Meritocracy across Countries*

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Abstract

Are labor markets in higher-income countries more meritocratic? 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 higher-income countries are more meritocratic in the sense that workers' skills better match the requirements of their jobs. We find evidence for three factors potentially underlying this: Higher-income countries have more aligned distributions of worker skills and job skill requirements, greater wage returns to skill-based matching, and lower residual wage dispersion conditional on skills. To interpret these facts and quantify the role of worker-job matching in development, we build an equilibrium model of matching with multidimensional skills, which we use to quantify the importance of three factors underpinning cross-country differences in worker-job matching: (i) endowments of 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 suggests that gaps in technology and endowments account for most cross-country income differences while matching frictions play a relatively modest role. At the same time, improved worker-job matching is key to unlocking the gains from economic development brought about by adopting frontier technology and endowments.

Keywords: Skills, Sorting, Matching, Development Accounting, Wage Inequality, Gender, Migration

JEL Codes: E24, J24, J31

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1 Introduction

The notion of meritocracy has an extensive tradition in political philosophy and the social sciences (Arrow et al., 2000; Sen, 2000). In a labor market setting, it entails matching workers to jobs along multiple skill dimensions in an output-maximizing way—that is, based on merit rather than idiosyncratic attributes unrelated to productivity.[1]

This paper is concerned with meritocracy across countries in the context of labