched to worker type x receives systematic profits given by

$$\nu(x,y) = f(x,y) - w(x,y) = \frac{\sigma}{2}\log\left(\frac{\mu(x,\varnothing)}{\mu(\varnothing,y)}\right) + \frac{f(x,y) - f_{x\varnothing}(x) + f_{\varnothing y}(y)}{2}. \tag{9}$$

In addition, we obtain the empirically relevant idiosyncratic wages, $\tilde{w}(x_i, y_k)$, which correspond to the observed wages in our data. These wages are based on total match surplus (6)—i.e., the sum of systematic match surplus $s(x,y)$ in (7) and agents' idiosyncratic matching wedges δ_{xk} and δ_{iy}. Importantly, there is wage variation within type (x,y) matches across workers indexed by i and across jobs indexed by k. We show in Appendix C that, under our assumptions, worker i of type x receives the following idiosyncratic wage from job k of type y:

$$\tilde{w}(x_i, y_k) = \tilde{w}(x_i, y) = w(x,y) + \delta_{iy}. \tag{10}$$

That is, worker i receives a payoff that consists of the systematic wage, $w(x,y)$, which pertains to any match between a type x worker and type y job, as well as worker i's idiosyncratic preference for a type y job, given by the matching wedge δ_{iy}. Intuitively, a higher value of δ_{iy} reflects a stronger idiosyncratic preference of worker i for matching with a job of type y. Since there is a unique worker i with that idiosyncratic preference but many jobs of type y, competition among type y jobs for worker i drives his wage up to the point of enjoying the full value of the idiosyncratic surplus component, δ_{iy}.[23] In turn, job k of type y receives the residual surplus from matching with worker i of type x in the form of idiosyncratic profits $\tilde{\nu}(x_i, y_k)$.

The existence of an equilibrium follows from an application of the results in Galichon et al. (2019) and Chen et al. (2021) to our labor market context. The argument is constructive and forms the basis of our numerical solution algorithm. Note that the match frequency, $\mu(x,y)$, is a function of two endogenous variables: the nonemployment rate of type x workers and the idleness rate of type y jobs. To make this explicit, we use (7) to write the matching frequency for a (x,y) match as

$$M_{xy}(\mu(x,\varnothing), \mu(\varnothing,y)) := \mu(x,y) = \exp\left(\frac{s(x,y)}{2\sigma}\right)\sqrt{\mu(x,\varnothing)\mu(\varnothing,y)}. \tag{11}$$

We can then solve for $(\mu(x,\varnothing))_{x\in\mathcal{X}}$ and $(\mu(\varnothing,y))_{y\in\mathcal{Y}}$ based on the feasibility constraints of workers and jobs, which give a system of nonlinear equations:

$$h(x)m^W = \mu(x,\varnothing) + \sum_{y\in\mathcal{Y}} M_{xy}\left(\mu(x,\varnothing), \mu(\varnothing,y)\right), \quad \forall x \in \mathcal{X}, \tag{12}$$

$$g(y)m^J = \mu(\varnothing,y) + \sum_{x\in\mathcal{X}} M_{xy}\left(\mu(x,\varnothing), \mu(\varnothing,y)\right), \quad \forall y \in \mathcal{Y}. \tag{13}$$

[23] We make two additional remarks. First, we assume that idiosyncratic wages $\tilde{w}(x_i, y_k)$ are monetary and equal in value to the sum of the systematic wage $w(x,y)$ and the worker's idiosyncratic matching wedge δ_{iy}. To guarantee these monetary payouts, we can think of some—unmodeled—financial endowment that is constant across jobs; see Appendix C for more details. Second, equilibrium wages in our model are augmented by the worker's preference over a given job type, δ_{iy}, in contrast to the standard logic of compensating differentials according to which jobs reduce their wage payment by that amount (Rosen, 1986).

Thus, finding an equilibrium is equivalent to solving the system of $|\mathcal{X}| + |\mathcal{Y}|$ equations (12)–(13) in the same number of unknowns. In our model, the assumptions from Theorem 3 in Galichon et al. (2019) are satisfied.[24] This guarantees that an iterative procedure operating on (12)–(13) monotonically converges to a solution for $(\mu(x,\emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset,y))_{y\in\mathcal{Y}}$, based on standard results on the convergence of monotone bounded sequences. This algorithm, called the Iterative Projective Fitting Procedure (IPFP), provides a computationally efficient solution to high-dimensional matching problems. Plugging the solution for $(\mu(x,\emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset,y))_{y\in\mathcal{Y}}$ into $M_{xy}(\mu(x,\emptyset),\mu(\emptyset,y))$, we obtain the equilibrium matching frequencies $(\mu(x,y))_{x\in\mathcal{X},y\in\mathcal{Y}}$. Similarly, plugging the solution for $(\mu(x,\emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset,y))_{y\in\mathcal{Y}}$ into (8) and (10), we obtain the equilibrium values of systematic wages $w(x,y)$ and idiosyncratic wages $\tilde{w}(x_i,y_k)$. This demonstrates that an equilibrium exists.

Moreover, the uniqueness of equilibrium follows from Theorem 2 in Galichon et al. (2019), which builds on Berry et al. (2013). Uniqueness crucially hinges on the assumption that the distributions of idiosyncratic components δ_x and δ_y are absolutely continuous and have full support—properties that are satisfied by the EV distribution we assume. While in matching problems with discrete types, like ours, uniqueness is not generally obtained absent idiosyncratic matching frictions (i.e., $\sigma \to 0$), the presence of idiosyncratic matching frictions (i.e., $\sigma > 0$) generates preference heterogeneity that overcomes problems that stem from the coarseness of worker and job types. Intuitively, workers and jobs are not only characterized by their own types, which are discrete, but also by their idiosyncratic preferences, which are continuously distributed. As a result, the combination of types and preferences, based on which decisions are made, is essentially continuously distributed. This renders our problem similar in its mathematical structure to a standard frictionless matching problem with continuous types, which is known to have a unique solution up to a constant of integration in the match transfers. This demonstrates that the equilibrium is unique.

4.4 Meritocracy

Our model allows us to formalize *meritocracy* as the degree to which workers with certain skills are sorted into jobs with certain skill requirements to maximize output. Denote a country's parameter vector by $\theta := \big(G(x), H(y), m^J, f(x,y), f_{x\emptyset}(x), \sigma\big)$, the actual worker-job match frequencies by $\mu(x,y)$, and the hypothetical worker-job match frequencies in the frictionless case with $\sigma \to 0$ by $\mu^*(x,y)$. The following definition makes precise our notion of meritocracy in the labor market.

Definition 2 (Meritocracy Index)**.** *A country's meritocracy index $\mathcal{M}(\theta)$ is defined as the ratio of actual output to potential (i.e., frictionless) output,*

$$\mathcal{M}(\theta) := \frac{\sum_{(x,y)} \mu(x,y) f(x,y)}{\sum_{(x,y)} \mu^*(x,y) f(x,y)}. \tag{14}$$

[24] These assumptions are (i) additive separability between the systematic and idiosyncratic parts of the match surplus, (ii) that the maximum utility an agent achieves in a match is finite, and (iii) that the distribution of idiosyncratic matching wedges is absolutely continuous over full support, which holds for the assumed EV distribution.

The meritocracy index, $\mathcal{M}(\theta)$, depends on three groups of model primitives in θ, which impact the worker-job allocation, $\mu(x,y)$: idiosyncratic matching frictions, technology, and endowments.

A lower degree of idiosyncratic matching frictions (i.e., lower σ) leads to more output-based sorting between workers and jobs, which is guided by the technological returns to productive attributes (x,y). This pushes $\mu(x,y)$ closer to $\mu^*(x,y)$, and thereby narrows the gap between actual and potential output and increases the meritocracy index, $\mathcal{M}(\theta)$. The meritocracy index is maximized (i.e., $\mathcal{M}(\theta) = 1$) in a frictionless economy (i.e., $\sigma \to 0$), regardless of a country's specific endowments or technology.[25] In contrast, $\mathcal{M}(\theta) < 1$ when idiosyncratic factors unrelated to productivity influence the worker-job allocation (i.e., $\sigma > 0$), in which case technology and endowments are able to differentially affect actual versus potential output and thus $\mathcal{M}(\theta)$.

The production technology, $f(x,y)$, net of outside options, $f_{x\varnothing}(x)$ and $f_{\varnothing y}(y)$, determines match surplus based on productive attributes (x,y). For a given level of matching frictions, $\sigma > 0$, a technology with greater relative worker-job complementarities in some dimensions yields larger returns to labor market sorting. Again, this pushes $\mu(x,y)$ toward $\mu^*(x,y)$, and thereby narrows the gap between actual and potential output and increases the meritocracy index $\mathcal{M}(\theta)$.

Better-aligned endowments of worker skills, $G(x)$, and job skill requirements, $(H(y), m^J)$, facilitate output-based sorting. For a given level of matching frictions, $\sigma > 0$, a better fit between skill supply and demand tends to support the formation of productive matches since it incentivizes workers to seek matches that cater to their skills simply because more suitable jobs are available. Once more, this pushes $\mu(x,y)$ closer to $\mu^*(x,y)$, and thereby narrows the gap between actual and potential output and increases the meritocracy index $\mathcal{M}(\theta)$.[26]

In sum, the meritocracy index, $\mathcal{M}(\theta)$ measures a country's potential output gains from improved worker-job matching, which are determined by the interplay of endowments, technology, and idiosyncratic matching frictions.

5 Identification

Our goal is to identify, for each country, the parameter vector

$$\theta = \Big(G(x), H(y), m^J, f(x,y), f_{x\varnothing}(x), \sigma\Big) \in \Theta,$$

where $G(x)$ is the distribution of worker types, $H(y)$ is the distribution of job types, m^J is the relative job mass, $f(x,y)$ is the production function, $f_{x\varnothing}(x)$ is the value of nonemployment, and σ is the dispersion of labor wedges, which we interpret as the degree of idiosyncratic matching frictions. Note that we normalize the overall mass of workers, $m^W = 1$, and the production value of idle jobs, $f_{\varnothing y} = 0$, so that neither appears in θ. For the purpose of our identification result only,

[25] In a frictionless economy (i.e., $\sigma \to 0$), the equilibrium is still unique in terms of aggregate match surplus.

[26] Greater technological returns—by changing $f(x,y)$, $\mu(x,y)$, and $\mu^*(x,y)$—or more aligned endowments—by changing $\mu(x,y)$ and $\mu^*(x,y)$—affect both actual and potential output. In simulations, however, the increase in actual output in the numerator dominates the change in potential output in the denominator of the meritocracy index.

we normalize the output of matches involving the lowest worker skill type $\underline{x} := (\underline{x_n}, \underline{x_\ell})$, where $\underline{x_n} := \min x_n$ and $\underline{x_\ell} := \min x_\ell$, to $f(\underline{x}, y) = 0$ for all job types $y = (y_n, y_\ell, y_s)$.[27]

Proposition 1 (Identification)**.** *All model parameters are identified—i.e., there exists a unique parameter vector θ that rationalizes data on worker and job types, matching patterns, within-(x, y)-cell wage dispersion, and the aggregate profit share.*

Proof. See Appendix D.1. □

We discuss the identification of each group of parameters—endowments, technology, and idiosyncratic matching frictions—in three steps, and focus on the intuition behind Proposition 1.

First, regarding endowments, $G(x)$ and $H(y)$ are distributions over observable worker and job types, so they are identified based on the empirical shares of worker skills and job skill requirements.[28] In turn, the relative job mass, m^J, is identified based on the aggregate profit share.[29]

Second, to identify the scale parameter of idiosyncratic matching frictions, σ, we use the fact that match transfers are observed in the labor market context—contrary to conventional marriage market applications, for which this parameter needs to be normalized (e.g., Choo and Siow, 2006). Specifically, building on the insights of Salanié (2015), we demonstrate that σ is identified based on wage dispersion across individuals in the same (x, y) match.[30] In a frictionless world (i.e., $\sigma \to 0$), the law of one price requires that any individuals of the same worker type x in the same job type y must earn the same wage, so there is no wage dispersion within a given (x, y) match. In an economy with frictions (i.e., $\sigma > 0$), the idiosyncratic matching wedges δ_{xk} and δ_{iy} result in differences in idiosyncratic match surplus, and thus total match surplus across type x workers who match with type y jobs. As a result, wage dispersion within a given (x, y) match is strictly increasing in σ and unaffected by all other model parameters. Therefore, the empirical within-(x, y)-cell wage dispersion identifies σ.

Third, technology $(f(x, y), f_{x\emptyset}(x))$ is identified based on observed matching patterns. Consider the outside option of workers, which is identified for each worker type x based on the worker's choice probability of nonemployment relative to that of a match with some job type y. Since the relative choice probability depends on the observed wage in a match, the degree of matching frictions already identified above, and the worker's outside option, we can identify $f_{x\emptyset}(x)$ for each $x \in \mathcal{X}$. In turn, given endowments $(G(x), H(y), m^J)$ and idiosyncratic matching frictions σ, we can identify the production function, $f(x, y)$, from matching patterns between workers of type x and jobs of type y. Here, we make use of our assumption that the least productive worker skill type $\underline{x}$ produces zero output in all jobs, $f(\underline{x}, y) = 0$. Under this assumption, the probability that a job of type y matches with a worker of type x relative to matching with the least

[27] Since we do not observe idle jobs, a normalization is necessary to identify the level of match output—an issue that does not arise in matching models of the marriage market, where the single rates of both men and women are observed.

[28] Note that we identify $H(y)$ of the distribution of *filled* jobs since we do not observe vacancies in our data. Therefore, we assume that the distributions of filled and unfilled jobs are identical in a given country.

[29] Intuitively, given production technology, outside options, and idiosyncratic matching frictions—all of which are shown to be identified below—the aggregate profit share decreases in the relative mass of jobs competing for workers.

[30] Ahlfeldt et al. (2015) and Hsieh et al. (2019) follow a similar approach to identify their Fréchet shape parameters.

productive worker depends only on the observed wage $w(x, y)$, the already-identified matching frictions σ, and match output $f(x, y)$, so we can identify $f(x, y)$ for each $(x, y) \in \mathcal{X} \times \mathcal{Y}$.[31]

6 Estimation

We estimate our model separately for each of the $N^C = 28$ countries in the PIAAC data. In doing so, we allow all model parameters—which correspond to endowments, technology, and idiosyncratic matching frictions—to flexibly differ across countries. We first introduce the model's parameterization, then discuss our estimation procedure informed by the previous section's identification arguments, and finally present estimation results.

6.1 Distributional and Functional-Form Assumptions

For estimation purposes, we make additional assumptions regarding the distributions of worker skills and job skill requirements, the production function, and agents' outside options.

Endowments. We discretize the distributions of worker skills and job skill requirements from PIAAC microdata using the following approach, which mirrors our treatment of the data in Sections 2 and 3. We discretize worker skills (x_n, x_ℓ) and job skill requirements (y_n, y_ℓ) into global quintiles by first partitioning their marginal distributions in each country into 5 country-specific quantiles and then assigning each a value that corresponds to the average global rank of its workers or jobs in that dimension. In addition, we classify workers into 2 genders, $x_g \in \{\text{female}, \text{male}\}$, and jobs into 2 firm-size groups, $y_s \in \{\text{small}, \text{large}\}$, where "small" corresponds to up to 50 employees and "large" to more than 50 employees.[32] For workers, since we observe both nonemployed and employed individuals on the PIAAC, we can directly infer the population distribution of types. For jobs, an additional assumption regarding the distribution of idle jobs is needed, since we have no information on vacancies by job type. To this end, we assume that the unobserved population of all (i.e., filled and idle) job types is congruent with the observed distribution of filled jobs in a given country, which we observe on the PIAAC.[33] As a result, we obtain probability mass functions over 50 worker types, $g(\cdot)$, and 50 job types, $h(\cdot)$.

[31] Systematic wages $w(x, y)$ are not directly observed but can be backed out from the observed average idiosyncratic wages, $\mathbb{E}[\tilde{w}(x_i, y_k)|x, y]$ in a given (x, y) match, using properties of the EV distribution; see Appendix D for details.

[32] We choose the number of grid points for worker and job distributions to balance two considerations. On the one hand, we want a large enough number of grid points to capture the rich worker and job heterogeneity in PIAAC data. On the other hand, we want a small enough number of grid points to keep (x, y) cells sufficiently densely populated to allow for reliable measures of within-(x, y)-cell wage dispersion, which our estimation strategy depends on.

[33] Selection forces naturally push toward the subset of idle jobs' being negatively selected among the population of all jobs. As is well known due to Heckman (1976, 1979), identifying the population distribution of market participants in the presence of endogenous selection into observable states requires additional assumptions. See also Honoré and Hu (2020) for a discussion of exclusion restrictions and alternative assumptions commonly used in this literature.

Technology. In terms of the production function, we assume a bilinear functional form for the output produced by a type x worker in a match with a type y job:

$$f(x, y) = \alpha_{nn} x_n y_n + \alpha_{n\ell} x_n y_\ell + \alpha_{ns} x_n y_s + \alpha_{\ell n} x_\ell y_n + \alpha_{\ell\ell} x_\ell y_\ell + \alpha_{\ell s} x_\ell y_s. \tag{15}$$

The production function interacts each of the two worker skills (x_n, x_ℓ) with all three productive job attributes (y_n, y_ℓ, y_s). A worker's gender x_g does not directly affect output but enters match surplus through gender-specific outside options. The 6 parameters $(\alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s})$ guide productive complementarities between worker and job attributes, which crucially shape equilibrium matching patterns. Equation (15) allows us to define TFP as $A := \alpha_{nn}$, which leaves us with five more complementarity parameters, $(\hat{\alpha}_{n\ell}, \hat{\alpha}_{ns}, \hat{\alpha}_{\ell\ell}, \hat{\alpha}_{\ell n}, \hat{\alpha}_{\ell s})$, each relative to A.

We allow for flexible workers' outside options, $f^{rg}_{x\emptyset}$, nonparametrically estimated across 6 groups of workers, consisting of 3 broad skill groups indexed by $r \in \{\text{low}, \text{medium}, \text{high}\}$ interacted with 2 gender groups indexed by $g \in \{\text{female}, \text{male}\}$.[34] We set the value of an idle job to zero, $f_{\emptyset y}(y_n, y_\ell, y_s) = 0$, which circumvents the need to identify this object based on our data.[35]

6.2 Estimation Procedure

Given our distributional and functional-form assumptions, the parameters to be estimated are

$$\theta = \left(g(\cdot), h(\cdot), m^J, \alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s}, (f^{rg}_{x\emptyset})_{r\in\{\text{low,medium,high}\}, g\in\{\text{female,male}\}}, \sigma \right).$$

The vector θ contains two distributions and 14 parameters, which we estimate separately for each country. Our estimation proceeds in two steps. In the first step, we estimate—outside the model—the probability mass $g(x)$ for each worker type x and $h(y)$ for each job type y. In the second step, we use the model to internally estimate the remaining 14 parameters based on the Simulated Methods of Moments (SMM). This involves finding the parameter vector θ that, for a given vector of model-based moments $\mathcal{S}^m(\theta)$ and the corresponding vector of data-based moments $\mathcal{S}^d$, minimizes an objective function $\Omega(\mathcal{S}^m(\theta), \mathcal{S}^d)$. Here, $\mathcal{S}^m(\theta)$ and $\mathcal{S}^d$ each contain 15 moments, based on the identification arguments in Proposition 1, which serve as targets in the SMM.

We use the ratio of within-(x, y)-cell log-wage dispersion to the overall log-wage dispersion to pin down σ/A. We use the mean log wage in 2017 PPP dollars as an additional moment that is sensitive to levels, not just relative terms, to separately determine TFP, $A = \alpha_{nn}$, and the scale parameter, σ.[36] We choose 6 skill-gender-specific nonemployment rates to pin down the 6 outside option values $f^{rg}_{x\emptyset}$, 6 moments that reflect the worker-job matching patterns to inform the 6 produc-

[34] Creating broad skill groups reduces the dimensionality of the estimation routine while retaining sufficient heterogeneity to match the data. Specifically, we take the sum of worker's numeracy and literacy skill quintiles and classify workers as "low-skilled" if the sum is 2–4, "medium-skilled" if it is 5–7, and "high-skilled" if it is 8–10.

[35] In theory, jobs' values of remaining idle may vary freely, akin to workers' values of nonemployment. In practice, though, the lack of information on vacancies by job type in conventional data prevents us from identifying this object.

[36] Proposition E.1 in Appendix E.1 states an important homogeneity property of our model, which implies that target moments that comprise only workers' and jobs' choice probabilities (i.e., sorting patterns), within-(x, y)-cell *log*-wage dispersion, and the profit share merely pin down the degree of matching frictions relative to TFP, σ/A.

tion technology parameters, $(\alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s})$, and the aggregate profit share to pin down the relative job mass m^J. For details, see Appendix E.2 for the construction of model and data moments, Appendix E.4 for the estimation procedure, and Appendix E.5 for the IPFP algorithm.

Discussion of Identification Threats. An advantage of our approach is that it allows for the transparent identification of all model parameters, as discussed above. At the same time, due to potential data issues, the sharpness of the identification result—especially concerning the identification of σ—might not carry over to its practical implementation in estimation.

The first issue regards the accuracy of the PIAAC data. If wages are reported with noise, we would obtain biased estimates of σ since some of the within-(x, y)-cell wage dispersion is not due to idiosyncratic matching wedges but rather to measurement error.[37] If this measurement error is uniform across countries, we expect some bias in the *level* of the estimated σ in each country. But we would be less concerned about bias in the *cross-country relation* of our estimates of idiosyncratic matching frictions; see Appendix E.7 for the formal argument. If, in turn, measurement error in wages were more pronounced in low-income countries, then we would mistakenly estimate a negative relationship between σ and GDP per capita. In this case, the true effect of σ on development would be less than what we currently estimate and our quantitative results on the role of σ in development accounting would reflect an upper bound.

A second issue pertains to our discretization of skills and skill requirements. With too coarse a grouping, within-(x, y)-cell wage dispersion may reflect productive heterogeneity in skills rather than unproductive idiosyncratic heterogeneity. Two aspects alleviate this concern: Theoretically, to the extent that the bias in the estimated σ induced by our discretization is constant across countries, an argument similar to that regarding measurement error applies. In practice, we verify that our choice of discretization is not essential for any subsequent results by trying alternative, either more or less coarse, groupings; see Figure B7 in Appendix B.4.

A third issue relates to the presence of unobserved productive attributes. If workers sort and get paid based on productive attributes that are omitted from our analysis, we may erroneously interpret some share of observed within-(x, y)-cell wage dispersion as reflecting frictions. Following a logic similar to that above, this is not a major threat if such unobserved attributes are distributed similarly across countries. Of potentially greater concern is the possibility that unobserved productive heterogeneity is more dispersed in less developed countries. Two related insights alleviate this concern. First, we find that observable skills are less (i.e., not more) dispersed in lower-income countries. Second, when we include in our analysis additional skill measures reported for a subset of countries in the PIAAC data (e.g., ICT skills), or indeed exclude some of the existing ones, we find similar results; see Figure B9 in Appendix B.4 for details.

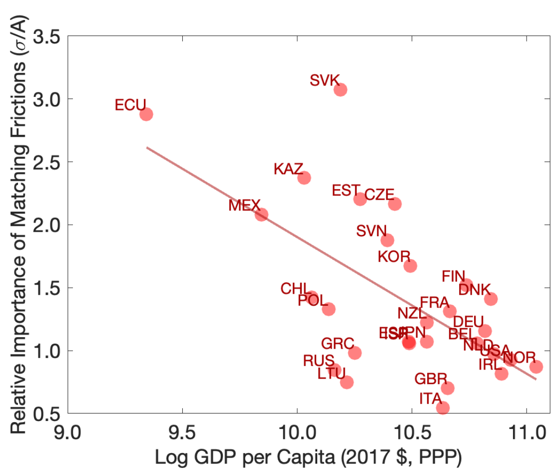
[37]Beyond noisily reported wages, we do not expect measurement error in skills to be a major issue given that they are assessed using standardized tests and are harmonized across countries as part of PIAAC data collection.

6.3 Estimation Results

We now present the parameter estimates, model fit based on targeted moments, and model validation based on untargeted data moments across countries.

Parameter Estimates. Figure 9 shows our estimates of the relative importance of idiosyncratic matching frictions, measured as the ratio of the scale parameter of the labor wedge distribution to TFP, σ/A. This ratio captures how much weight is given to idiosyncratic factors as opposed to productive attributes in the matching of workers and jobs. We find that the relative importance of idiosyncratic matching frictions is considerably higher in less developed countries. For example, the estimated σ/A in Ecuador, the lowest-income country on the PIAAC, is around three times higher than in Norway, the highest-income country on the PIAAC. These estimates directly reflect the empirical within-cell wage dispersion across countries, which is higher in low-income countries; see Figure 7 in Section 3.2. Through the lens of our model, this suggests that worker-job matching is closer to random in poorer countries. A descriptive analysis that relates our estimates of σ/A to observables suggests that these frictions are positively related to levels of corruption, obstacles to the ease of doing business, lack of regulatory quality, and lack of merit in job allocation across countries; see Appendix E.9 for details.

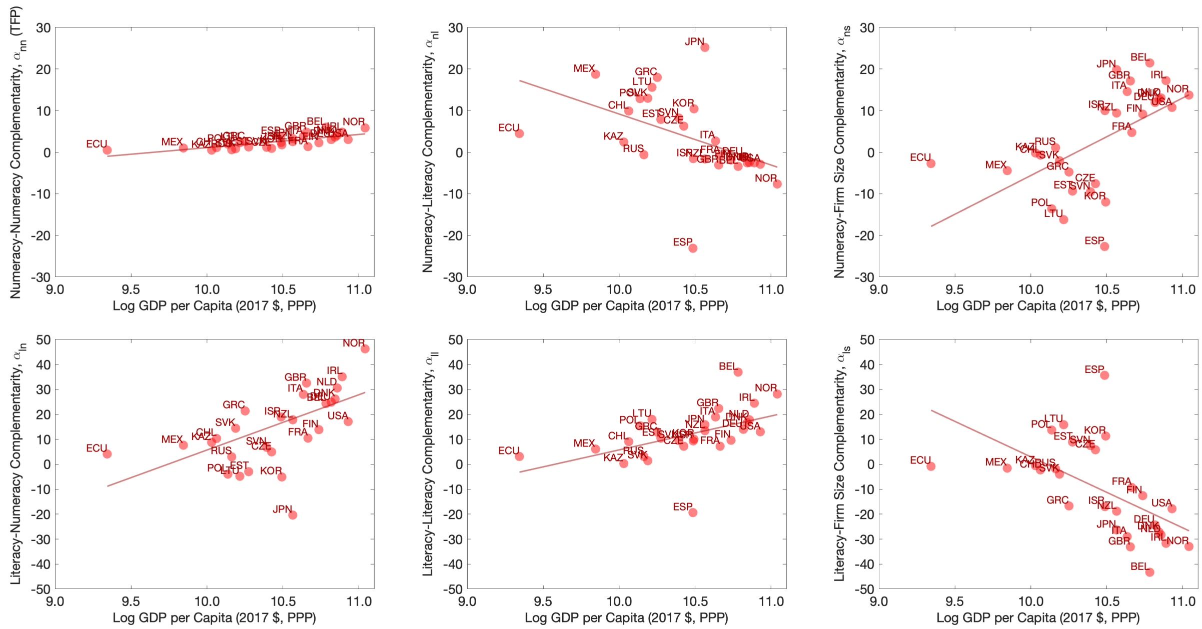
Figure 9: Estimated Relative Importance of Matching Frictions across Countries



Notes: This figure plots the estimated relative importance of idiosyncratic matching frictions, measured as the ratio of the scale parameter of the labor wedge distribution to TFP, σ/A, against log GDP per capita across countries. Each red dot represents one country. The solid line represents the linear best fit. *Source:* Model estimates.

Figure 10 displays how the estimated production function parameters vary with log GDP per capita across countries. A clear pattern emerges: Complementarities between most worker skills and job skill requirements are greater in high-income countries. This is particularly true for the coefficient on the numeracy-numeracy interaction, α_{nn}, and that on the literacy-literacy interaction, $\alpha_{\ell\ell}$. These estimates reflect stronger empirical sorting patterns between worker and job traits in high-income countries; see Figures 2 and 3 in Section 3.1.

Figure 10: Estimated Production Function Parameters across Countries

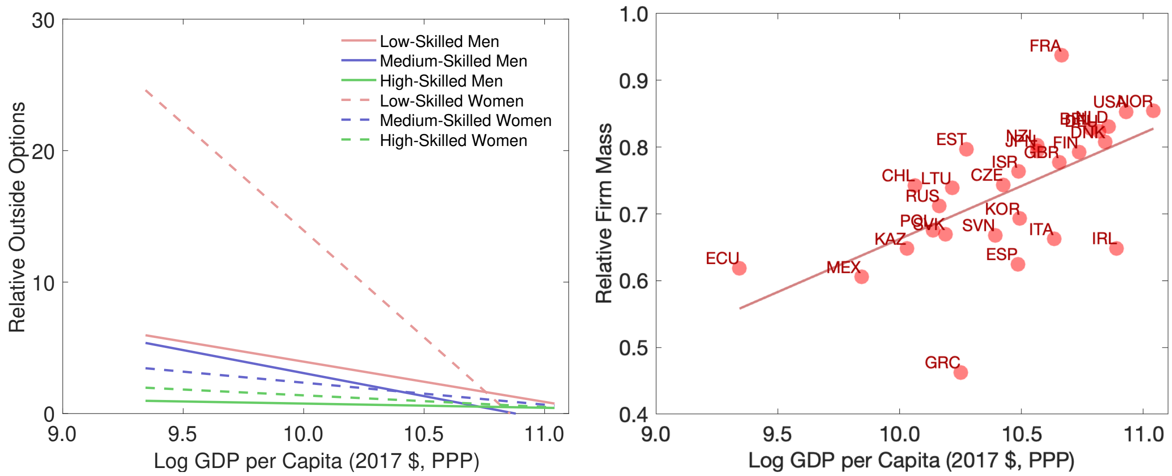


Notes: This figure plots estimates of the production function parameters $(\alpha_{nn}, \alpha_{nl}, \alpha_{ns}, \alpha_{ln}, \alpha_{ll}, \alpha_{ls})$ against log GDP per capita across countries. Each red dot represents one country. Solid lines indicate the linear best fit. *Source:* Model estimates.

The left panel of Figure 11 shows the relative value of home production, measured as the payoff from nonemployment relative to the mean value of market production, across the development spectrum for workers of different broad skill groups and genders. We find that the relative value of home production tends to be higher for all skills in lower-income countries, which reflects their higher nonemployment rates; see the left and middle panels of Figure E1 in Appendix E.3. Strikingly, the negative cross-country pattern is considerably more pronounced for low-skilled women (dashed pink line) than low-skilled men (solid pink line), consistent with low-skilled women's high nonemployment rates in poor countries (Ngai et al., 2022; Doss et al., 2023). The right panel of Figure 11 shows that the relative mass of firms is lower in low-income countries, which suggests that their labor markets are less competitive or subject to higher entry costs. These estimates are informed by both higher nonemployment rates and higher aggregate profit shares in less developed countries; see Figure E1 in Appendix E.3.

Model Fit Based on Targeted Moments. To showcase the model's fit based on targeted moments, Figure 12 focuses on Ecuador, the lowest-income country in our sample, and Norway, the highest-income country in our sample. The model fit for the complete set of 28 countries is reported in Figures E2 and E3 in Appendix E.8. Each panel plots the model-based moments against targeted data moments, where the 15 moments are split into six categories, denoted by different-colored markers. Our parsimonious model fits the data from all countries well, with the targeted moments lined up near the 45-degree line, which indicates a perfect model fit. This is not unexpected but confirms that our estimation strategy based on the formal identification result in

Figure 11: Estimated Outside Options and Relative Firm Masses across Countries



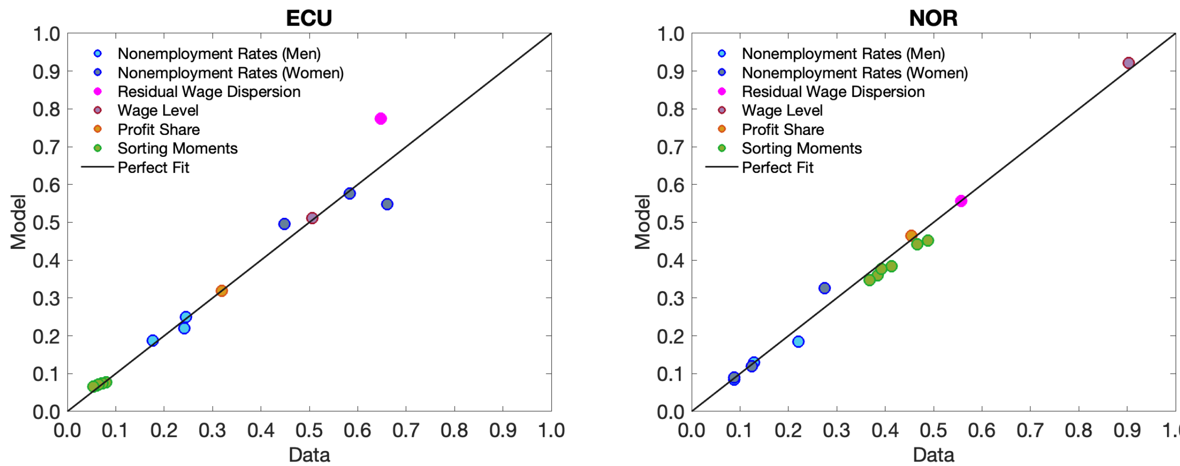
Notes: This figure plots estimates of outside options $f^{rg}_{x\varnothing}$ relative to the mean value of market production for broad worker groups (left panel) and the relative firm mass m^J (right panel) against log GDP per capita across countries. Each line in the left panel represents the linear best fit for one broad worker group. See Appendix E.2 for the definition of these groups. Each red dot in the right panel represents a structural estimate of m^J for one country, and the solid line indicates the linear best fit. *Source:* Model estimates.

Proposition 1 works well in practice, which suggests that the distributional and functional-form assumptions we imposed are not overly restrictive. Several features of the model fit are worth highlighting. First, in both the data and the model, the moments related to sorting patterns (green markers) are increasing in GDP per capita, consistent with our empirical finding that there is stronger worker-job sorting in high-income countries; see Figures 2 and 3 in Section 3.1. Second, our model matches that nonemployment rates for both genders (blue markers) are decreasing in GDP per capita, especially for women. Third, the within-cell wage dispersion (pink markers) is decreasing in GDP per capita; see Figure 7 in Section 3.2. Finally, our model matches the fact that average wages (purple markers) are increasing in GDP per capita.

Model Validation Based on Untargeted Moments. We are interested in the extent to which the estimated model—through variation in worker-job mismatch across countries—accounts for the empirical cross-country heterogeneity in untargeted moments, including aggregate output and wage inequality. The top panels of Figure 13 show the model reproducing the empirical differences in hourly output per worker or hourly output per capita. In our model, high-income countries produce more output due to a more skilled workforce, more demanding jobs, superior technology, and lower idiosyncratic matching frictions. These three fundamentals not only directly affect productivity but also indirectly by reducing worker-job mismatch.

The bottom panels of Figure 13 show the model reproducing greater wage inequality in low-income countries, both in terms of overall dispersion measured by the 90–10 log wage ratio and in terms of lower-tail dispersion measured by the 50–10 log wage ratio. In our model, the workforce in less developed countries tends to be tilted toward workers with lower skill levels, which leads to a more pronounced left tail of the income distribution. Also contributing to this pattern are

Figure 12: Model Fit for Select Countries



Notes: This figure illustrates model fit by plotting model moments against data moments for Ecuador (ECU), the lowest-income country in our sample, and Norway (NOR), the highest-income country in our sample. The 45-degree line indicates a perfect fit between the model and the data. See Appendix E.2 for details of the construction of moments. The purple markers show mean log wage levels scaled by a factor of 1/3.5 to fit on the same axes as other moments. *Source:* PIAAC, OECD, FRED, and model estimates.

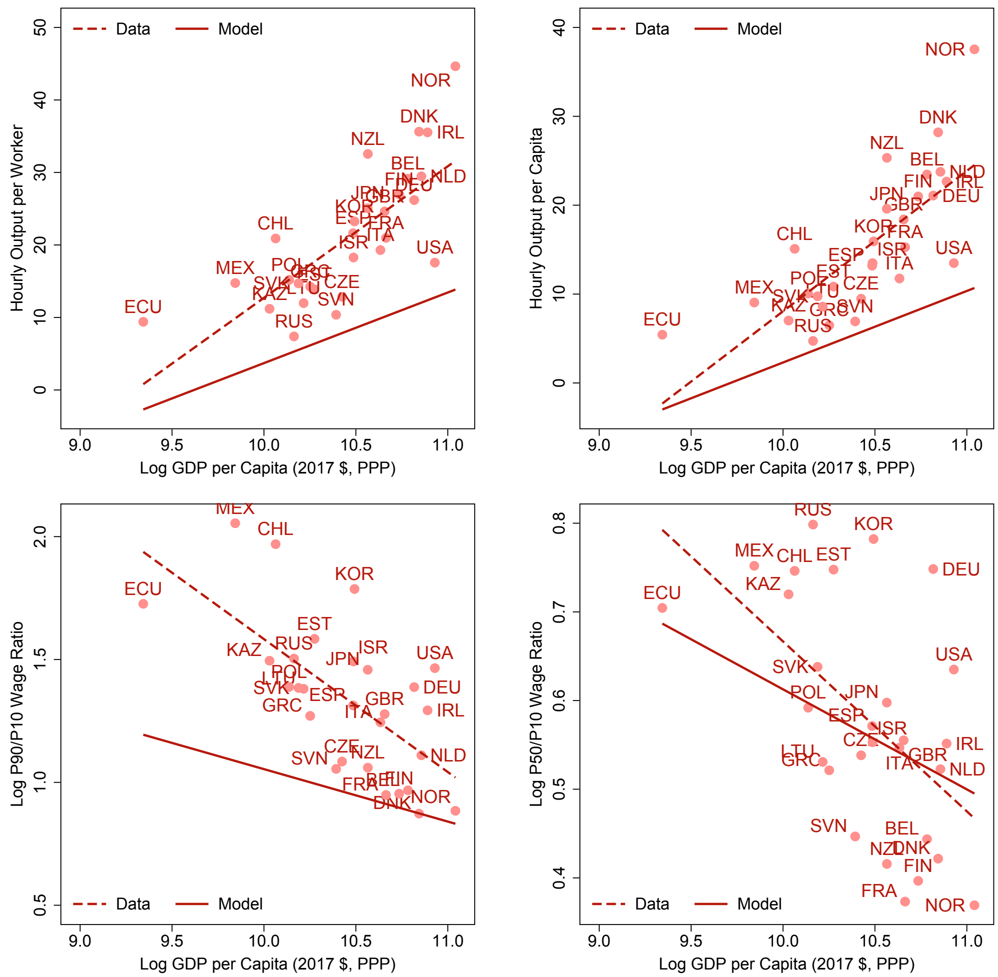
greater idiosyncratic matching frictions in low-income countries, which give rise to wage dispersion across identical workers and jobs, and thereby increase overall wage inequality.

Overall, while our model misses some of the levels of these untargeted moments in the data, it matches reasonably well the cross-country gradients.

Cross-Country Differences in Worker-Job Matching. Our estimated model predicts significant differences in worker-job matching patterns—and thus meritocracy in the labor market—across the development spectrum. On the intensive margin, the left panel of Figure 14 captures the output losses from the misallocation of workers across jobs by use of the meritocracy index $\mathcal{M}(\theta)$, defined as the ratio of a country's actual to potential output. The average country's meritocracy index is around 0.55, which reflects substantial misallocation of workers across jobs. At the same time, there is a lot of cross-country variation, whereby more developed countries have higher meritocracy indices. For instance, Norway—the highest-income country in our sample—has a meritocracy index of 0.75, which is almost four times that of Ecuador, the lowest-income country in our sample. That is, Norway could increase its output by around one-third in the absence of matching frictions, while Ecuador could increase its output by around five fold. Importantly, these large output losses in Ecuador are due to a lack of workers' incentives to sort across jobs based on misaligned endowments, inferior technology, and a high degree of matching frictions.

On the extensive margin, the right panel of Figure 14 shows that our model predicts stronger skill-based selection into employment in high-income countries. Given the scarcity of jobs—i.e., a relative job mass below unity estimated in the right panel of Figure 11—actual output is enhanced when more skilled workers select into employment, while less skilled workers remain nonem-

Figure 13: Model Validation Based on Untargeted Moments across Countries

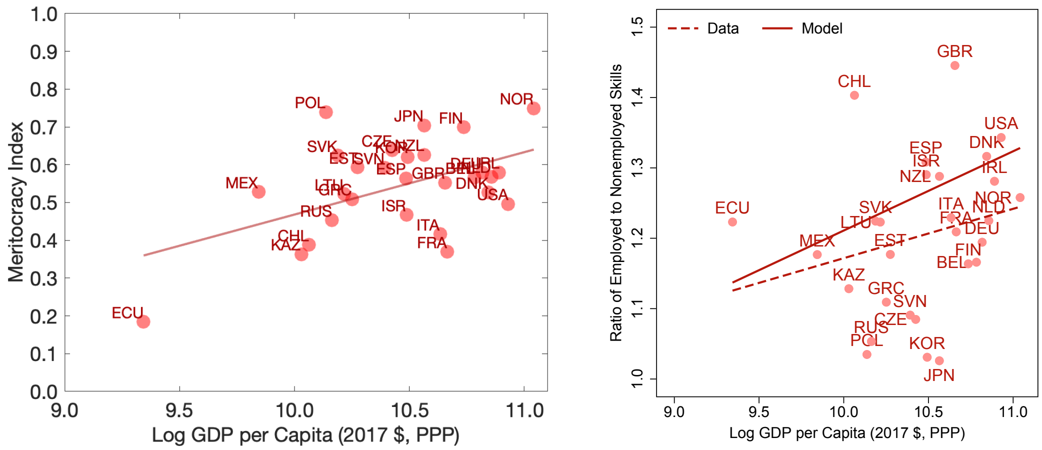


Notes: This figure shows the fit of the model vis-à-vis the data based on a set of untargeted moments against log GDP per capita across countries. The top panels show cross-country differences in hourly output per worker and hourly output per capita. The bottom panels show the 90-10 log wage ratio and the 50-10 log wage ratio. Each red marker represents one country in the data. Dashed lines indicate the linear best fit to the data, and solid lines indicate the linear best fit to the model. *Source:* PIAAC, World Bank, and model estimates.

ployed.[38] All else equal, skill-based selection into employment is more important for output in low-income countries where jobs are relatively more scarce. However, our estimates in the right panel of Figure 14 suggest that selection is less (i.e., not more) positive in less developed countries. In both the data and the model, the average skill advantage of employed over nonemployed workers is more than 13 percentage points larger in high-income countries. Altogether, these findings suggest that labor markets in lower-income countries are less meritocratic.

[38]This is especially true if the outside option is greater for less skilled workers, as shown in the left panel of Figure 11.

Figure 14: Intensive and Extensive Margins of the Worker-Job Allocation across Countries



Notes: The left panel plots the meritocracy index, defined as a country's estimated output relative to its potential output without idiosyncratic matching frictions (i.e., $\sigma \to 0$) against GDP per capita across countries. Each of the red dot represents one country in the estimated model. The solid line indicates the linear best fit. The right panel plots the ratio of the average skills of employed workers and nonemployed workers against GDP per capita across countries in the estimated model and in the data. See Figure 4 for more details. Each label represents one country in the data. The dashed line indicates the linear best data fit. The solid line indicates the linear best model fit. *Source:* PIAAC and model estimates.

7 Sources and Consequences of Meritocracy across Countries

To understand the sources of meritocracy in the labor market and its consequences for economic development, our analysis proceeds in two steps. In the first, we focus on the sources by asking: Why are some countries more meritocratic? Is it because of differences in endowments, technology, or idiosyncratic matching frictions? In the second step, we study the consequences of meritocracy by asking: How do worker-job sorting patterns affect aggregate output and wage inequality across countries?

Whether the lack of meritocracy is a quantitatively important hurdle for development depends on the combination of idiosyncratic matching frictions together with endowments and technology. Reducing frictions in lower-income countries (i.e., $\sigma \to 0$) while fixing their technology and endowments increases aggregate output toward its potential and, thus, their meritocracy index. However, if potential output in these countries is relatively low to begin with—due to either inferior endowments of worker skills and job skill requirements or their backward technology—then the gains from increasing meritocracy are limited. In this case, cross-country convergence in national incomes requires upgrades to endowments and technology in low-income countries, which not only increase the returns to worker-job sorting and thus actual output but also boost their potential output. The result is increased meritocracy through a narrower gap between actual and *now-increased* potential output.[39]

[39] That is, upgrades in endowments and technology increase both the numerator and also the denominator of the meritocracy index in a way that increases their ratio.

7.1 Development Accounting for Aggregate Output and Inequality across Countries

We now use our estimated model for a development accounting exercise by simulating a sequence of equilibrium counterfactuals to decompose aggregate output and how it varies across countries into contributions due to endowments, technology, and idiosyncratic matching frictions.[40]

The Role of Endowments. To account for cross-country income differences, we first quantify the contribution of endowments. We recompute equilibrium after counterfactually assigning each country the endowments of worker skills and job skill requirements of the frontier country, Norway, which has the highest national income in our sample.[41] This has two distinct effects, especially on less developed countries. First, it directly increases output as high-skilled workers and jobs become more abundant. Second, it indirectly increases output by improving worker-job allocation due to a better alignment of worker skills and job skill requirements.

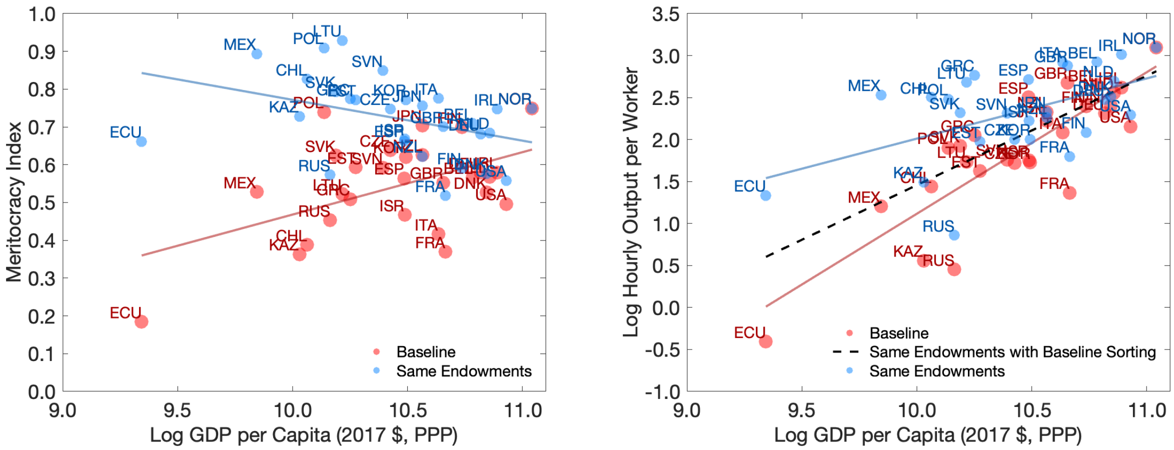
Figure 15 shows the results of this experiment. The left panel shows a pronounced increase in the meritocracy index in lower-income countries, which reflects the fact that a better alignment of skill supply and demand incentivizes more sorting for any given level of idiosyncratic matching frictions $\sigma > 0$. In fact, the sorting incentives increase so much in lower-income countries that the slope of the meritocracy index across countries flips from positive to negative. The right panel shows that this leads to sizable output gains, especially in lower-income countries, which are associated with a 25 percent reduction in the coefficient of variation of output per worker across countries. Importantly, more than half of these output gains are due to an improved worker-job allocation, as indicated by the dashed black line in the right panel, which shows output per worker when adopting frontier endowments while holding each country's meritocracy index fixed at baseline.

The Role of Technology. Next, we assess the role of technology. To do so, we recompute the equilibrium worker-job allocation and aggregate output after assigning all countries Norway's frontier production technology. Figure 16 shows the results of this counterfactual. In the left panel, we see improved worker-job matching in most countries. Intuitively, adopting the frontier technology with stronger worker-job complementarities—for a given level of idiosyncratic matching frictions $\sigma > 0$—increases the returns to skill-based labor market sorting, and thus reduces worker-job misallocation. The right panel shows that, as a result, log hourly output per worker increases more in lower-income countries. This implies a large decrease in cross-country inequality and is associated with a 35 percent reduction in the coefficient of variation. Most of these output changes are due to the direct effect of technology improvements rather than the indirect effect of improved worker-job matching, as illustrated by the dashed black line in the right panel, which fixes the meritocracy index at its baseline.

[40] We provide details on the implementation of these counterfactuals in Appendix F.1.

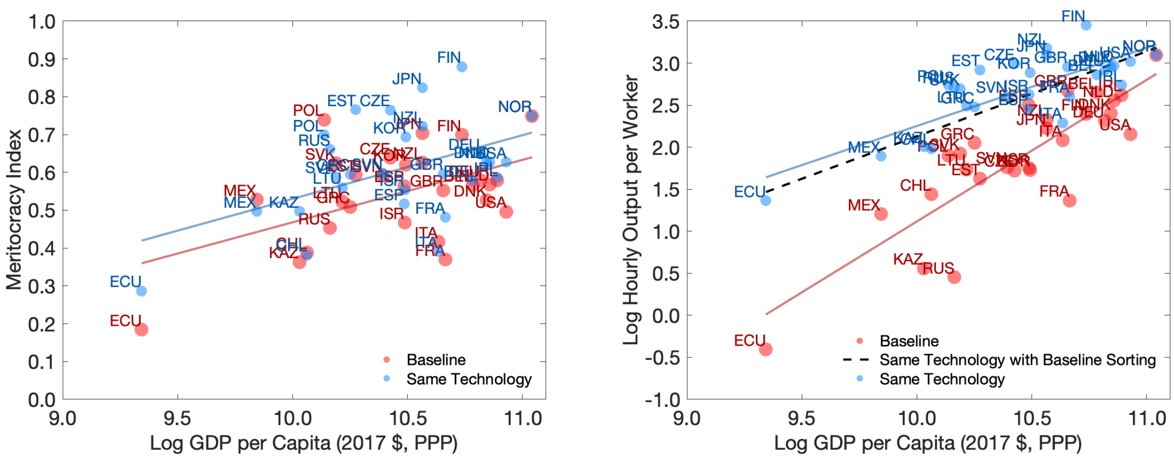
[41] We repeated the same exercise using the United States as the frontier country, with similar results.

Figure 15: Counterfactual Imposing Frontier Endowments across Countries



Notes: This figure shows the model-based counterfactual effects of implementing Norway's frontier endowments of worker skills and job skill requirements in all countries on the meritocracy index (left panel) and log hourly output per worker (right panel). Red circles represent the baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue circles represent the counterfactual outcomes for each country, with blue solid lines indicating the linear best fit across log GDP per capita. The dashed black line in the right panel indicates the linear best fit across log GDP per capita in the counterfactual while keeping worker-job sorting, measured by the meritocracy index, at its baseline. *Source:* Model simulations.

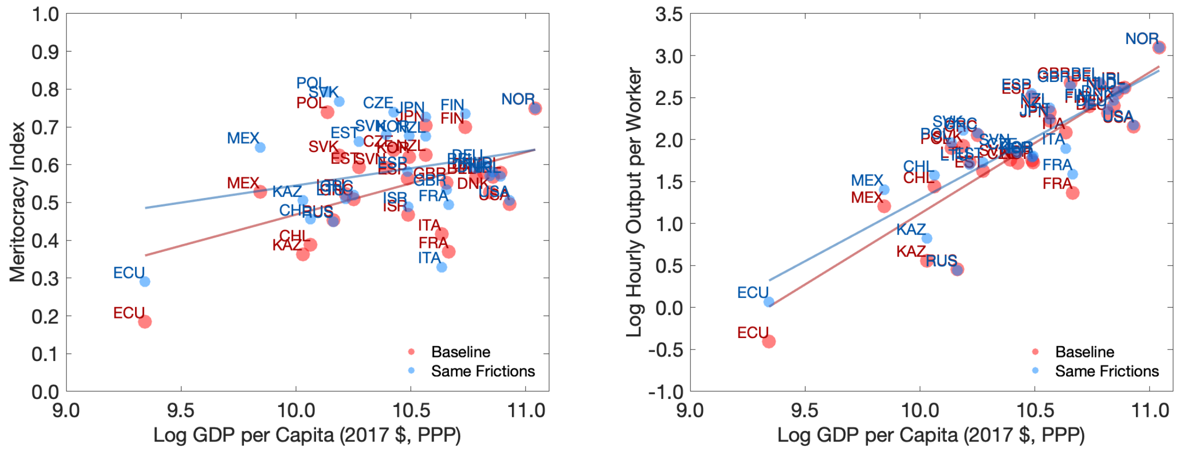
Figure 16: Counterfactual Imposing Frontier Technology across Countries



Notes: This figure shows the model-based counterfactual effects of implementing Norway's frontier production technology in all countries on the meritocracy index (left panel) and log hourly output per worker (right panel). Red circles represent the baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue circles represent the counterfactual outcomes for each country, with blue solid lines indicating the linear best fit across log GDP per capita. The dashed black line in the right panel indicates the linear best fit across log GDP per capita in the counterfactual while keeping worker-job sorting, measured by the meritocracy index, at its baseline. *Source:* Model simulations.

The Role of Idiosyncratic Matching Frictions. Finally, we evaluate the impact of idiosyncratic matching frictions. Figure 17 shows the results of counterfactually adopting Norway's frontier matching frictions, which are comparably low. The left panel shows that, consequently, worker-job matching improves, especially in the lowest-income countries in which frictions were initially high, with increases in the meritocracy index between 20 and 80 percent over baseline. However, the right panel shows that this has only modest effects on aggregate output differences across countries. This finding reflects the important reality that it is primarily other factors—i.e., the

Figure 17: Counterfactual Imposing Frontier Matching Frictions across Countries



Notes: This figure shows the model-based counterfactual effects of implementing Norway's frontier matching frictions in all countries on the meritocracy index (left panel) and log hourly output per worker (right panel). Red circles represent the baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue circles represent the counterfactual outcomes for each country, with blue solid lines indicating the linear best fit across log GDP per capita. *Source:* Model simulations.

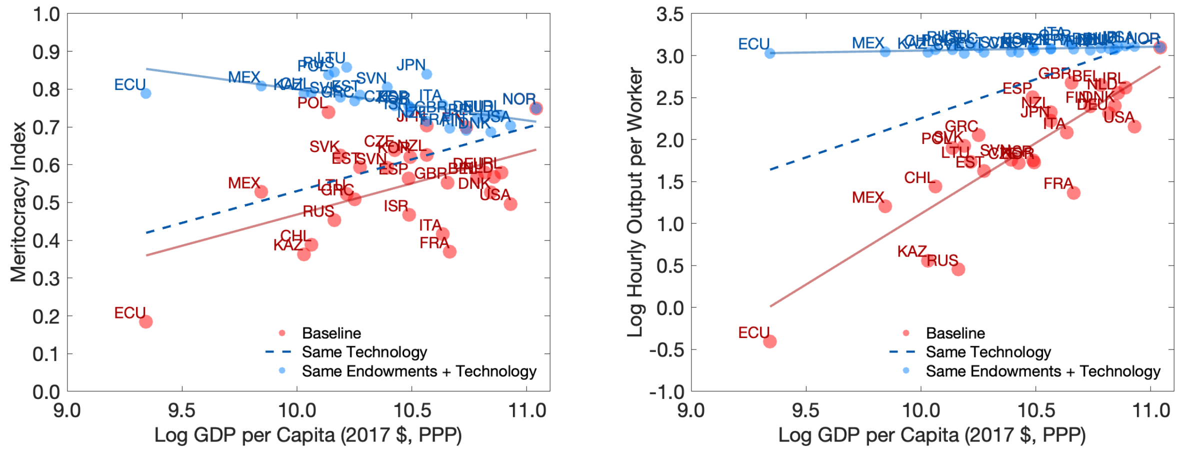
scarcity of high-skilled workers and jobs and backward technology—that constrain low-income countries and render their potential output levels low compared with the actual output levels of more developed countries. From this exercise, we conclude that idiosyncratic matching frictions disproportionally affect lower-income countries, though their effects on cross-country income differences are relatively small. This is because strengthening worker-job sorting helps low-income countries catch up only if the returns from sorting are sufficiently high.

Complementarities. Each of the previous three counterfactuals isolated the effects of a single model fundamental—endowments, technology, or matching frictions. While each fundamental in isolation shaped aggregate outcomes, we have so far ignored any complementarities between them. In this section, we show that the returns to improving worker-job allocation depend on a country's entire set of fundamentals. Thus, incremental reforms that target one fundamental at a time fail to realize the potential gains from improving multiple fundamentals simultaneously.

Here, we highlight the complementarity between endowments and technology, which we find to be quantitatively most important.[42] Figure 18 shows the results of counterfactually adopting Norway's frontier endowments of worker skills and job skill requirements together with its frontier technology in all countries. Worker-job matching, measured by the meritocracy index, in the left panel, improves markedly, and more so in low-income countries. Consequently, output per worker in the right panel increases overall, especially in less developed countries. Notably, output in low-income countries grows significantly more than the sum of the two counterfactuals in isolation would suggest. These complementarities between endowments and technology reflect increased returns to sorting, which lead to further improvements in worker-job matching that push actual output toward now-increased potential output. As a result, this dual counterfactual

[42] Appendix F.2 studies the complete list of all possible complementarities between fundamentals.

Figure 18: Counterfactual Imposing Frontier Endowments and Technology across Countries



Notes: This figure shows the model-based counterfactual effects of assigning Norway's frontier endowments of worker skills and job skill requirements as well as their production technology simultaneously to all countries on the meritocracy index (left panel) and log hourly output per worker (right panel). Red circles represent baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue circles represent the counterfactual outcomes for each country, with blue solid lines indicating the linear best fit across log GDP per capita. Dashed blue lines indicate the intermediate counterfactual simulation of changing only the production technology in each country but keeping the endowments of worker skills and job skill requirements unchanged. *Source:* Model simulations.

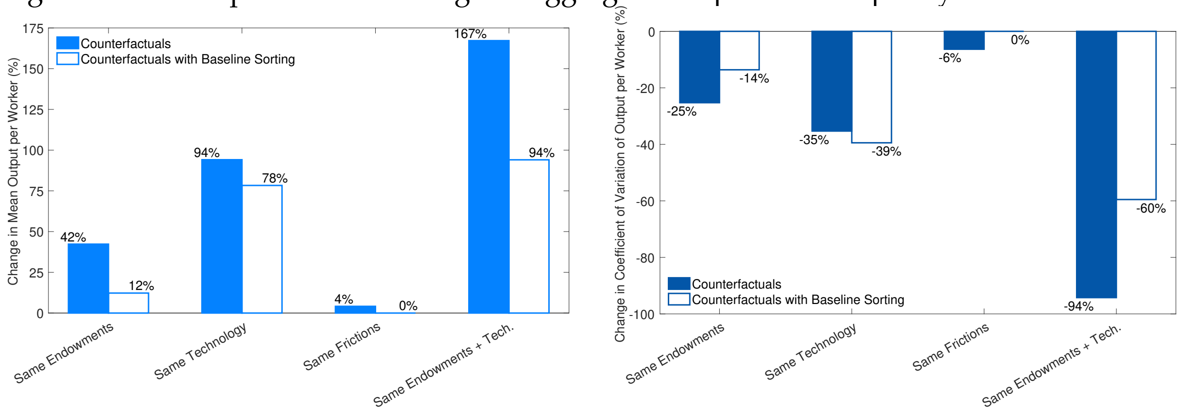
erases 94 percent of the cross-country variation in output per worker. Around 40 percent of this convergence is due to improved worker-job sorting; see the left panel of Figure F3 in Appendix F.2. Complementarities between improved skill endowments and technology also lead to a disproportional increase in global output per worker by 167 percent.

Development Accounting for Aggregate Output and Inequality across Countries. Figure 19 summarizes the counterfactual effects on global output in the left panel and on cross-country income inequality in the right panel. For each counterfactual, the solid blue bars represent the overall equilibrium effect, while the hollow blue bars represent the partial-equilibrium effect holding fixed baseline worker-job sorting as summarized by each country's meritocracy index.

Starting with aggregate output in the left panel, a few observations are worth highlighting. First, the global output gains associated with a single fundamental are largest when adopting Norway's frontier technology (+94 percent), compared with the gains from equalizing endowments (+42 percent) and matching frictions (+4 percent). Second, the complementarities between endowments and technology are large, with the effects of simultaneously adopting frontier endowments and technology being around 23 percent larger (+167 percent) than the sum of the individual counterfactuals (+136 percent). Third, a significant share of the total gains is due to improved worker-job sorting (e.g., +73 percent out of +167 percent when simultaneously adopting frontier endowments and technology).

Moving to cross-country income inequality in the right panel—measured by the coefficient of variation of hourly output per worker across countries—the most important single driver is technology (−35 percent), followed by endowments (−25 percent) and matching frictions (−6

Figure 19: Development Accounting for Aggregate Output and Inequality Across Countries



Notes: This figure summarizes the results from all counterfactual simulations in terms of their effects on mean output per worker across countries (left panel) and the coefficient of variation of output per worker across countries (right panel). Solid bars represent outcomes based on the counterfactual exercises. Hollow bars represent the counterfactual while keeping each country's meritocracy index at its baseline level. Numbers at the bars indicate the percentage change relative to the baseline. *Source:* Model simulations.

percent). While the effect of technology is mostly direct, improved worker-job allocation is key for the convergence across countries due to equalized endowments (-11 out of -25 percent) and drives all of the effects due to lower frictions (-6 percent). Third, there are again strong complementarities. Simultaneously adopting frontier endowments and technology closes 94 percent of the cross-country income gap—considerably more than the sum of the two counterfactuals in isolation (-60 percent). Importantly, a significant share of the effects of this dual counterfactual is due to improved worker-job sorting ($-$ 34 out of -94 percent).

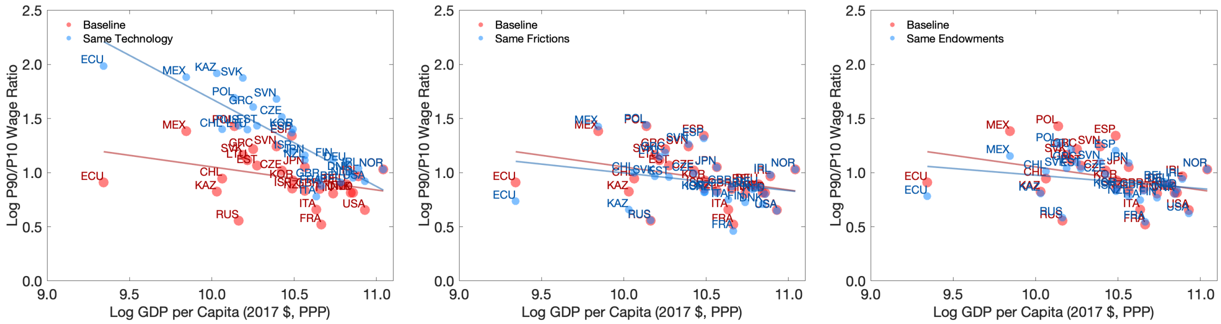
In summary, improved worker-job matching is crucial for harvesting the gains from improved endowments and technology. Improvements in endowments and technology increase the returns to worker-job sorting, and thereby narrow the gap between actual and now-increased potential output. Conversely, the payoff from lowering idiosyncratic matching frictions, which materializes through improved worker-job sorting, are limited in economies in which inferior endowments or technology pin potential output to a low level. In this case, narrowing the gap between actual and potential output triggers little benefit in the cross-country comparison. We conclude that greater meritocracy in high-income countries is mostly a consequence, rather than a source, of economic development, which can result from investing in the workforce, upgrading jobs, and adopting frontier technology.

7.2 Accounting for Differences in Wage Inequality across Countries

So far, our emphasis has been on aggregate output. However, changes in worker-job matching also have distributional consequences across individuals within labor markets. Here, we use a sequence of counterfactuals to account for wage inequality across the development spectrum.

Equalizing technology significantly increases wage inequality across the board, and more so in low-income countries; see the left panel of Figure 20. This is because both the direct effects of stronger worker-job complementarities and the indirect effects of improved worker-job sorting

Figure 20: Counterfactual Effects on Wage Inequality from Adopting either Frontier Technology, Matching Frictions or Endowments across Countries



Notes: This figure shows the model-based counterfactual effects of implementing in all countries Norway's frontier production technology (left panel), matching frictions (middle panel) and endowments (right panel) on wage inequality. Red circles represent the baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue circles represent the counterfactual outcomes for each country, with blue solid lines indicating the linear best fit across log GDP per capita. *Source:* Model simulations.

increase wage inequality. The main beneficiaries of technological improvements are high-skilled workers, who are scarce in less developed countries, which thus increases wage inequality.

In contrast, equalizing matching frictions reduces wage inequality overall, and more so in lower-income countries (middle panel). The indirect inequality-enhancing effect through improved worker-job matching is more than offset by the direct inequality-reducing effect through lower idiosyncratic heterogeneity in wages within match types. Intuitively, these effects are larger in low-income countries, in which idiosyncratic matching frictions are initially more pronounced.

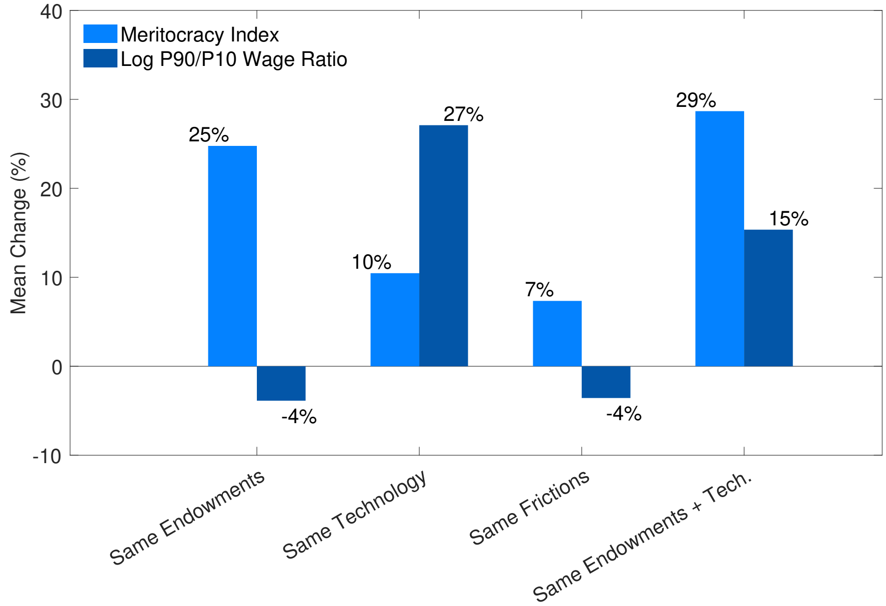
Finally, equalizing endowments reduces wage inequality in most economies, and more so in less developed ones; see the right panel of Figure 20. In spite of the improved worker-job matching this causes, wage inequality declines mostly due to the direct effect of increasing the supply of high-skilled workers in lower-income countries, which reduces skill returns.

Figure 21 summarizes changes in wage inequality across counterfactuals. Importantly, wage inequality can either increase or decrease (dark blue bars) under improved worker-job matching proxied by the meritocracy index (light blue bars), depending on the fundamental drivers.

7.3 Gender Gaps in Employment and Pay across Countries

Our framework naturally lends itself to studying the misallocation of workers across jobs along the intensive margin (i.e., matching between employed workers and jobs) and the extensive margin (i.e., selection into employment). Here, we study a particularly salient dimension of misallocation: gender differences in labor market outcomes across the development spectrum. Despite near-universal increases in female labor force participation over the past decades, most countries are still characterized by significant gender imbalances in employment. Reasons include both supply-side factors (e.g., marriage, fertility, and social norms that limit women's labor force at-

Figure 21: Development Accounting for Meritocracy and Wage Inequality across Countries



Notes: This figure summarizes the results from all counterfactual simulations in terms of their effects on worker-job matching, as measured by the meritocracy index (light blue bars) and wage inequality, as measured by the log P90-P10 wage ratio (dark blue bars). Numbers above or below each counterfactual bar indicate the percentage change relative to the baseline meritocracy index and the baseline log P90-P10 wage ratio, respectively. *Source:* Model simulations.

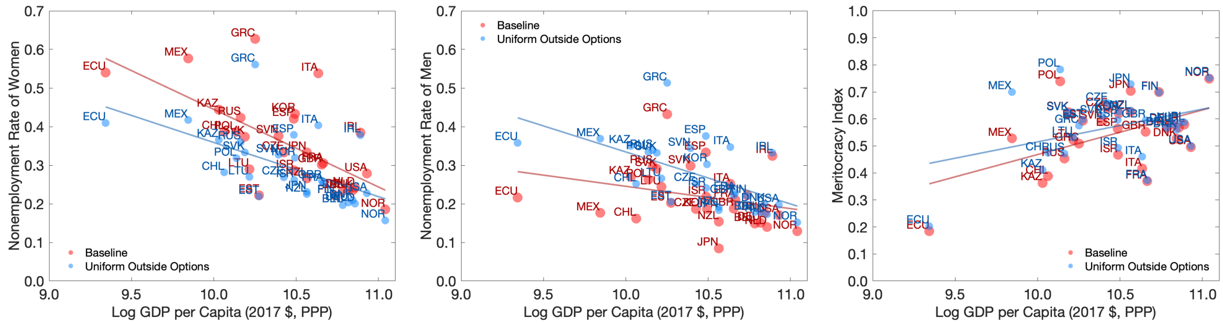
tachment) and demand-side factors (e.g., discrimination).[43] Our model captures a mix of such factors through estimated differences in women's—relative to men's—outside options; see the left panel of Figure 11 in Section 6.3.

On the extensive margin, although women are similarly skilled as men, Figure 22 shows that female nonemployment rates are up to 30 percentage points higher than men's in our lowest-income countries, compared with a gap of around 5 percentage points in our highest-income countries (red markers in the left and middle panels). Turning to the intensive margin, high-skilled women are more underrepresented in high-skilled jobs in lower-income countries. The reverse is true for low-skilled women, who are more overrepresented in low-skilled jobs in low-income countries, see Figure F6 in Appendix F.3. Compared with gender differences on the extensive margin, however, these intensive-margin differences are comparatively small.

We relate gender differences in worker-job matching to aggregate outcomes by considering two counterfactuals. First, we assign all women the male outside option $f^{r,\text{male}}_{x\varnothing}$. On the extensive margin, the left and middle panels of Figure 22 show that this counterfactual pushes a large number of women into employment, particularly in low-income countries in which gender differences in outside options are initially higher. However, given the fixed number of available jobs, this counterfactual leads to an almost one-for-one crowding out of men's employment. Thus, the effect of changes in the gender composition of the workforce depends on whether the women who

[43]Figure F5 in Appendix F.3 shows that skills are relatively similar between men and women within most countries. Thus, the underqualification of women is likely not the main driver of gender differences in labor market outcomes.

Figure 22: Misallocation of Women and Men on the Extensive and Intensive Margins



Notes: This figure shows the model-based counterfactual effects of giving women in each country the same outside options as that of men on women's nonemployment rates (left panel), men's nonemployment rates (middle panel), and worker-job sorting measured by the meritocracy index (right panel). Red circles and solid red best-fit lines show the baseline results. Blue circles and solid blue best-fit lines show the counterfactual outcomes. *Source:* Model simulations.

enter employment are more skilled than the men they replace (Ashraf et al., 2023; Hsieh et al., 2019). On the intensive margin, the right panel of Figure 22 shows that pulling women into the workforce also improves the overall worker-job allocation, driven by the increased competition among workers for jobs. This is especially true in low-income countries that had more worker-job mismatch to begin with. As a result, there is a flattening of the meritocracy index across countries.

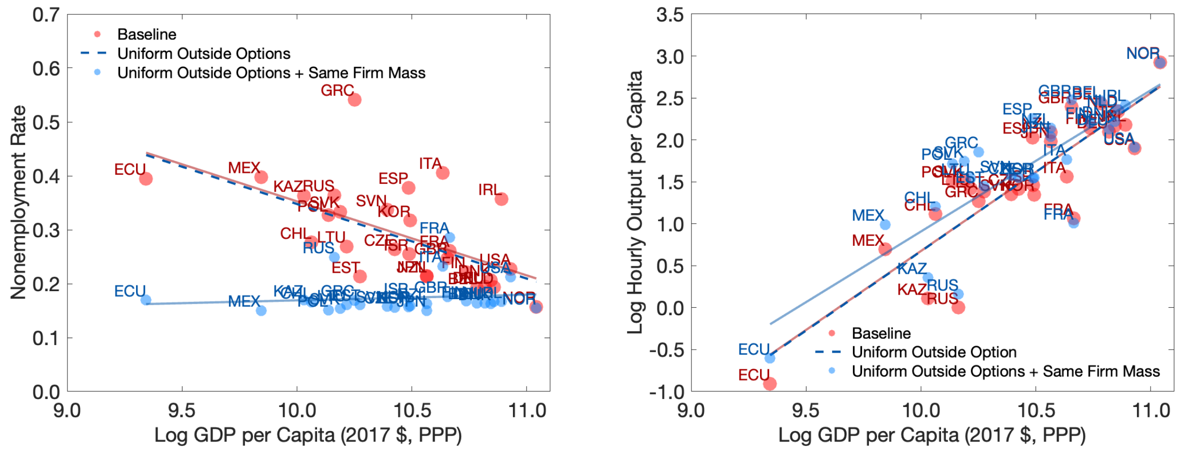
Figure 23 shows that, by itself, this counterfactual has little aggregate effect on nonemployment (dashed line, left panel) and aggregate output (dashed line, right panel), which reflects large crowding-out and small gender differentials in skills. In contrast, if, in a second counterfactual, we also adjust countries' job masses to match that of Norway, the frontier country, we find a sharp drop in nonemployment rates in low-income countries (blue markers in the left panel), which yields a near-constant nonemployment rate of around 17 percent across countries. Associated with this are substantial gains in hourly output per worker (blue markers in the right panel), especially for the lowest-income countries. We conclude that a scarcity of jobs may be an obstacle to increasing female employment rates and, as a result, to economic development.

7.4 Integrating Labor Markets across Countries

In this section, we study the effects of labor market integration on output across countries through its effects on worker-job allocation. In our baseline model, the assignment of workers to jobs took place within each country's labor market. In reality, though most workers remain in their country of birth, international migration is associated with large wage and welfare gains for migrants (Borjas, 1999; Hendricks and Schoellman, 2018; Lagakos et al., 2018a; Dustmann and Preston, 2019).

We investigate the equilibrium effects of labor market integration in two counterfactuals. First, we simulate regional labor market integration, allowing for free mobility of workers across countries within each of seven regions. Second, we simulate global labor market integration, allowing for free mobility across all countries. In each scenario, we set the endowment of worker skills within an integrated labor market equal to the pooled endowments of its member countries. Moreover, we assume that technology and skill requirements remain country-specific and that workers

Figure 23: Counterfactual Effects on Nonemployment Rates from Equalizing Outside Options across Gender, with and without Fixed Jobs



Notes: This figure shows the model-based counterfactual effects of giving women in each country the same outside options as men on aggregate nonemployment rates (left panel) and log hourly output per capita (right panel). Red circles and solid best-fit lines show the baseline results. Dashed blue lines show the best fit of the counterfactual that equates women's outside options to men's. Blue circles and solid best-fit lines show the counterfactual that additionally adopts Norway's frontier relative mass of firms. *Source:* Model simulations.

within an integrated labor market are subject to the regional average degree of matching frictions.

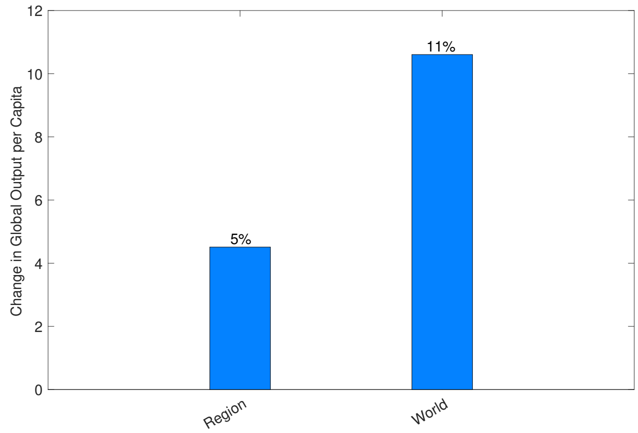
Figure 24 presents the effects on aggregate output from increasingly integrated labor markets. Compared with the baseline, output per capita increases by 5 percent under regional integration. The gains are more than twice as high (11 percent) when moving to a single integrated world labor market. By allowing for international labor mobility while keeping all other factors constant, these counterfactuals highlight the gains from trade in worker skills across countries through improved worker-job matching. Our simulations neglect several important aspects of international migration, including moving costs and other nonpecuniary aspects of location decisions. Nevertheless, this exercise highlights the possibility of substantial output gains from increased worker mobility due to improved worker-job matching—the central mechanism highlighted in this paper.

8 Conclusion

From family firms elevating the founder's son to CEO, to doctors inheriting their parents' occupational choices, numerous anecdotes highlight the lack of meritocracy in labor markets, particularly in low-income settings. In this paper, we study how meritocracy—defined as the extent to which workers match with jobs based on skills to maximize output rather than based on idiosyncratic attributes unrelated to productivity—differs across countries. We then ask why we see these patterns and what are the aggregate consequences.

We find that worker-job matching in high-income countries is closer to the output-maximizing allocation due to more aligned endowments of skills and skill requirements, stronger complementarities in production, and lower matching frictions. Furthermore, differences in technology and

Figure 24: Global Output per Capita for Different Levels of Labor Market Integration



Notes: This figure shows output per capita in the model for two scenarios that represent different levels of labor market integration comprising either (i) seven regions consisting of Continental Europe plus Great Britain, Scandinavia, Southern Europe, the former Soviet Union, Asia plus New Zealand, North America, and South America, or (ii) a single integrated world labor market. In each scenario, workers in an integrated labor market have access to the technology and skill requirement distribution of the country they work in and to the average degree of idiosyncratic matching frictions in the region. Numbers above each counterfactual bar indicate the percentage change relative to the baseline. *Source:* Model simulations.

the endowments of worker skills and job skill requirements account for most cross-country income differences, while matching frictions play a relatively modest role. From this, we conclude that the gains from improving worker-job sorting in low-income countries are constrained by their endowments and technology, which render their potential output relatively low—our first key insight. At the same time, a large share of the gains from adopting better endowments and technology are realized through improved worker-job sorting—our second key insight.

Broadly, our findings suggest that greater meritocracy in high-income countries is mostly a consequence, rather than a source, of economic development. Thus, policies aimed at improving worker-job matching alone will not effectively eradicate cross-country income differences unless combined with interventions that enhance match productivity.

While our accounting exercise points to the important effects of technology and endowments on economic development—both in isolation and in combination—we were silent on the sources of these fundamentals. To the extent that they are endogenously determined, interesting dynamics can emerge. For example, countries could be trapped in a "low meritocracy equilibrium," in which inferior endowments and technology constrain the returns to improved worker-job matching, but investments in endowments or technology are unprofitable given the existing matching frictions. As such, a "Big Push" in one of the three fundamentals may jump-start a chain reaction in the others that can lead to rapid economic development (Rosenstein-Rodan, 1943, 1961; Murphy et al., 1989; Buera et al., 2023)—a hypothesis we plan to explore in future work.

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Appendix for
"Meritocracy across Countries"

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April 17, 2024

Appendix Outline. This appendix is structured as follows. Appendix A gives further details of the data based on the PIAAC survey and supplemental datasets used in the empirical analysis in Section 2 of the paper. Appendix B presents additional materials pertaining to the facts presented in Section 3 of the paper. Appendix C contains derivations pertaining to the equilibrium model in Section 4 of the paper. Appendix D states the identification proof as well as the proof of the homogeneity property of the model in Section 5 of the paper. Appendix E describes further details of the numerical estimation procedure introduced in Section 6 of the paper. Finally, Appendix F shows additional results relating to the counterfactual analysis in Section 7 of the paper.

A Data Appendix

In this appendix section, we include further details on the PIAAC data and other data sources introduced in Section 2 of the paper.

A.1 Details on the PIAAC Dataset

Our main data source is the Survey of Adult Skills of the PIAAC administered by the OECD between 2012 and 2018, which comprises a representative sample of the working-age population in each participating country. The target population for the survey is all non-institutionalized adults between the ages of 16 and 65 who reside in the country at the time of data collection. The data comprise over 230,000 respondents, representing 815 million adults aged 16 to 65 surveyed in 38 countries. Of these, 28 countries have all the information (e.g., continuous wages) required for our study. The countries included in our study are Belgium, Chile, the Czech Republic, Denmark, Ecuador, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Lithuania, Mexico, the Netherlands, New Zealand, Norway, Poland, Russia, Slovakia, Slovenia, Spain, the United Kingdom, and the United States. The countries available in PIAAC but excluded from our study due to missing key variables are Australia, Austria, Canada, Cyprus, Hungary, Indonesia, Peru, Singapore, Sweden, and Turkey. Technical documentation for the PIAAC microdata is available from OECD (2019), and the original microdata are available for download from OECD (2024).

A.2 Key Variables in the PIAAC Data

Worker Skills and Job Skill Requirements. PIAAC formally assesses three cognitive skill domains: literacy, numeracy, and information communication technology (ICT). For our analysis, we use only numeracy and literacy skills, as ICT skill information is missing for several key countries in our sample. PIAAC reports scores from incentivized tests for numeracy and literacy skills on a scale from 0 to 500, which we use to construct country-specific skill distributions (see Section 2 of the paper for details). These scores can be interpreted as follows. A numeracy score below 176 means that the respondent can perform simple processes such as counting, sorting, performing basic arithmetic operations, or understanding simple percentages; a score of 176-225 implies that the respondent is comfortable with basic mathematical processes in common, concrete contexts where the mathematical content is explicit; a score of 226-275 implies that the respondent can identify and act on mathematical information embedded in common contexts; scores in the range 276-325 mean that the respondent understands mathematical information which may be less clear, whose representation may be more complex or in unfamiliar contexts; scores in the range 326-375 imply that the respondent understands complex mathematical information and ideas, which may involve chained processes; and finally, a score of 376-500 implies that the respondent understands complex representations and abstract and formal mathematical and statistical ideas, possibly embedded in complex texts.

To measure skill requirements for a given job defined by the four-digit ISCO occupation code, we use self-reported data from PIAAC on the task composition of workers' jobs. The survey asks workers to report whether they perform certain tasks in each skill area. For instance, for numeracy, these tasks are (1) use a calculator, (2) calculate costs or budgets, (3) use or calculate fractions or percentages, (4) prepare charts graphs or tables, (5) use simple algebra or formulas, (6) use advanced math or statistic. We sum the number of tasks that each worker completes in each skill domain—numeracy and literacy—and weigh each task performed by its difficulty. To do so, we match each task in the PIAAC questionnaire to the closest skill proficiency level based on the descriptions provided in the PIAAC documentation (OECD, 2019), where proficiency levels range between 1 and 5.

For example, the description for difficulty level 1 for numeracy is *"... carry out basic mathematical processes in common, concrete contexts where the mathematical content is explicit with little text and minimal distractors. Tasks usually require simple one-step or two-step processes involving, for example, performing basic arithmetic operations; understanding simple percents such as 50%; or locating, identifying and using elements of simple or common graphical or spatial representations."* We assign the task of using a calculator to numeracy difficulty level 1 because it mentions basic arithmetic operations. Similarly, based on the descriptions of other numeracy proficiency levels, we assign each of the six numeracy tasks a difficulty level. Working with fractions and preparing charts and tables span proficiency levels 1 and 2, so we assign a weight of 1.5 to these tasks. Calculating costs and budgets is assigned a weight of 3, using simple algebra is assigned a weight of 4, and using advanced mathematics or statistics is assigned a weight of 5. We similarly assign weights to each of the twelve literacy tasks based on their proficiency levels. We then take the average of this measure across all workers in a country who report the same occupation code to arrive at an occupation-specific skill requirement of literacy and numeracy.

To deal with the fact that skills and skill requirements are measured in different units and need to be comparable for analyzing worker-job sorting, we transform both raw measures using "global quantiles"; see Section 2 of the paper for details.

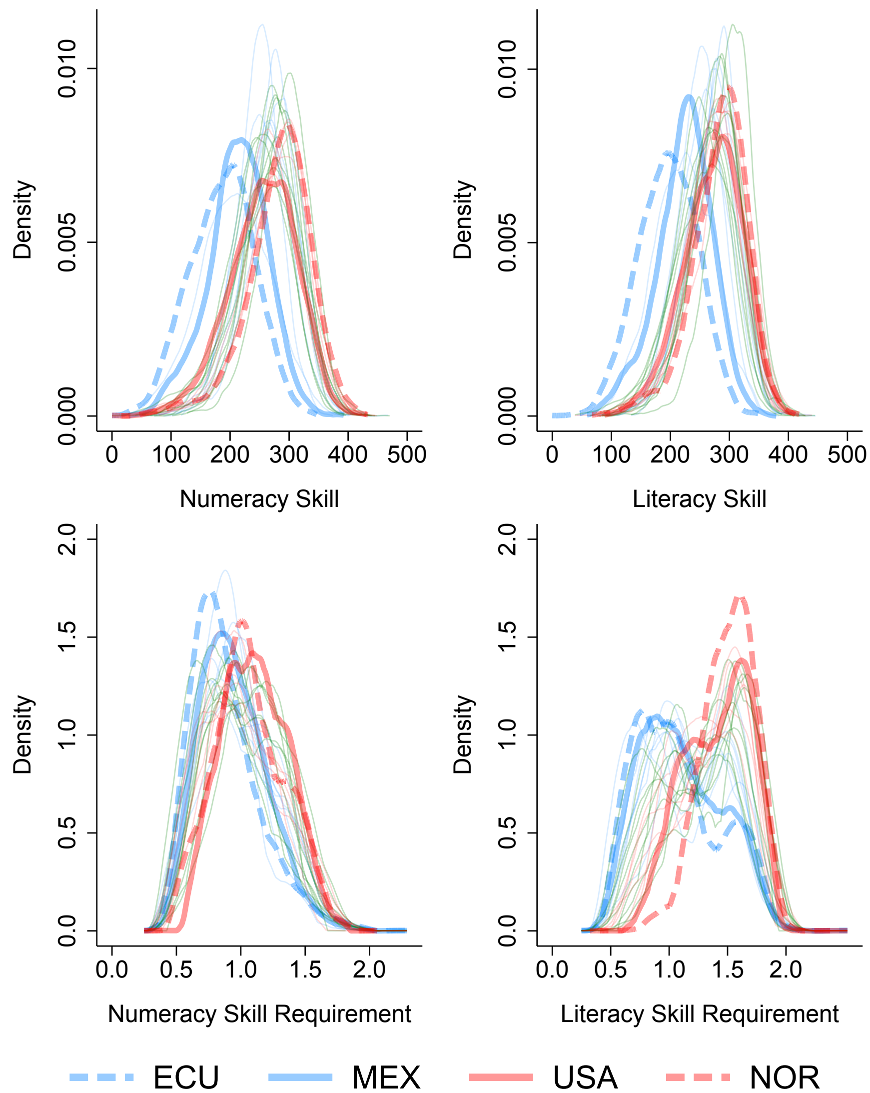
Demographics, Labor Markets, and Firms. In addition to data on workers' skills and skill requirements, we also use the PIAAC background questionnaire for data on the following variables: years of schooling, years of experience in the labor market, gender, age, occupation (4-digit ISCO codes), hourly wage in PPP US $, and employment status. We combine workers who are unemployed and out of the labor force so that each worker in our data is either employed or non-employed. Finally, we use data on the size of the firm a worker reports working in as a proxy for overall job productivity. This is a categorical variable from which we classify workers as employed in a "small" firm if their firm has up to 50 employees and as employed in a "large" firm if their firm has more than 50 employees.

A.3 Other Data Sources

We obtain GDP per capita (2017 $, PPP) from the World Development Indicators of the World Bank. We obtain data on labor shares from the OECD and Federal Reserve Economic Data (FRED). We use 2012 as the reference year to merge these external data into our sample of PIAAC countries.

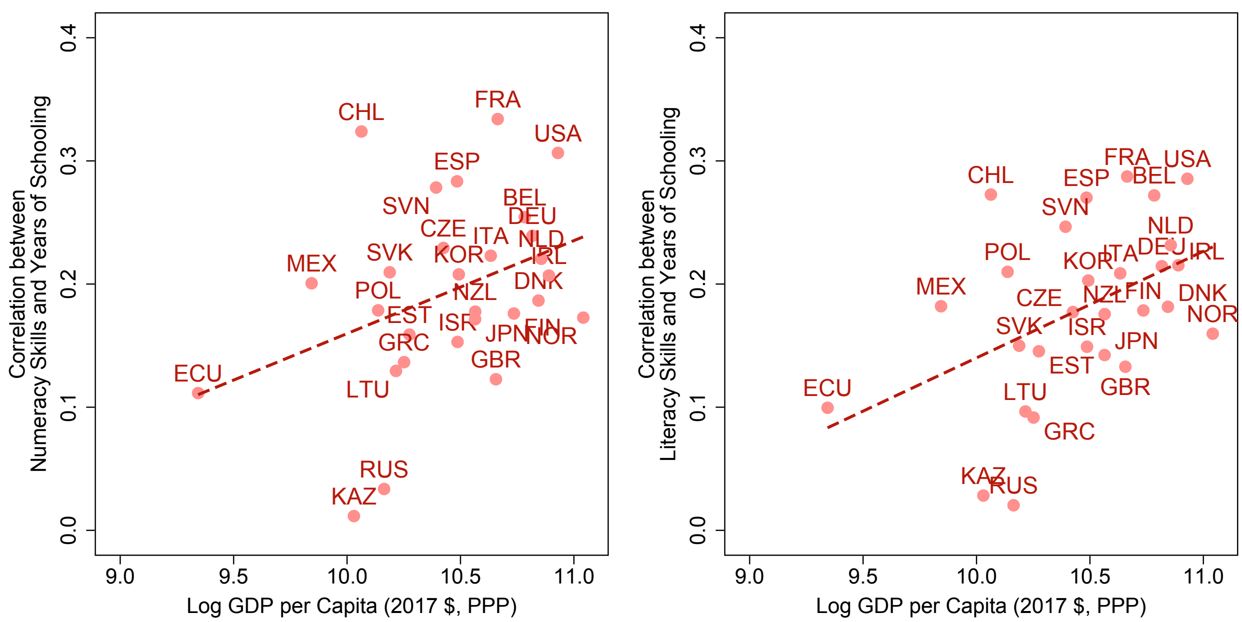
A.4 Summary Statistics and Data Validation

Figure A1: Distributions of Worker Skills and Job Skill Requirements across Countries



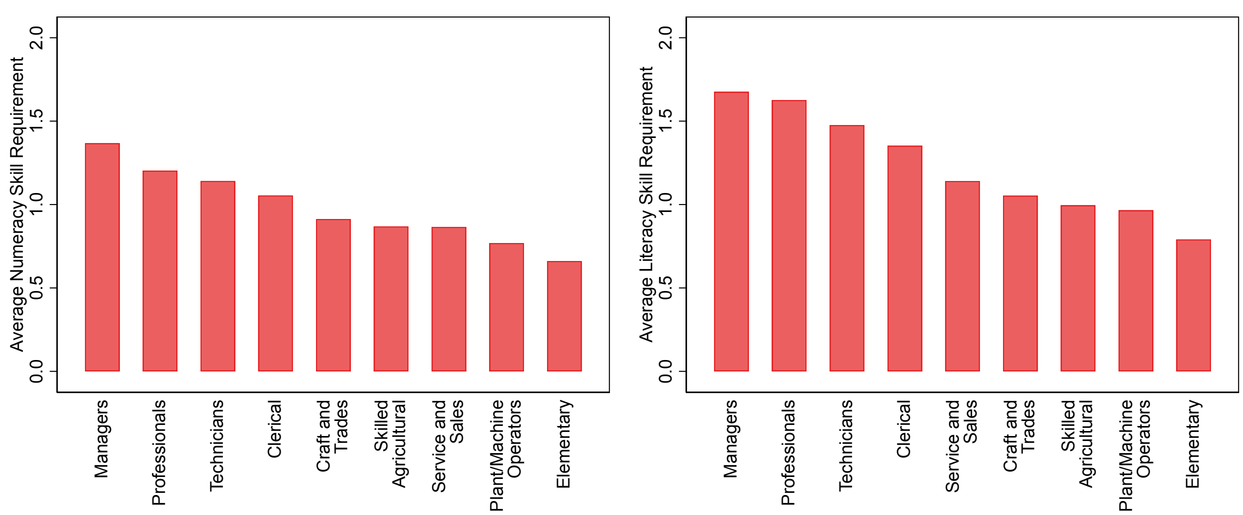
Notes: This figure shows the empirical distributions of worker skills (top panels) and job skill requirements (bottom panels) for numeracy (left panels) and literacy (right panels). The black solid line indicates the global distribution obtained by pooling all countries. Each thin solid line represents one country, with the thick lines highlighting the two lowest-income countries—Ecuador in dashed blue and Mexico in solid blue—and the two highest-income countries—the United States in solid red and Norway in dashed red. *Source:* PIAAC.

Figure A2: Correlation between Skills and Education



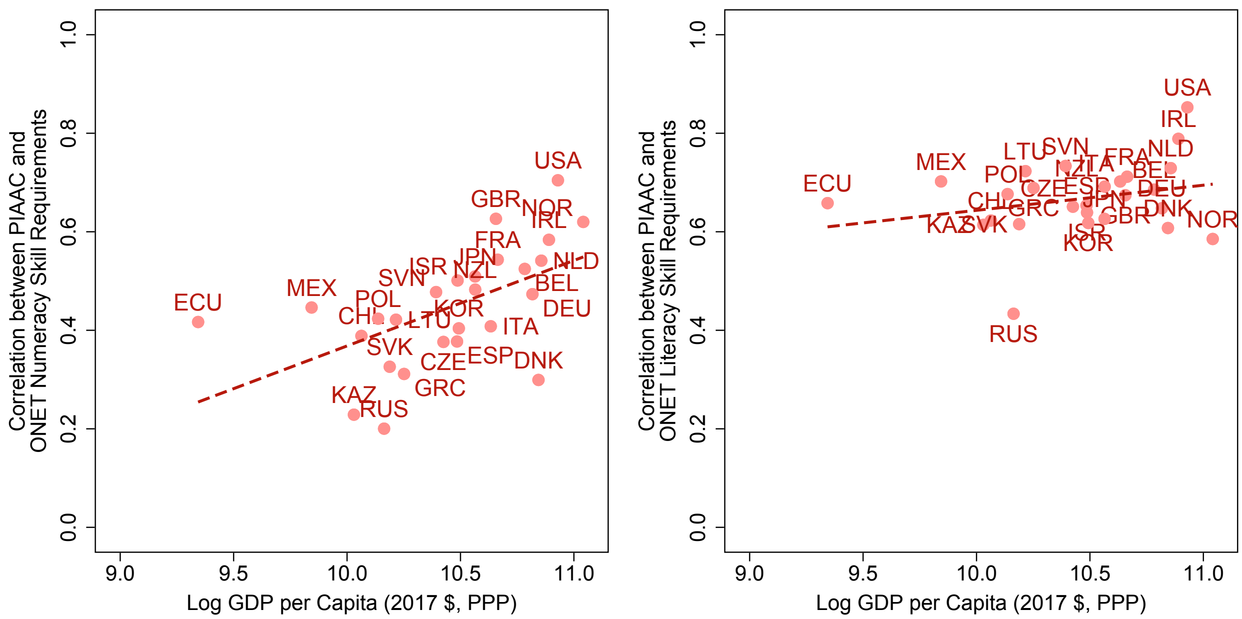
Notes: Both panels report the R^2 of a regression of PIAAC skill scores on years of education, the left panel for numeracy skills and the right panel for literacy skills. *Source:* PIAAC.

Figure A3: Average Skill Requirements across Occupations



Note: This figure shows average numeracy skill requirements (left panel) and literacy skill requirements (right panel) for each 1-digit occupation based on ISCO-08 occupation codes. The horizontal axis shows ISCO-08 codes 1 to 9 in ascending order, omitting the 1-digit code 0, representing Armed Forces Occupations. To compute skill requirements, we sum the number of tasks a worker completes in each skill dimension—i.e., numeracy and literacy—and weigh them by their difficulty; see Appendix A.2 for details. We then take the average of this measure across all workers in a given occupation in each country to arrive at a set of country-specific numeracy and literacy skill requirements for each job. *Source:* PIAAC.

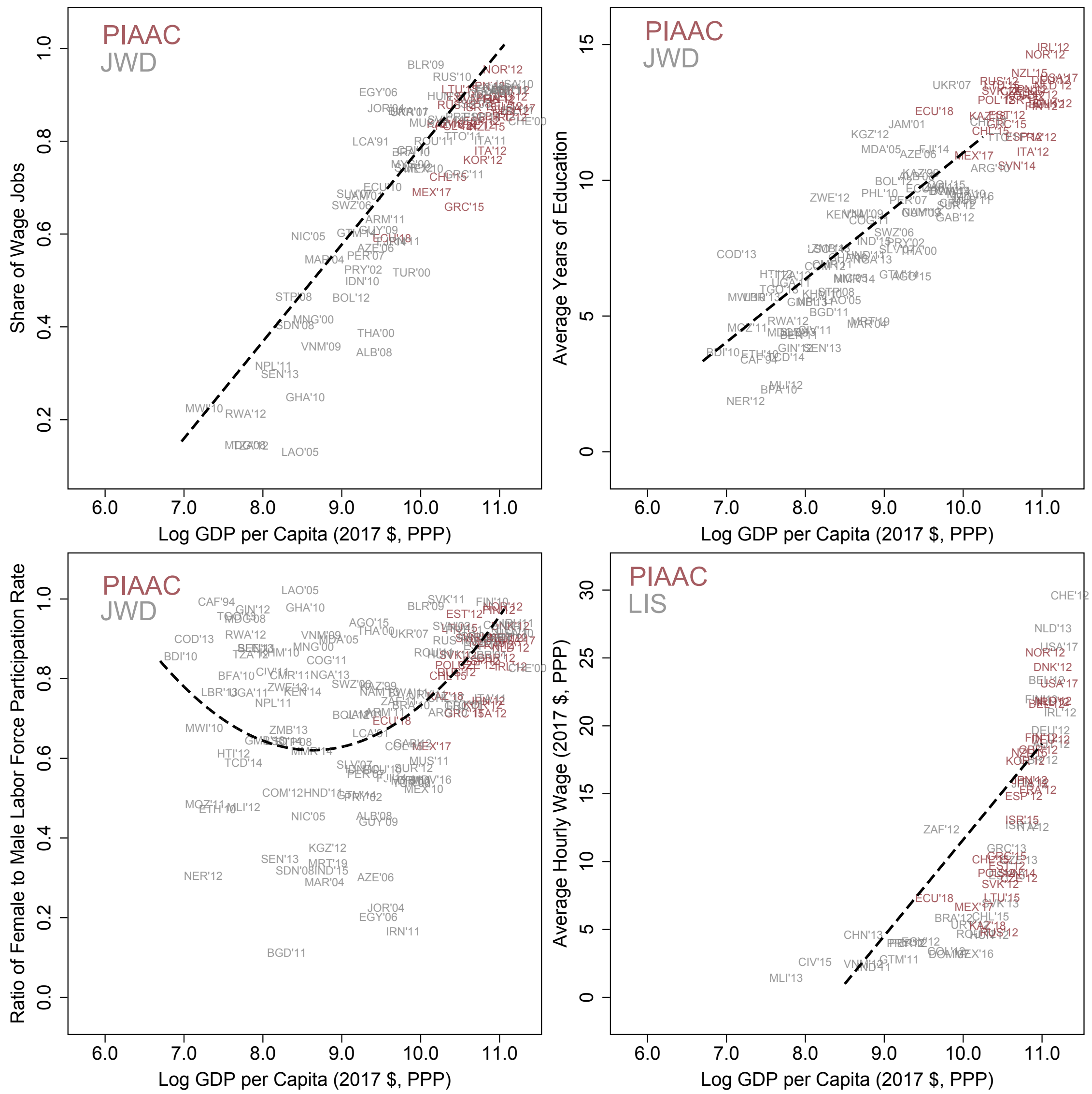
Figure A4: Correlation between PIAAC and O*NET Measures of Skill Requirements



Notes: Both panels report the R^2 of a regression of the PIAAC skill requirement measures on the O*NET measures, the left panel for numeracy skill requirements, and the right panel for literacy skill requirements. Skill requirement scores from O*NET data are computed as follows. We use three modules of the O*NET that provide numeracy and literacy task contents in the form of 128 skill requirements. These are characterized under the broad headings of (i) work activities, (ii) skills, and (iii) abilities for each of O*NET's 873 occupations under the O*NET *Standard Occupational Classification (SOC)* occupation nomenclature. Using a crosswalk between O*NET SOC and ISCO-08 occupation codes, we can assign a skill requirement score to 441 4-digit ISCO-08 occupations. We merge this occupation-level data with individual-level PIAAC data using the most detailed ISCO code available for each PIAAC observation. To reduce the dimension of the 128 skill requirements, we follow Lise and Postel-Vinay (2020) and Lindenlaub and Postel-Vinay (2023) to obtain two indices that capture skill requirements in the two dimensions of interest: numeracy and literacy. First, we run Principal Component Analysis (PCA) on our large set of O*NET measures and keep the first two principal components. We then recover our numeracy and literacy skill requirement indices by recombining those two principal components, which by default are constructed to be orthonormal, in such a way that they satisfy the following two exclusion restrictions: (1) the "mathematics" score only reflects numeracy skill requirements, and (2) the "written comprehension" score only reflects literacy requirements. We rescale our skill requirement indices to lie in $[0, 1]$ by subtracting the minimum value and dividing by the range of values. *Sources:* PIAAC and O*NET.

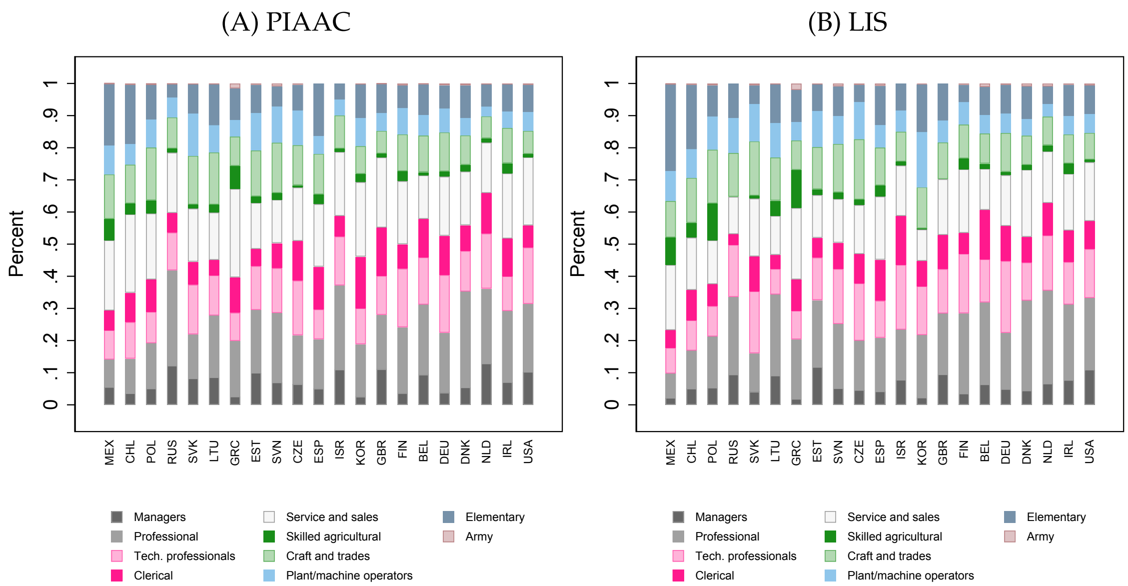
A.5 Labor Market and Educational Outcomes across the Development Spectrum

Figure A5: Comparison of Cross-Country Labor Market Data in PIAAC with other Cross-Country Census and Survey Data



Notes: The first three panels are based on cross-country data from PIAAC and The Jobs of The World Dataset (JWD); the last panel is based on PIAAC and the Luxembourg Income Study (LIS). The JWD harmonizes cross-country census data on labor market outcomes from the Integrated Public Use Microdata Series (IPUMS) and the Demographic and Health Surveys (DHS). The year of the respective survey is indicated along the country labels. The top-left panel plots the share of workers in wage jobs (as opposed to being self-employed) for all countries in the JWD (gray) and PIAAC (red) data. The top-right panel plots the average years of education of the population in the JWD and PIAAC. The bottom-left panel plots the ratio of female to male labor force participation rate in the JWD and PIAAC. Finally, the bottom-right panel compares average hourly wages in PIAAC (red) to average hourly wages of the same countries in the LIS (gray). *Source:* PIAAC, JWD, and LIS.

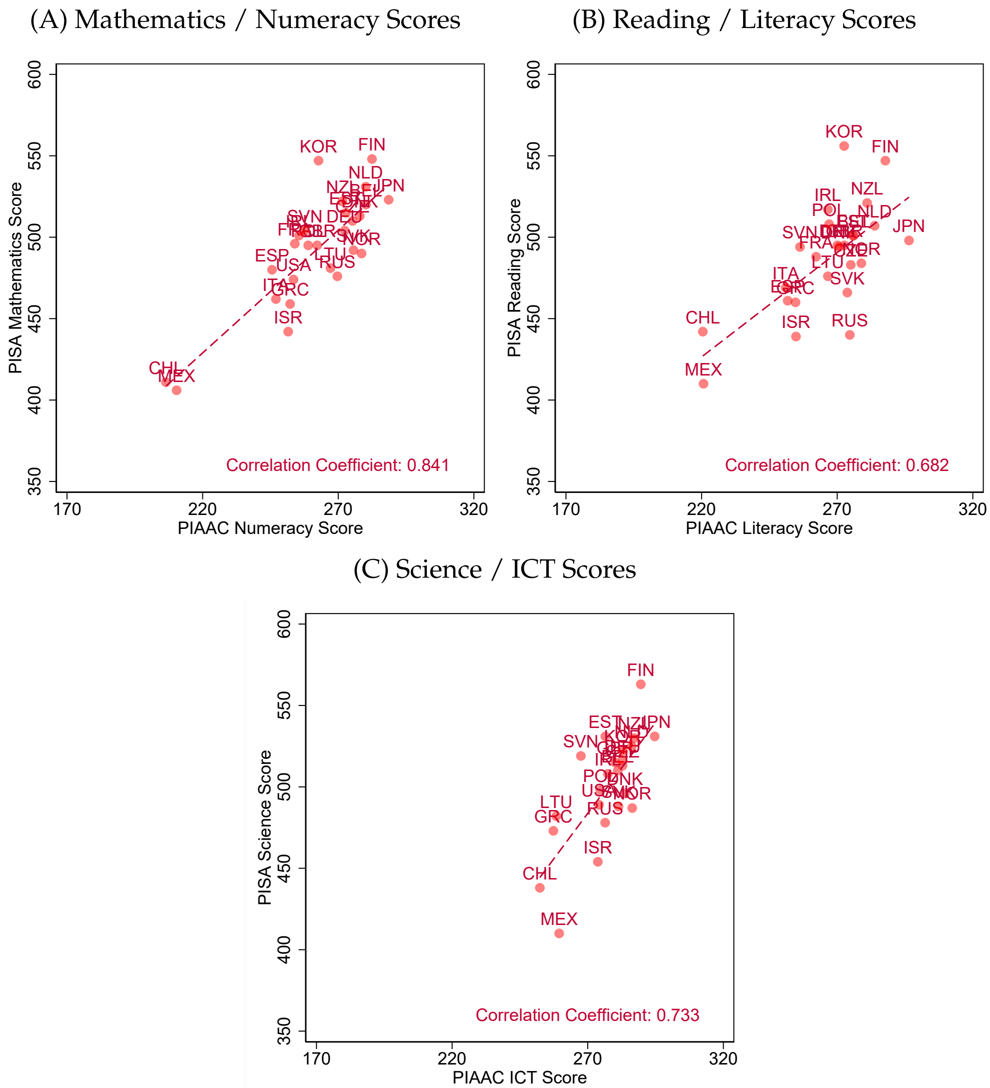
Figure A6: Comparison between Occupational Structures in PIAAC and LIS Data



Notes: This figure compares the occupational composition in the PIAAC (left panel) with the occupational composition in the LIS (right panel). Occupations are grouped into ten categories according to 1-digit ISCO-08 occupation codes. We report information for the 21 countries for which both PIAAC and LIS data are available. *Source:* PIAAC and LIS.

A.6 Comparison between Childhood and Working-Age Skill Measures

Figure A7: Correlation between Various PIAAC Test Scores and Corresponding PISA Test Scores



Notes: This figure shows scatter plots of the country means of various skill dimensions measured in the PISA (where tests were completed by 15-year-old students) and the corresponding skill dimensions in the PIAAC (where tests were completed by working-age adults) in the same countries for mathematics/numeracy skills (panel A), reading/literacy skills (panel B), and science/ICT scores (panel C). To account for the fact that individuals take PISA tests at a younger age, all PISA test scores are taken from the 2006 wave, except Lithuania, for which data is available only in the 2018 wave. *Source:* PISA and PIAAC.

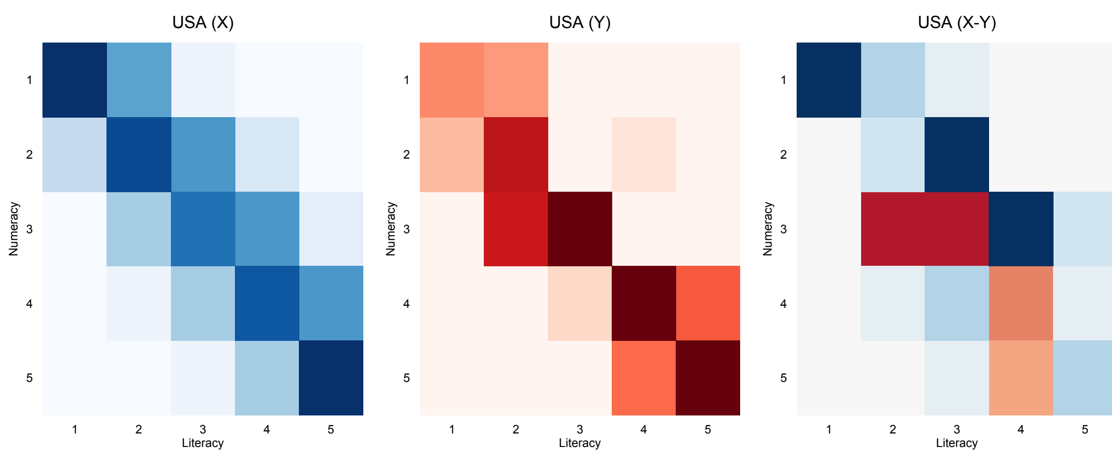
B Facts Appendix

In this appendix, we present additional evidence on worker-job matching related to the facts contained in Section 3 of the paper.

B.1 Endowments of Worker Skills and Job Skill Requirements across Countries

To compare the distributions of skill supply and demand, we first compute quintiles of both numeracy and literacy skills of all workers (i.e., not just matched workers) and also of numeracy and literacy skill requirements of all jobs. We form 5×5 cells on each side of the market. Then, we take the difference between the number of workers in each skill cell and the number of jobs in the corresponding skill requirement cell. Figure B1 illustrates this approach using the United States as an example. The first panel shows every combination of numeracy and literacy skills, where the color intensity is proportional to the size of the group with that combination. The second panel shows every combination of numeracy and literacy skills requirements, color-coded in the same way. Two patterns are of note. First, several observations outside the diagonal indicate that while skills and skill requirements on the two dimensions are correlated on each side of the market, this correlation is far from perfect. Second, skill requirements are less symmetrical than skill endowments, so some cells are in excess demand and others in excess supply. This can be seen more easily in the third panel, which shows the difference between the first two. The cells are color-coded so that blue represents an excess supply of skills, while red signifies excess demand. In addition, more intense colors represent a greater excess supply or demand.

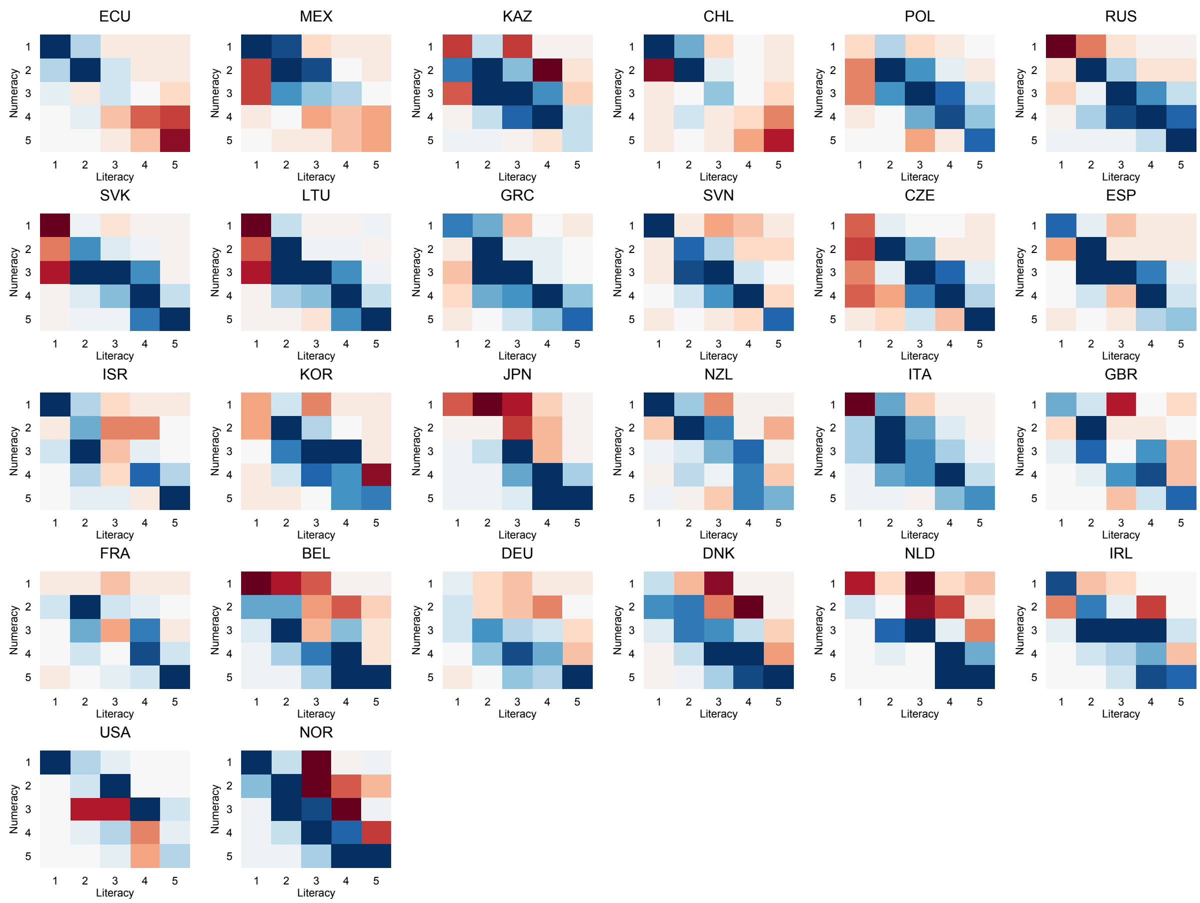
Figure B1: Endowments of Worker Skills, Job Skill Requirements, and their Difference in the United States



Notes: This figure shows skill cells (left panel) and skill requirement cells (middle panel) based on country-specific quintiles in each skill dimension. The left panel shows every combination of numeracy and literacy skills, where the color intensity is proportional to the size of the group with that combination. The middle panel shows every combination of numeracy and literacy skills requirements, color-coded in the same way. The right panel shows the difference between the number of workers in each skill cell and the number of jobs in the corresponding skill requirement cell. In the right panel, an excess supply of skills is denoted in blue, and an excess demand of skill requirements is in red. The figure is based on all workers and jobs in the economy, irrespective of employment status. *Source:* PIAAC.

Figure [B2](#) below shows the difference heatmaps separately for each country in our sample. Lower-income countries tend to have an excess supply of skills at the lower end of the distribution and an excess demand for skills at the higher end. The opposite is true for higher-income countries. This suggests that upskilling the workforce of low-income countries would lead to a closer match between worker skills and job skill requirements in those countries.

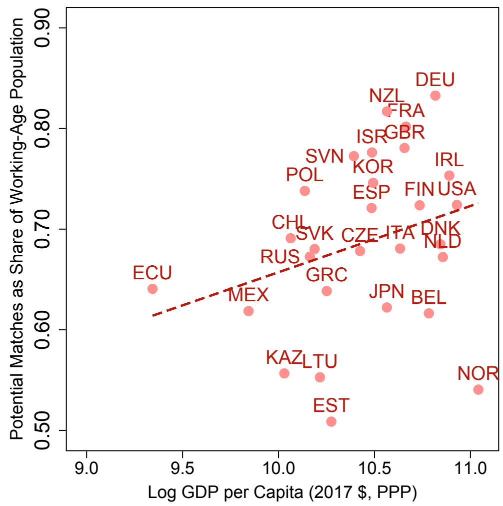
Figure B2: Differences between Endowments of Worker Skills and Job Skill Requirements across Countries



Notes: This figure replicates the right panel of Figure B1 for 26 countries—we drop Estonia and Finland from this exercise as they only report 1-digit occupation codes, making their skill requirement scores incomparable to the rest of the countries. The figure shows 5 ×5 cells that plot the difference between the number of workers in each skill cell and the number of jobs in the corresponding skill requirement cell. Each skill and skill requirement cell is obtained by interacting skill and skill requirement quintiles in two dimensions: numeracy and literacy. An excess supply of skills is denoted in blue, and an excess demand of skill requirements in red. The figure is based on all workers and jobs in the economy, irrespective of employment status. See the notes of Figure B1 for details. *Source:* PIAAC.

Figure B3 below summarizes the information contained in the heatmaps by calculating the share of potential perfect matches between worker skill quintiles and job skill requirement quintiles. From this, we see that the share of potential perfect matches is increasing in GDP per capita across countries.

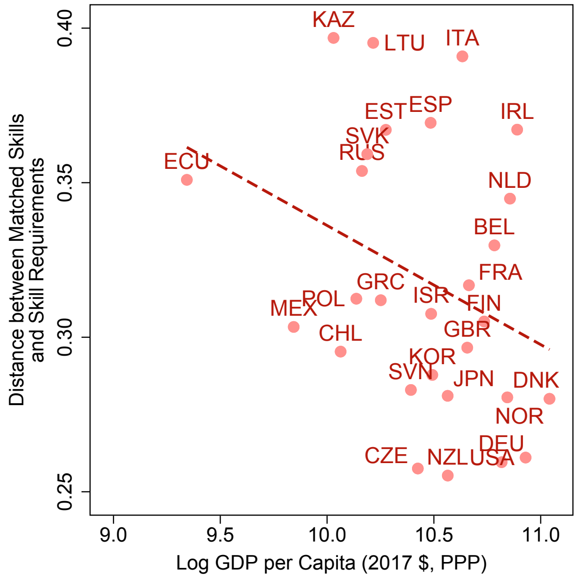
Figure B3: Endowments: More Overlap between Worker Skills and Job Skill Requirement Distributions in Higher-Income Countries



Notes: This figure summarizes the content of Figure B2 and shows the overlap between the distributions of worker skills and of job skill requirements against GDP per capita across countries. In each country, the overlap is computed as the minimum of the probability mass of workers and jobs in each cell (defined by the intersection of skills and skill requirement quintiles), divided by the total population. See Figure B2 for more details. *Source:* PIAAC.

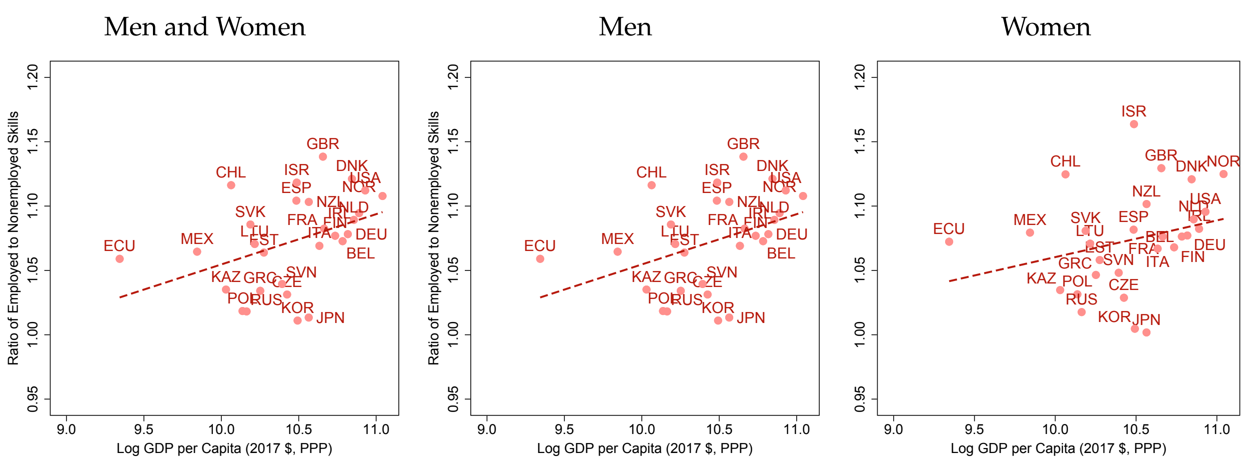
B.2 Robustness: Stronger Worker-Job Sorting and More Positive Selection into Employment in Higher-Income Countries

Figure B4: Smaller Distance between Workers' Skills and their Jobs' Skill Requirements in Higher-Income Countries using Raw Skill and Skill-Requirement Scores (Robustness)



Notes: The figure plots the mean distance between workers' skills and the skill requirements of the job that they are employed in by country. Distances are computed as the Euclidean distance between the 2×1 vector containing the raw worker skill scores, each normalized to lie between 0 and 1 by subtracting the minimum and dividing by the range, and the 2×1 vector containing the workers' jobs' raw numeracy and literacy skill requirement scores, each again normalized to lie between 0 and 1 by subtracting the minimum and dividing by the range. *Source:* PIAAC.

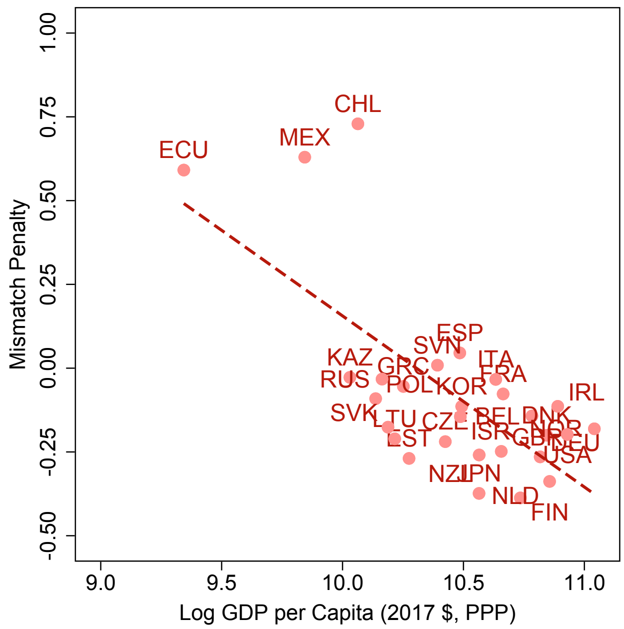
Figure B5: More Positive Skill-Based Selection into Employment in Higher-Income Countries using Raw Skill Scores (Robustness)



Notes: This figure plots the ratio of average skills of employed workers and average skills of nonemployed workers against GDP per capita across countries. For each individual, we average their raw numeracy and literacy skill scores and then compute the ratio of average skill scores of the employed and the nonemployed. *Source:* PIAAC.

B.3 Robustness: Lower Mismatch Penalty in Higher-Income Countries

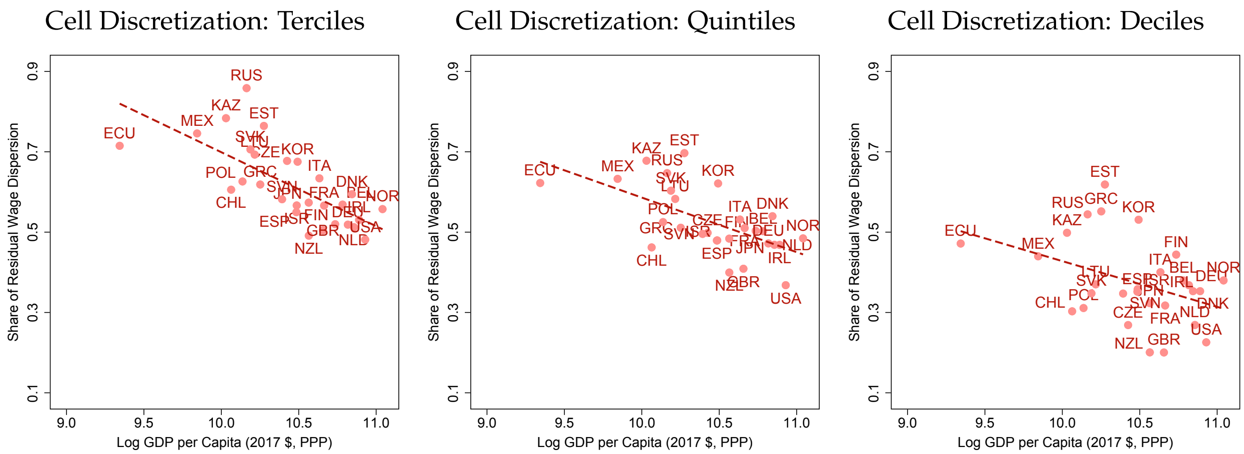
Figure B6: Greater Penalty for Worker-Job Skill Mismatch in Higher-Income Countries without Mincer Controls (Robustness)



Notes: We plot the estimates of the coefficient β from the following regression, run within each country, against log GDP per capita: $\ln(w_i) = \alpha + \beta \text{Dist}_i + \varepsilon_i$, where Dist_i is the average Euclidean distance between workers' skills and their jobs' skill requirements. See the Notes of Figure 6, with the only difference that here we do not include Mincer variables as controls. *Source:* PIAAC.

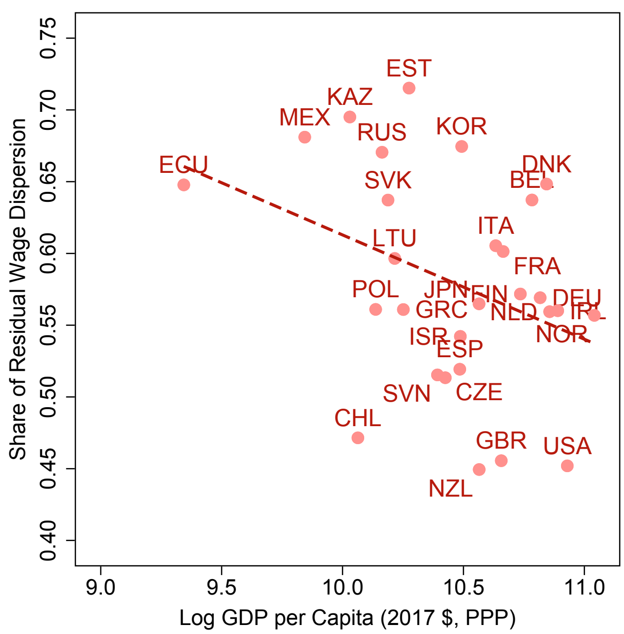
B.4 Robustness: Lower Residual Wage Dispersion in Higher-Income Countries

Figure B7: Lower Residual Wage Dispersion in Higher-Income Countries using Alternative Cell Discretizations (Robustness)



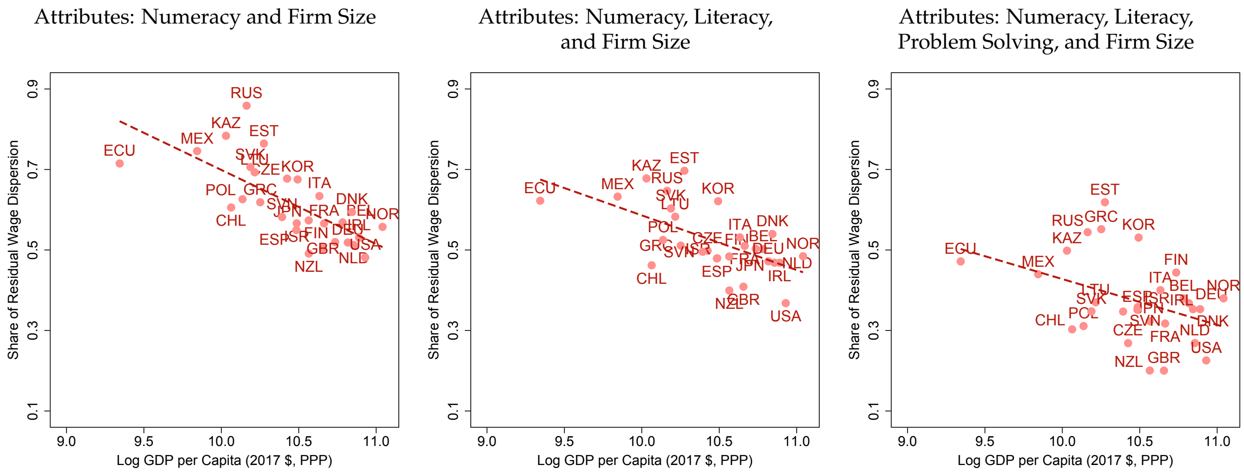
Note: The figure plots the share of wage dispersion not explained by cell dummies defined as the interaction between worker skills and job skill requirements, as in Figure 7, but for alternative cell discretizations. The left panel forms cells by using skill and skill requirement terciles. The middle panel is our baseline specification, which uses skill and skill requirement quintiles. The right panel uses skill and skill requirement deciles. See the notes in Figure 7 for further details. *Source:* PIAAC.

Figure B8: Lower Residual Wage Dispersion in Higher-Income Countries without Mincerian Controls (Robustness)



Notes: This figure plots the share of dispersion in log wages not explained by cell dummies defined as the interaction between worker skills and job skill requirements, as in Figure 7 with the only difference that here we do not control for Mincer variables in the wage regression. *Source:* PIAAC.

Figure B9: Lower Residual Wage Dispersion in Higher-Income Countries under More or Fewer Skill and Skill Requirement Attributes (Robustness)



Note: This figure plots the share of dispersion in log wages not explained by cell dummies defined as the interaction between worker skills and job skill requirements, as in Figure 7, but also for cases where we add or remove one of the production-relevant characteristics. The left panel forms cells by removing literacy skills and skill requirements. The middle panel is our baseline specification, where we use both literacy and numeracy characteristics and also firm size. The right panel adds problem-solving or ICT skills and skill requirements to our baseline specification. Note that data on problem-solving or ICT skills is not available for Italy, France, and Spain, and thus these countries are omitted from the last panel. Note also that we use terciles to define cells for the right panel (as opposed to our baseline specification of quintiles), to avoid issues with sparse cells. *Source:* PIAAC.

C Model Appendix

In this appendix, we spell out the derivations of the equilibrium properties discussed in Section 4.

Match Surplus. To derive match surplus $s(x,y)$, we combine equations (3)–(4) as well as equations (1)–(2) to obtain the relative choice probabilities

$$\log\left(\frac{\mu_{x|y}}{\mu_{\varnothing|y}}\right) = \log\left(\frac{\mu^J(x,y)}{\mu^J(\varnothing,y)}\right) = \frac{f(x,y) - w(x,y) - f_{\varnothing y}(y)}{\sigma}, \tag{C.1}$$

$$\log\left(\frac{\mu_{y|x}}{\mu_{\varnothing|x}}\right) = \log\left(\frac{\mu^W(x,y)}{\mu^W(x,\varnothing)}\right) = \frac{w(x,y) - f_{x\varnothing}(x)}{\sigma}. \tag{C.2}$$

Combining equations (C.1)–(C.2) by substituting out the wage function $w(x,y)$ and imposing labor market clearing (5), we obtain

$$\sigma \log\left(\frac{\mu(x,y)}{\mu(\varnothing,y)}\right) = f(x,y) - \left(\sigma\log\left(\frac{\mu(x,y)}{\mu(x,\varnothing)}\right) + f_{x\varnothing}(x)\right) - f_{\varnothing y}(y). \tag{C.3}$$

We solve (C.3) for $s(x,y) := f(x,y) - f_{x\varnothing}(x) - f_{\varnothing y}(y)$ to obtain the expression for systematic surplus, $s(x,y)$, in (7).

Systematic Wages. Solving (C.2) for the wage function, $w(x,y)$, and imposing labor market clearing (5), we obtain

$$w(x,y) = \sigma \log\left(\frac{\mu(x,y)}{\mu(x,\varnothing)}\right) + f_{x\varnothing}(x) \tag{C.4}$$

Now plug the matching frequency $\mu(x,y)$ from (11) into (C.4) to obtain the expression for systematic wages, $w(x,y)$, in (8).

Idiosyncratic Wages. We follow Salanié (2015) in deriving idiosyncratic wages. We start general and then impose assumptions on how the idiosyncratic component of the surplus is split. As above, denote the transfer from job k of type y to worker i of type x by $\tilde{w}(x_i, y_k)$.

Note that the post-transfer surplus of jobs and workers can each be expressed in two ways

$$f(x,y) - f_{\varnothing y}(y) + \delta_{i\to k,y} + \delta_{x,k\to k} - \tilde{w}(x_i,y_k) = f(x,y) - f_{\varnothing y}(y) - w(x,y) + \delta_{xk}, \tag{C.5}$$

$$\tilde{w}(x_i,y_k) - f_{x\varnothing}(x) + \delta_{i\to i,y} + \delta_{x,k\to i} = -f_{x\varnothing}(x) + w(x,y) + \delta_{iy}, \tag{C.6}$$

where (C.5) is the post-transfer surplus of job k of type y and (C.6) is the post-transfer surplus of worker i of type x. Here, $\delta_{x,k\to k} + \delta_{x,k\to i} = \delta_{xk}$ captures any arbitrary pre-transfer split of the idiosyncratic surplus, δ_{xk}, of a job k for workers of type x into a component that accrues to the job k (i.e., $\delta_{x,k\to k}$) and a component that accrues to worker i of type x (i.e., $\delta_{x,k\to i}$) *before* any transfer is paid. Similarly, $\delta_{i\to k,y} + \delta_{i\to i,y} = \delta_{iy}$ captures any arbitrary pre-transfer split of the idiosyncratic surplus δ_{iy} of a worker i for jobs of type y into a component that accrues to the worker i (i.e., $\delta_{i\to i,y}$) and a component that accrues to job k of type y (i.e., $\delta_{i\to k,y}$) *before* any transfer is paid. Taken literally, these surplus splits encapsulate the preferences of, say, an individual worker for a specific job of type y before any transfer is paid and, similarly, the preferences of a specific job over a worker of type x).

Based on equation (C.5) or (C.6) above, we can solve for the idiosyncratic wage of worker i of type x in job k of type y:

$$\begin{aligned}\tilde{w}(x_i, y_k) &= w(x,y) - \delta_{xk} + \delta_{i\to k,y} + \delta_{x,k\to k} \\ &= w(x,y) + \delta_{i\to k,y} - \delta_{x,k\to i}.\end{aligned}$$

Following a set of assumptions proposed by Salanié (2015), we now impose some restrictions on the pre-transfer split of the idiosyncratic surplus components:

$$\delta_{x,k\to i} = 0 \quad \Longrightarrow \quad \delta_{xk} = \delta_{x,k\to k}, \tag{C.7}$$

$$\delta_{i\to i,y} = 0 \quad \Longrightarrow \quad \delta_{iy} = \delta_{i\to k,y}. \tag{C.8}$$

That is, workers do not appropriate any share of the idiosyncratic surplus components before transfers. Intuitively, this implies that all workers are indifferent between jobs of the same y type before transfers. Under restrictions (C.7)–(C.8), we obtain the expression for idiosyncratic wages $\tilde{w}(x_i, y_k)$ in equation (10).

We assume that these idiosyncratic wages, $\tilde{w}(x_i, y_k)$, are monetary (i.e., paid in terms of units of the produced good), equal in value to the sum of the systematic wage $w(x,y)$ and the worker's idiosyncratic matching wedge δ_{iy}. Purely monetary payouts to workers can be ensured by assuming that, in the background, there is some—unmodeled—financial endowment K, which is constant across jobs, added to match output, and fully accrues to jobs. Jobs tap into K if $\tilde{w}(x_i, y_k)$ exceeds match output. Although, in theory, the support of δ_{iy} is unbounded, in practice, the finite number of agents in our model implies that shock realizations are also finite, so we can always find such a constant by setting $K = \max_i \delta_{iy}$.

D Identification Appendix

In this appendix, we prove the result stated in Proposition 1 in Section 5 of the paper.

D.1 Proof of Proposition 1

Proof. Our goal is to identify the parameter vector $\theta := \left(G(x), H(y), m^J, f(x,y), f_{x\emptyset}(x), \sigma\right)$. As stated in the text, we normalize the output of matches involving workers of the lowest skill type $\underline{x} = (\underline{x_n}, \underline{x_\ell})$, where $\underline{x_n} := \min x_n$ and $\underline{x_\ell} := \min x_\ell$, to be $f(\underline{x}, y_n, y_\ell, y_s) = 0$ for all $y = (y_n, y_\ell, y_s)$. We also assume that the distribution of filled jobs is representative of the population distribution $H(y)$. The proof proceeds in five steps.

Step 1: Identifying the worker type distribution $G(\cdot)$ and the job type distribution $H(\cdot)$.
Since $G(x)$ and $H(y)$ are distributions over observable worker attributes x and job attributes y, they are identified since they can be readily read off the data.

Step 2: Identifying the scale parameter σ of the idiosyncratic matching wedge distribution.
Based on (10) and following Salanié (2015), wages within type (x,y) matches follow an EV Type I distribution with scale parameter σ, and so within (x,y) wage dispersion is given by:

$$Var\left(\tilde{w}(x_i, y_k)|x,y\right) = \frac{\pi^2\sigma^2}{6}. \tag{D.1}$$

Thus, we can invert (D.1) for *any* match type (x,y) to uniquely pin down σ.

Step 3: Identifying workers' nonemployment value $f_{x\emptyset}(x,y)$.
Computing the log relative choice probabilities of worker type x staying nonemployed compared to that of matching with job type y based on (1)–(2), we have

$$\log\left(\frac{\mu(x,\emptyset)}{\mu(x,y)}\right) = \frac{f_{x\emptyset}(x) - w(x,y)}{\sigma}. \tag{D.2}$$

On the left-hand side of (D.2), both the share $\mu(x,\emptyset)$ of nonemployed workers and the share $\mu(x,y)$ of type (x,y) matches are observed. On the right-hand side, σ is known from Step 2 above, and $w(x,y)$ can be backed out from the observed mean wage among (x,y) type matches, $\mathbb{E}[w(x_i,y_k)|x,y] = w(x,y) - \sigma \log \mu_{y|x} + \sigma\gamma$, due to the well-known result that the maximum of EV Type I variables itself follows an EV Type I distribution. Note that we have already identified σ in Step 2, the choice probability $\mu_{y|x}$ is directly observed, and $\gamma \approx 0.577$ denotes Euler's constant. Thus, we can solve (D.2) for the outside option $f_{x\emptyset}(x)$ for each worker type x.

Step 4: Identifying the production function $f(x,y)$.
Consider the log relative choice probabilities of job type y matching with worker type x compared to that of matching with the least productive worker type $\underline{x} := (\underline{x_n}, \underline{x_\ell}, x_g)$ based on (1)–(2):

$$\log\left(\frac{\mu(x,y)}{\mu(\underline{x},y)}\right) = \frac{f(x,y) - w(x,y) - (f(\underline{x},y) - w(\underline{x},y))}{\sigma}.$$

Under our assumption that $f(\underline{x}, y) = 0, \forall y$—and thus $w(\underline{x}, y) = 0, \forall y$—we can write

$$\log\left(\frac{\mu(x,y)}{\mu(\underline{x},y)}\right) = \frac{f(x,y) - w(x,y)}{\sigma}. \tag{D.3}$$

On the left-hand side of (D.3), both the share of type (x, y) matches and the share of type $(\underline{x}, y)$ matches are observed. On the right-hand side, σ is known from Step 2, and wages $w(x, y)$ are backed out in Step 3. Thus, we can solve (D.3) for the value of the production function $f(x, y)$ for each worker type $x \in \mathcal{X} \setminus \underline{x}$ and each job type $y \in \mathcal{Y}$.

Step 5: Identifying the relative job mass m^J.

Using (7) and (8) along with market clearing (5), we can write the profit share of match (x, y) as

$$\frac{f(x,y) - w(x,y)}{f(x,y)} = \frac{\sigma \log\left(\frac{\mu(x,\varnothing)}{\mu(\varnothing,y)}\right) + s(x,y) + 2f_{\varnothing y}(y)}{2f(x,y)}.$$

Into these expressions, we plug

$$\mu(x,\varnothing) = m^W h(x) \frac{\exp(f_{x\varnothing}(x)/\sigma)}{\exp(f_{x\varnothing}(x)/\sigma) + \sum_{\tilde{y}\in\mathcal{Y}} \exp(w(x,\tilde{y}))/\sigma)},$$
$$\mu(\varnothing,y) = m^J g(y) \frac{\exp(f_{\varnothing y}(y)/\sigma)}{\exp(f_{\varnothing y}(y)/\sigma) + \sum_{\tilde{x}\in\mathcal{X}} \exp(f(\tilde{x},y) - w(\tilde{x},y))/\sigma)},$$

after imposing the normalizations $m^W = 1$ and $f_{\varnothing y}(y) = 0, \forall y$. Now let us define the following components of $\mu(x, \varnothing)$ and $\mu(\varnothing, y)$:

$$\widehat{\mu}(x,\varnothing) := \frac{\mu(x,\varnothing)}{m^W} = \mu(x,\varnothing) = h(x) \frac{\exp(f_{x\varnothing}(x)/\sigma)}{\exp(f_{x\varnothing}(x)/\sigma) + \sum_{\tilde{y}\in\mathcal{Y}} \exp(w(x,\tilde{y}))/\sigma)}, \tag{D.4}$$

$$\widehat{\mu}(\varnothing,y) := \frac{\mu(\varnothing,y)}{m^J} = g(y) \frac{\exp(f_{\varnothing y}(y)/\sigma)}{\exp(f_{\varnothing y}(y)/\sigma) + \sum_{\tilde{x}\in\mathcal{X}} \exp(f(\tilde{x},y) - w(\tilde{x},y))/\sigma)}. \tag{D.5}$$

Note that $\widehat{\mu}(x, \varnothing)$ in (D.4) is observed in our data since it represents the share of all workers of type x who are nonemployed. Furthermore, all terms in the expression for $\widehat{\mu}(\varnothing, y)$ on the right-hand side of (D.5) are already identified. Then, we can express the profit share in match (x, y) as

$$\frac{f(x,y) - w(x,y)}{f(x,y)} = \frac{\frac{\sigma}{2}\left[\log\left(\frac{\widehat{\mu}(x,\varnothing)}{\widehat{\mu}(\varnothing,y)}\right) - \log\left(m^J\right)\right] + \frac{1}{2}s(x,y)}{f(x,y)}, \tag{D.6}$$

where we used our assumption that $f_{\varnothing y}(y) = 0$ for all y. Taking expectations over worker types x and firm types y, separately in the numerator and the denominator on each side of equation (D.6), the left-hand side becomes the observed profit share in a country, while the right-hand side contains the relative mass of firms m^J as the only unknown. Thus, we can solve for m^J.

To summarize, all model parameters $\theta = \big(G(x), H(y), m^J, f(x,y), f_{x\varnothing}(x), \sigma\big)$ are identified. $\square$

E Estimation Appendix

In this appendix, we state and prove a useful homogeneity property of our model; discuss targeted moments; state the computational requirements for solving and estimating the model; outline the solution algorithm; discuss identification threats; present details of the model fit by country; and provide empirical correlates of some structural parameter estimates relating to Section 6 of the paper.

E.1 Homogeneity Properties

Proposition E.1 (Homogeneity Properties)**.** *Systematic wages $w(x, y)$, idiosyncratic wages $\tilde{w}(x_i, y_k)$, systematic profits $\nu(x, y)$, and systematic surplus $s(x, y)$ are all homogeneous of degree 1 in*

$$\mathcal{P} := (f(x, y), f_{x\emptyset}(x), f_{\emptyset y}(y), \sigma).$$

As a result, the matching frequencies $(\mu(x, y), \mu(\emptyset, y), \mu(x, \emptyset))$, the within-worker-job-cell share of log-wage dispersion out of overall log-wage dispersion, the economy-wide profit share, and the Meritocracy Index $M(\theta)$ are all homogeneous of degree 0 in $\mathcal{P}$.

Proof. Let $\lambda > 0$ be an arbitrary scalar. For now, assume that $(\mu(x, y), \mu(\emptyset, y), \mu(x, \emptyset))$ are homogeneous of degree 0 in $\mathcal{P}$. We will verify this property below.

Indexing the wage function by the set of parameters $\mathcal{P}$, $w(x, y; \mathcal{P})$, it follows that for all (x, y)

$$\begin{aligned} w(x, y; \lambda\mathcal{P}) &= (\lambda\sigma) \log\left(\frac{\mu(x, y)}{\mu(x, \emptyset)}\right) + (\lambda f_{x\emptyset}(x)) \\ &= \lambda w(x, y; \mathcal{P}), \end{aligned}$$

so the systematic wage function w is homogeneous of degree 1 in $\mathcal{P}$.

Similarly, for the systematic profit function, $\nu(x, y; \mathcal{P})$, we have for all (x, y)

$$\begin{aligned} \nu(x, y; \lambda\mathcal{P}) &= \lambda f(x, y) - w(x, y; \lambda\mathcal{P}) \\ &= \lambda\nu(x, y; \mathcal{P}), \end{aligned}$$

where the second equality follows from the previous result, so the systematic profit function, ν, is also homogeneous of degree 1 in $\mathcal{P}$.

Next, note that for any random variable $\delta \sim$ EV Type I$(0, \sigma)$, the cumulative distribution function $s(\delta; \sigma)$ satisfies

$$\begin{aligned} s(\delta; \lambda\sigma) &= \exp\left(-\exp\left(-\delta/(\lambda\sigma)\right)\right) \\ &= s(\delta/\lambda; \sigma). \end{aligned}$$

Therefore, if $\delta \sim$ EV Type I$(0, \sigma)$, then $\lambda\delta \sim$ EV Type I$(0, \lambda\sigma)$.

From this, it follows that the idiosyncratic wage function, $\tilde{w}(x, y; \mathcal{P})$, has for all (x_i, y_k) the property

$$\begin{aligned} \tilde{w}(x_i, y_k; \lambda\mathcal{P}) &= \lambda w(x, y) + \lambda\delta_{iy} \\ &= \lambda\tilde{w}(x_i, y_k; \mathcal{P}), \end{aligned}$$

so the idiosyncratic wage function, $\tilde{w}$, is homogeneous of degree 1 in $\mathcal{P}$.

Next, for all (x, y), we can write the systematic surplus, $s(x, y; \mathcal{P})$, as

$$\begin{aligned} s(x, y; \lambda\mathcal{P}) &= \lambda f(x, y) - \lambda f_{x\emptyset}(x) - \lambda f_{\emptyset y}(y) \\ &= \lambda s(x, y; \mathcal{P}), \end{aligned}$$

so the systematic surplus function s is homogeneous of degree 1 in $\mathcal{P}$.

To summarize, we have shown that systematic wages $w(x, y)$, idiosyncratic wages $\tilde{w}(x_i, y_k)$, systematic profits $v(x, y)$, and systematic surplus $s(x, y)$ are all homogeneous of degree 1 in $\mathcal{P}$.

Given the results above, it follows from equations (1)–(4) that the conditional choice probabilities of workers and jobs are all homogeneous of degree 0 in $\mathcal{P}$ and so are matching frequencies $(\mu(x, y), \mu(\emptyset, y), \mu(x, \emptyset))$, which verifies the claim made at the beginning of this proof.

Since $\tilde{w}(x_i, y_k)$ is homogeneous of degree 1 in $\mathcal{P}$, we have

$$\log \tilde{w}(x_i, y_k; \lambda\mathcal{P}) = \log \lambda + \log \tilde{w}(x_i, y_k; \mathcal{P}).$$

Therefore,

$$\begin{aligned} Var(\log \tilde{w}(x_i, y_k; \lambda\mathcal{P})) &= Var(\log \lambda + \log \tilde{w}(x_i, y_k; \mathcal{P})) \\ &= Var(\log \tilde{w}(x_i, y_k; \mathcal{P})), \end{aligned}$$

so the dispersion of log idiosyncratic wages, $Var(\log \tilde{w}(x_i, y_k; \mathcal{P}))$, is homogeneous of degree 0 in $\mathcal{P}$. An analogous argument shows that the coefficient of determination (R^2) from a regression of log wages, $\log \tilde{w}(x_i, y_k)$, on indicators for interacted worker and job types (x, y) is homogeneous of degree 0 in $\mathcal{P}$. Note that $1 - R^2$ in the above-referenced regression is simply the within-worker-job-cell share of log-wage dispersion out of overall log-wage dispersion, which is then also homogeneous of degree 0 in $\mathcal{P}$.

Due to the homogeneity properties of output and wages established above, it also follows that the job-level profit share (D.6) is homogeneous of degree 0 in $\mathcal{P}$, and so is the economy-wide average profit share.

Finally, that the Meritocracy Index $M(\theta; \mathcal{P})$ is homogeneous of degree 0 in $\mathcal{P}$ is a direct consequence of the fact that $f(x, y; \mathcal{P})$ is homogeneous of degree 1 in $\mathcal{P}$ while $\mu(x, y)$ is homogeneous of degree 0 in $\mathcal{P}$. □

E.2 Targeted Moments

In this section, we describe how each of the targeted moments used in estimation is constructed. As described in Section 6.1, we discretize worker skills and job skill requirements by first partitioning their marginal distributions in each country into 5 country-specific quantiles and then assigning each country-specific quantile of a given worker skill or job skill requirement a value corresponding to the average global rank of workers or jobs belonging to that quantile. We thus obtain 25 worker skill cells by interacting each worker's numeracy and literacy skills and 50 job cells by interacting a job's numeracy and literacy skill requirements with firm size (which we discretize as small and large). For some exercises and plots, we also construct "broad" skill cells—low, medium and high—as follows: We add each worker's numeracy and literacy scores, which range from (quintiles) 1–5 after our discretization, and then classify workers as "low-skill" if the sum of their scores is between 2 and 4, as "medium-skill" if it is between 5 and 7, and as "high-skill" if it is between 8 and 10. When computing moments in the data, we only consider cells with at least 5 observations.

The vector of moments based on the parameterized model, $\mathcal{S}^m(\theta)$, and the vector of moments based on the data, $\mathcal{S}^d$, each contain 15 elements consisting of:

- 6 moments reflecting the nonemployment rates by broad skill group (see above on how these groups are constructed) and gender:
  - the nonemployment share among low-skilled men;
  - the nonemployment share among middle-skilled men;
  - the nonemployment share among high-skilled men;
  - the nonemployment share among low-skilled women;
  - the nonemployment share among middle-skilled women; and
  - the nonemployment share among high-skilled women.
- 2 moments reflecting the total mean wage as well as the within-worker-job-cell share of log-wage dispersion out of overall log-wage dispersion:
  - mean of log wages; and
  - the unexplained variance share, $1 - R^2 = RSS/TSS$, where RSS is the residual sum of squares and TSS is the total sum of squares in a regression of log wages on dummies for cells defined as the intersection of worker types and job types.
- 1 moment reflecting the distribution of output between workers and jobs:
  - the share of profits in aggregate value added, computed as one minus the labor share.
- 6 moments reflecting the matching pattern between workers and jobs, using the *basis function* approach proposed by Galichon and Salanié (2021):

– the match-share-weighted product of workers' numerical skill and jobs' numerical skill requirement;

– the match-share-weighted product of workers' numerical skill and jobs' literacy skill requirement;

– the match-share-weighted product of workers' numerical skill and jobs' firm size;

– the match-share-weighted product of workers' literacy skill and jobs' numerical skill requirement;

– the match-share-weighted product of workers' literacy skill and jobs' literacy skill requirement; and

– the match-share-weighted product of workers' literacy skill and jobs' firm size.

To see the rationale behind these basis functions, recall that $\mu(x,y)$ is the mass of matches where the worker belongs to type x, and the job belongs to type y; and $f(x,y)$ is the output of this type of match, which we aim to estimate. A necessary assumption underlying this estimation approach is that match output is linear in the parameter vector:

$$f(x,y;\vec{\lambda}) = \sum_{n=1}^{N} \lambda_n \phi_n(x,y)$$

where $\vec{\lambda} \in \mathbb{R}^N$ is the parameter vector to be estimated and $\vec{\phi} := (\phi_1, \ldots, \phi_N)$ are N known linearly independent basis surplus vectors. In our case, $\vec{\lambda} = \{\alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell n}, \alpha_{\ell\ell}, \alpha_{\ell s}\}$ and $N = 6$ with $\vec{\phi} = \{x_n y_n, x_n y_\ell, x_n y_s, x_\ell y_n, x_\ell y_\ell, x_\ell y_s\}$. We then compute the joint moments of any feasible matching μ as the average values of the basis output vectors

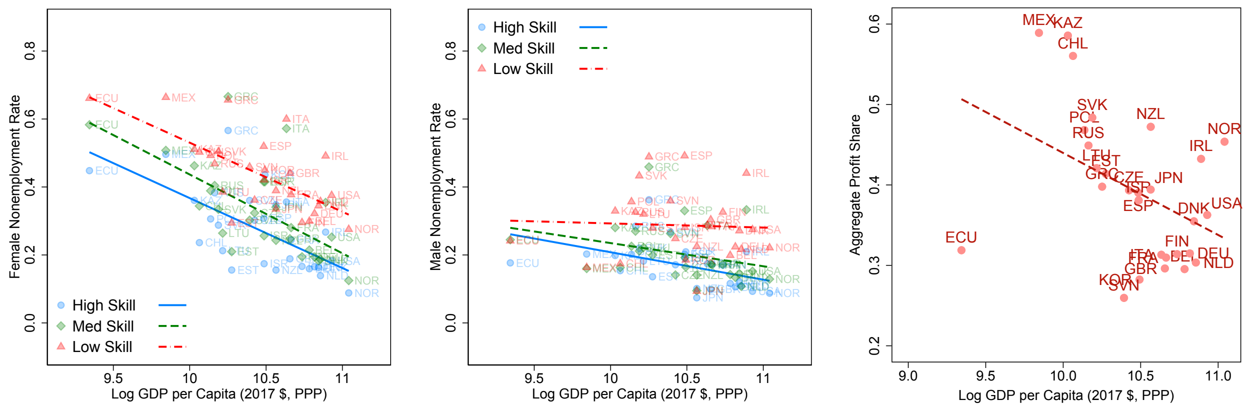
$$C_n(\mu) = \sum_{(x,y)\in\mathcal{X}\times\mathcal{Y}} \mu(x,y)\phi_n(x,y).$$

In particular, the empirical moments are associated with the observed matching frequencies, $\hat{\mu}(x,y)$, while the model moments are computed based on the matching that is generated under surplus parameterization $\vec{\lambda}$, denoted by $\mu(x,y;\vec{\lambda})$. The moment-matching estimator of $\vec{\lambda}$ proposed by Galichon and Salanié (2021) then matches the moments predicted by the model with the empirical moments—i.e., it solves the following system of equations:

$$C_n(\hat{\mu}(x,y)) = C_n\left(\mu(x,y;\vec{\lambda})\right), \quad \forall n.$$

E.3 Aggregate Profit Shares and Nonemployment Rates across Countries

Figure E1: Nonemployment Rates and Aggregate Profit Share across Countries



Note: The left and middle panels of this figure show the female and male nonemployment rates by broad skill groups across countries. See Appendix E.2 for how these skill groups are constructed. The right panel shows aggregate profit shares across countries. For each country, the aggregate profit share is computed as $1 -$ aggregate labor share. *Source:* FRED, OECD, and PIAAC.

E.4 Estimation Procedure

Our estimation procedure solves for the parameter vector

$$\theta^* = \underset{\theta \in \Theta}{\arg\min}\, \Omega\left(\mathcal{S}^m(\theta), \mathcal{S}^d\right). \tag{E.1}$$

The objective function is the weighted sum of squared percentage differences between 15 pairs of moments from the parameterized model and the data

$$\Omega(\mathcal{S}^m(\theta), \mathcal{S}^d) = ((\mathcal{S}^m(\theta) - \mathcal{S}^d) \oslash \mathcal{S}^d)'\mathbf{W}((\mathcal{S}^m(\theta) - \mathcal{S}^d) \oslash \mathcal{S}^d),$$

where percentage deviations between model and data moments are formed through *Hadamard division*, denoted by $\oslash$.[44] Here, $\mathbf{W}$ is a 15-by-15 weighting matrix, which we set equal to the identity matrix—i.e., we attach equal weights to each of the 15 moments. We solve (E.1) by using a global optimization algorithm, followed by a local optimization algorithm that refines the global solution.

E.5 Solution Algorithm

For a given parameter vector, we compute the equilibrium in each country using the IPFP—see Section 4.3 for details. To find the parameter vector that minimizes the distance between the model and data moments in equation (E.1), we repeatedly solve the model for a set of parameter

[44] The Hadamard division of a matrix A by another matrix B of the same dimension is $C = A \oslash B$, with each entry in C reflecting the element-wise division of the corresponding scalar entries in A and B (i.e., $C_{ij} = A_{ij}/B_{ij}$ for all i, j).

vectors that span the vector space. As this is a highly nonlinear optimization problem, we tackle it using a *genetic algorithm*—i.e., a stochastic, population-based global solver (Goldberg, 1989)—which we combine with a derivative-free local solver based on the *simplex search method* (Lagarias et al., 1998). To account for the global nature of our optimization problem, we first span the 14-dimensional parameter space using a population consisting of a large number of points generated from a quasirandom low-discrepancy sequence due to Sobol' (1967). We then compare our optimization results across different global and local solvers as well as across different populations.

E.6 Computational Requirements

Since each country's economy is independent from those of other countries, the estimation procedure is parallelizable across countries. In practice, the estimation for all countries runs for around 2 days on a server equipped with 112 cores, namely Intel Xeon Gold 6150 64-bit x86 multi-socket high-performance microprocessors with 2.70GHz clock speed.

E.7 Details of Identification Threats

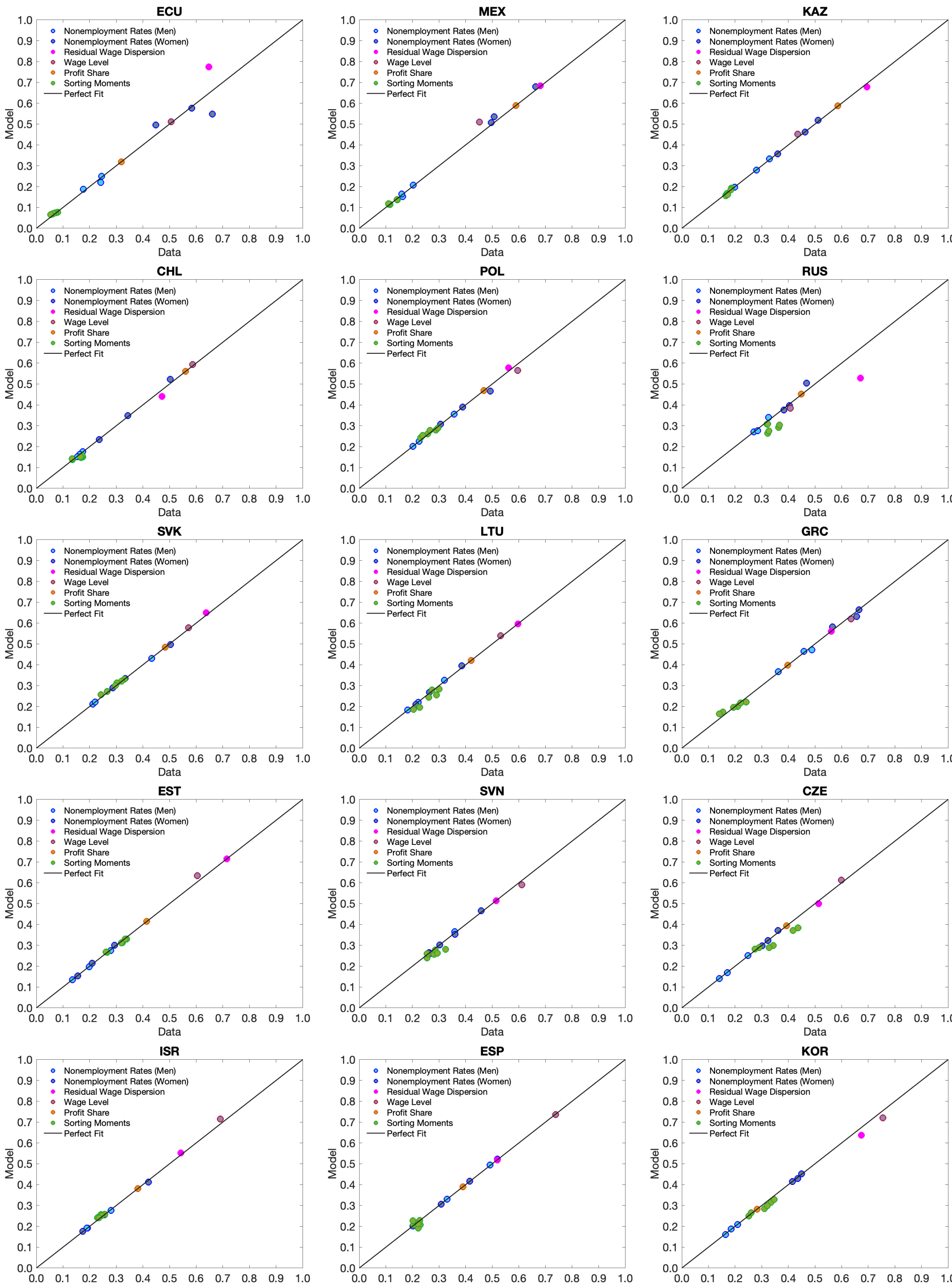
Here, we provide additional details of the identification threats discussed in Section 6.2 of the main paper. Specifically, we formalize the argument concerning measurement error in wages. Suppose we observe wages with measurement error $\varepsilon_c \sim F(\cdot;\mu_\varepsilon,\sigma_\varepsilon^2)$ in each country c, so that $\tilde{w}(x_i,y_k) = w(x,y) + \delta_{iy} + \varepsilon_c$, where $\varepsilon_c \perp (x,y,\delta_i^y)$. Using the properties of the EV distribution,

$$Var\left(\tilde{w}(x_i,y_k)|x,y\right) = Var\left(\delta_{iy}\right) + Var\left(\varepsilon_c\right) = \frac{\pi^2}{6}\sigma^2 + \sigma_\varepsilon^2. \tag{E.2}$$

Equation (E.2) shows that the empirical within-(x,y)-cell wage dispersion identifies $\pi^2\sigma^2/6 + \sigma_\varepsilon^2$. With measurement error in wages (i.e., $\sigma_\varepsilon^2 > 0$), we erroneously infer $\hat{\sigma}^2 = 6Var(\tilde{w}(x_i,y_k)|x,y)/\pi^2$, whereas the true value is $\sigma^2 = 6[Var(\tilde{w}(x_i,y_k)|x,y) - \sigma_\varepsilon^2]/\pi^2$. The two are related through an affine transformation, so any cross-country relationship involving the estimated $\hat{\sigma}$ closely mirrors the relationship involving the true σ. In our later counterfactual analysis, we will set σ of all countries to that of a frontier country. If our equilibrium model were linear, then any level bias of the type described above would not affect our results. Given that our equilibrium model is nonlinear, we expect some bias due to this issue, which could be assessed in counterfactuals with simulated measurement error for robustness. If, in turn, measurement error in wages is more pronounced in lower-income countries, then we would mistakenly estimate a negative relationship between σ and GDP, so the true effect of σ on development would be less than what we currently estimate. For this reason, one may treat our numbers for the quantitative effects of σ as an upper bound.

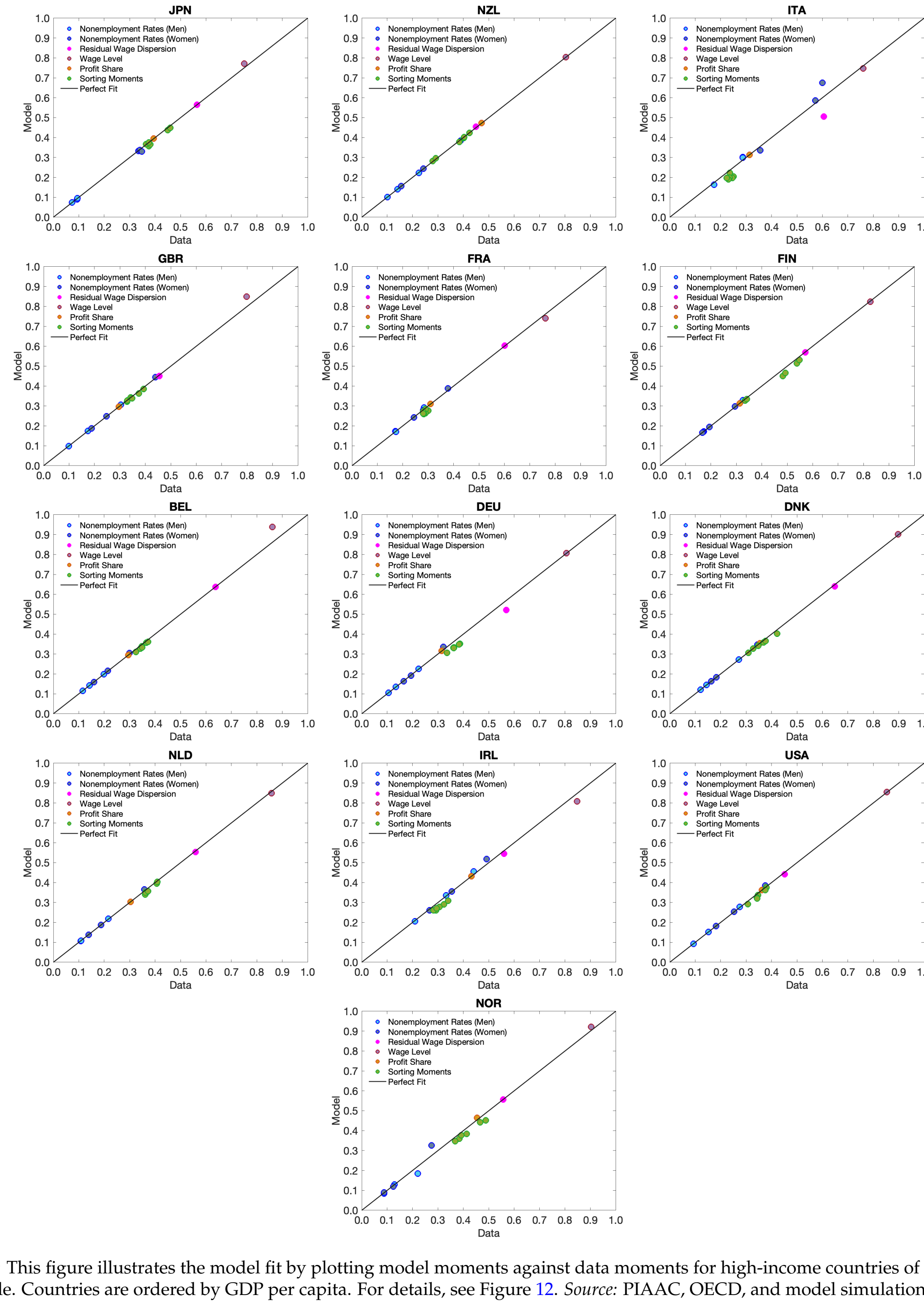
E.8 Details of Model Fit

Figure E2: Model Fit for Middle- to High-Income Countries



Notes: This figure illustrates the model fit by plotting model moments against data moments for low-income and medium-income countries of the PIAAC sample. Countries are ordered by GDP per capita. For details, see Figure 12. *Source:* PIAAC, OECD, and model simulations.

Figure E3: Model Fit for High-Income Countries

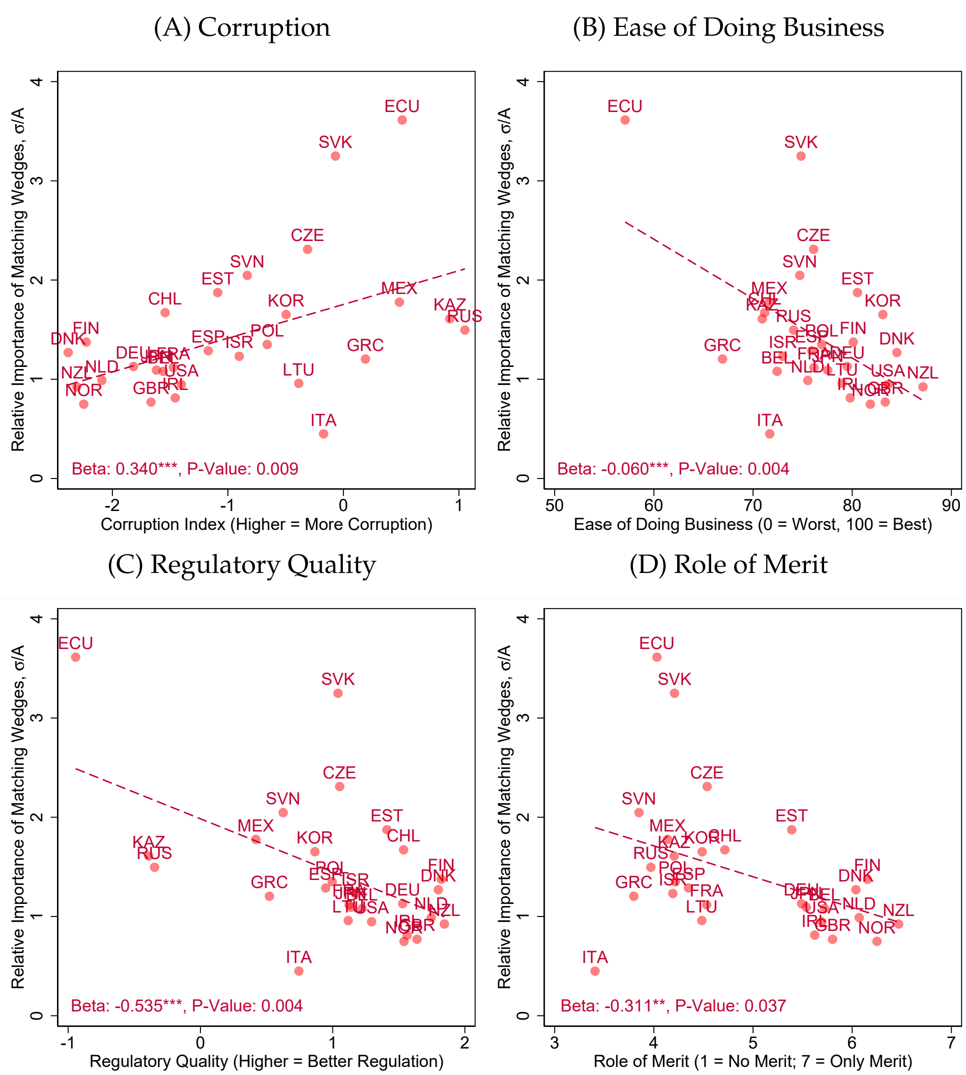


Notes: This figure illustrates the model fit by plotting model moments against data moments for high-income countries of the PIAAC sample. Countries are ordered by GDP per capita. For details, see Figure 12. *Source:* PIAAC, OECD, and model simulations.

E.9 Correlates of Model Estimates

Figure E4 projects our model estimates of the relative importance of idiosyncratic matching frictions, σ/A, separately onto each of three explanatory variables: a corruption index, an ease-of-doing-business index, a measure of regulatory quality, and a measure of the role of merit in job allocation. All four projections show statistically significant correlations, suggesting that our estimates of the relative importance of idiosyncratic matching frictions reflect the quality of institutions, the business environment, and management practices.

Figure E4: Correlates of the Relative Importance of Idiosyncratic Matching Frictions



Notes: This figure projects our model estimates of the relative importance of idiosyncratic matching frictions, σ/A, separately onto each of four explanatory variables: a corruption index (panel A), an ease-of-doing-business index (panel B), a regulatory-quality index (panel C), and the role of merit in job allocation (panel D). Panels A to C rely on data from the World Bank's World Development Indicators. Panel D relies on data from the World Economic Forum's Executive Opinion Survey. The "Beta" coefficient and "P-Value" reported in each panel correspond to the coefficient estimate and significance level in a univariate regression of σ/A on the respective explanatory variable on each figure's horizontal axis. Stars denote statistical significance (i.e., * for the 10% level, ** for the 5% level, and *** for the 1% level). *Source:* World Bank, World Economic Forum, and model simulations.

F Counterfactuals Appendix

In this appendix, we discuss the implementation of the counterfactuals presented in Section 7 of the paper and show additional results.

F.1 Implementation of Counterfactuals

In this section, we describe the details of how we implement our counterfactual simulations. Throughout, when computing the meritocracy index, we approximate vanishing frictions, $\sigma = 0$, in its denominator by 5% of the country's original σ (i.e., $0.05 \times \sigma$) for computational purposes.

Counterfactual 1: Same Endowments. We impose Norway's skill distribution $G_{\text{Norway}}(x)$, skill requirement distribution $H_{\text{Norway}}(y)$ and job mass m^{J}_{Norway} in each country c.

Counterfactual 2: Same Technology. We impose Norway's technology $f_{\text{Norway}}(x, y)$ in each country c while keeping the effective severity of matching frictions, σ_c / A_c, at each country's baseline level. That is, we compute and implement for each country c the counterfactual degree of matching frictions as $\sigma_c^{\text{counterfactual}} = A_{\text{Norway}} \times \sigma_c / A_c$.

Counterfactual 3: Same Matching Frictions. We impose Norway's effective severity of matching frictions in each country c. That is, country c faces the counterfactual scale parameter of matching frictions $\sigma_c^{\text{counterfactual}} = A_c \times \sigma_{\text{Norway}} / A_{\text{Norway}}$.

Counterfactual 4: Same Endowments and Technology. This counterfactual combines Counterfactuals 1 and 2.

Counterfactual 5: Same Technology and Matching Frictions. This counterfactual combines Counterfactuals 2 and 3.

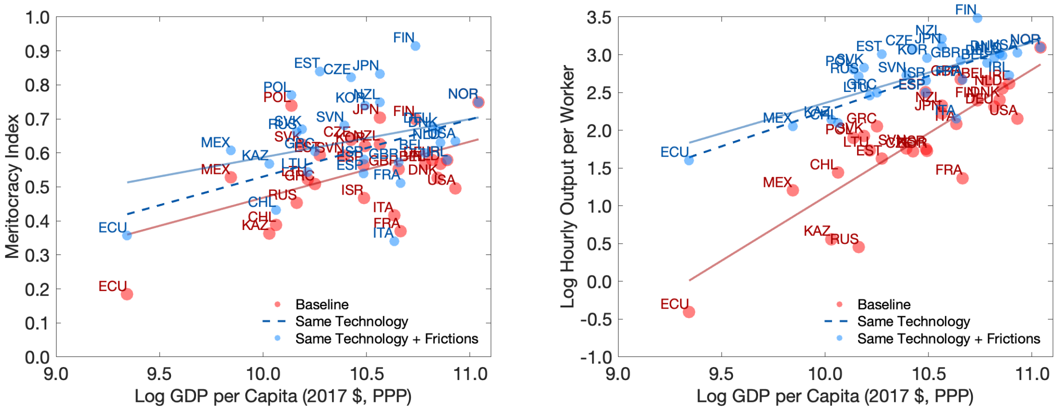
Counterfactual 6: Same Endowments and Matching Frictions. This counterfactual combines Counterfactuals 1 and 3.

Additional Counterfactuals with Fixed Worker-Job Matching based on the Meritocracy Index. To compute output per worker in Counterfactuals 1–6 above while keeping worker-job matching based on the Meritocracy Index at the baseline level in each country c, we compute

$$\sum_{x,y} \mu_c^{\text{fixed merit}}(x, y) f_c^{\text{fixed merit}}(x, y) = \sum_{x,y} \mu_c^{*}(x, y) f_c^{\text{counterfactual}}(x, y) \times \frac{\sum_{x,y} \mu_c(x, y) f_c(x, y)}{\sum_{x,y} \mu_c^{*}(x, y) f_c(x, y)}.$$

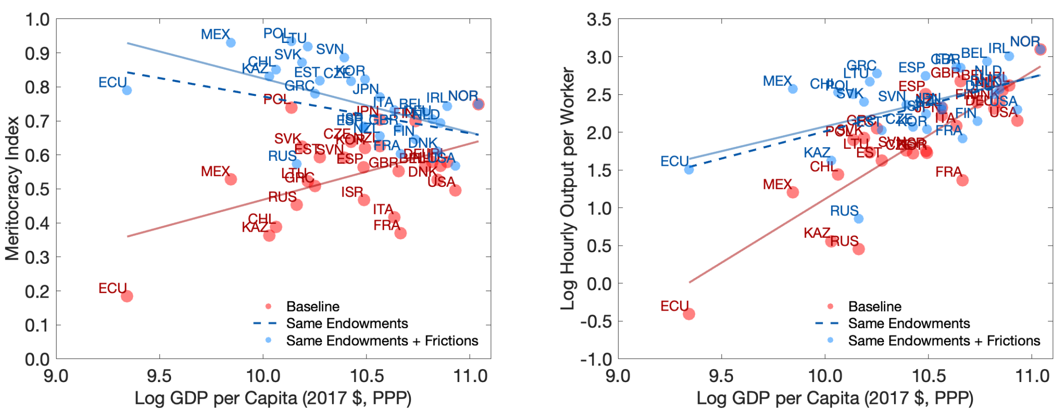
F.2 Additional Counterfactual Simulations

Figure F1: Counterfactual Imposing Frontier Technology and Matching Frictions across Countries



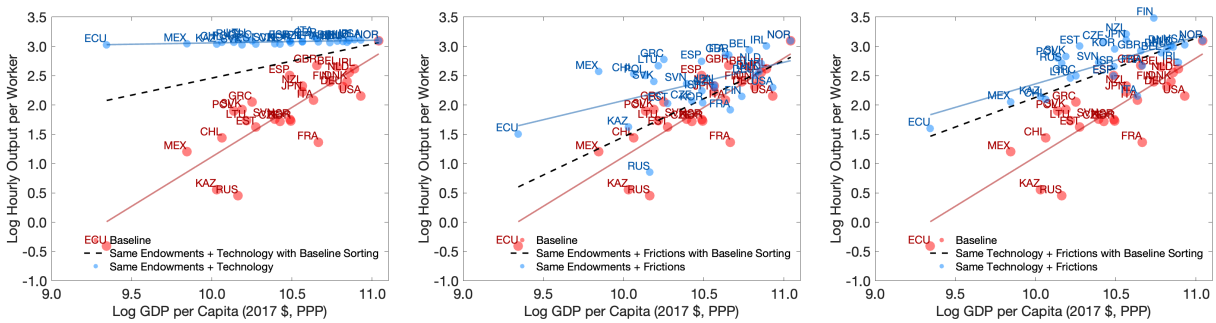
Notes: This figure shows the model-based counterfactual effects of implementing Norway's technology and matching frictions simultaneously in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue circles represent the counterfactual results for each country, with blue solid lines indicating the linear best fit across log GDP per capita. Dashed lines indicate the intermediate counterfactual simulation of changing only the technology in each country but keeping matching frictions unchanged. *Source:* Model simulations.

Figure F2: Counterfactual Imposing Frontier Endowments and Matching Frictions across Countries



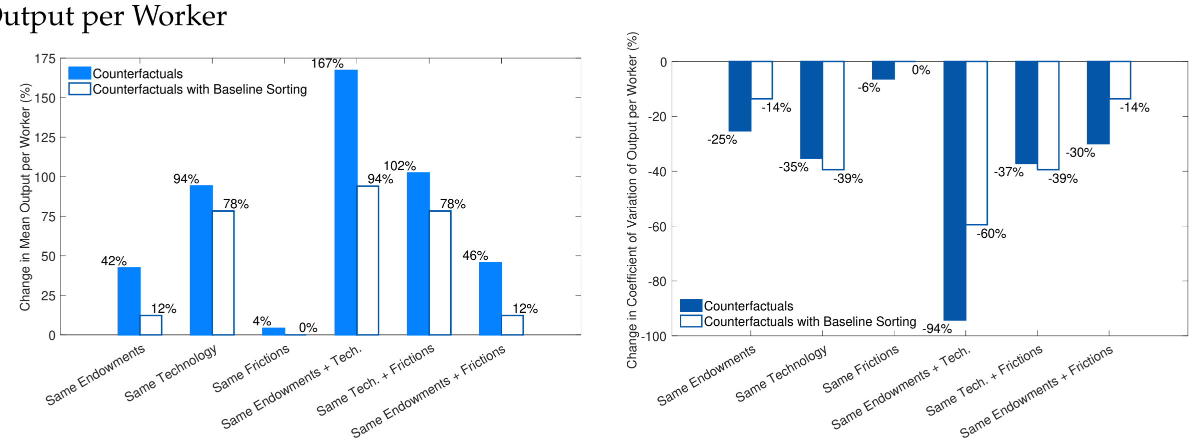
Notes: This figure shows the model-based counterfactual effects of implementing Norway's distributions and matching frictions simultaneously in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue circles represent the counterfactual results for each country, with blue solid lines indicating the linear best fit across log GDP per capita. Dashed lines indicate the intermediate counterfactual simulation of changing only the distributions in each country but keeping matching frictions unchanged. *Source:* Model simulations.

Figure F3: Counterfactual Imposing Frontier Endowments, Technology, and Matching Frictions across Countries: The Role of Worker-Job Sorting



Notes: This figure shows the model-based counterfactual effects of implementing Norway's endowments and technology (left panel), Norway's endowments and matching frictions (middle panel), and Norway's technology and matching frictions (right panel) in all countries. Red dots represent the baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue dots represent the counterfactual results for each country, with blue solid lines indicating the linear best fit across log GDP per capita. Black dashed lines indicate the linear best fit across log GDP per capita in the respective counterfactual while keeping each country's worker-job sorting based on its meritocracy index at its baseline. *Source:* Model simulations.

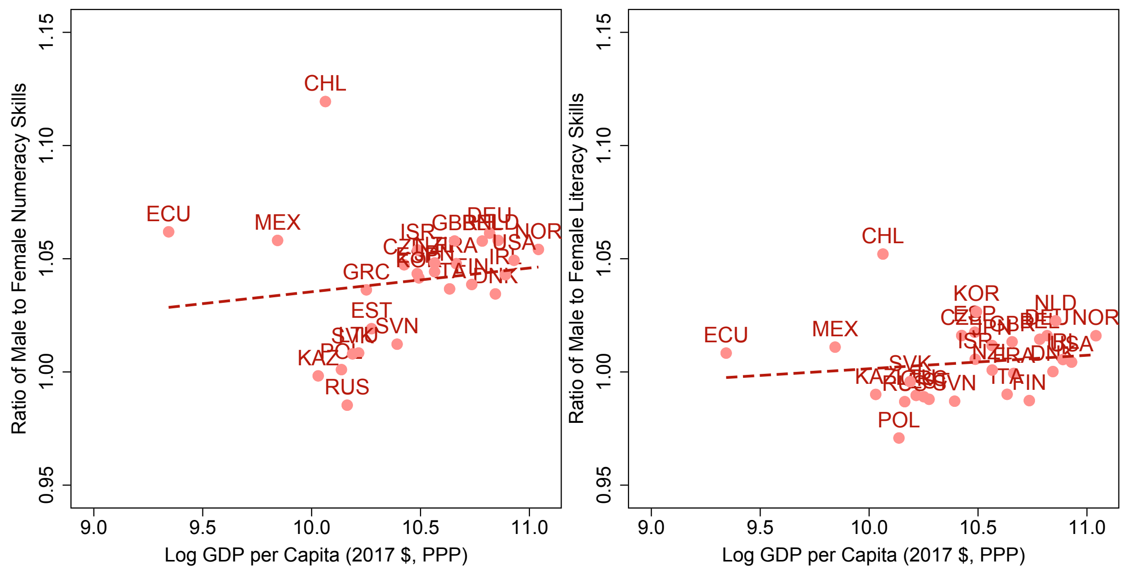
Figure F4: Detailed Summary of Counterfactuals: Global Mean and Coefficient of Variation of Output per Worker



Notes: This figure summarizes the results from all counterfactual simulations in terms of their effects on global mean output per worker (left panel) and coefficient of variation of output per worker across countries (right panel). Compared to Figure 19, we here report the interactions between all model primitives. The solid bars indicate outcomes based on the equilibrium counterfactuals. The hollow bars indicate outcomes in the counterfactual exercises while keeping each country's meritocracy index at its baseline level. The numbers above each counterfactual bar indicate the percentage change relative to the baseline. *Source:* Model simulations.

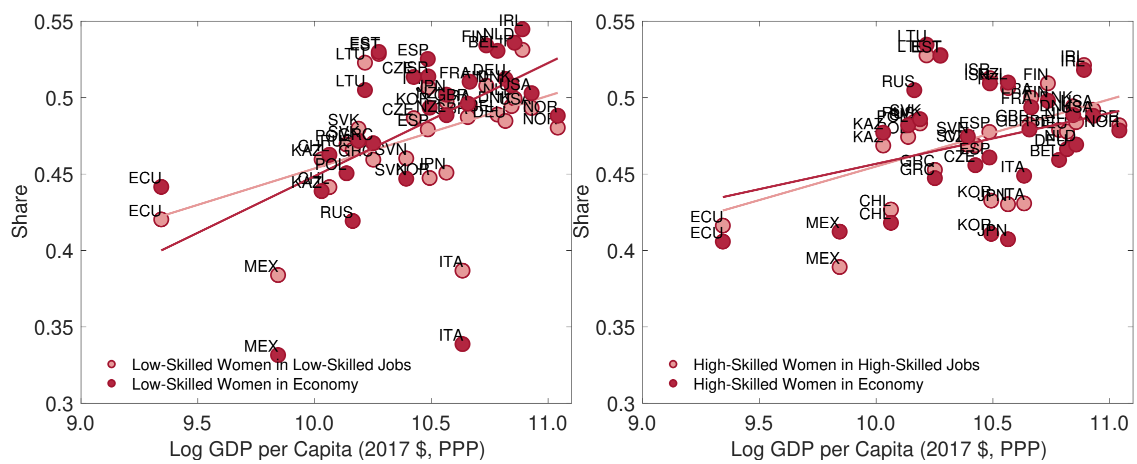
F.3 Skill Misallocation by Gender in the Data

Figure F5: Gender Differences in Skills across Countries



Notes: We report the ratio of male to female skill in each country as a function of their log GDP per capita. Dashed lines indicate the linear best fit. The left panel shows numeracy skills and the right panel shows literacy skills. *Source:* PIAAC.

Figure F6: Share of Low/High-Skilled Women in the Economy and in Low/High-Skilled Jobs



Notes: In the left panel, we plot the model share of low-skilled women in each country (red) and the share of low-skilled women in low-skilled jobs in each country (pink), where lines indicate the linear fit of the statistic under consideration with countries' log GDP per capita. The right panel has the same structure but focuses on high-skilled women. See the definition of these broad skill groups in Appendix E.2. *Source:* Model simulations.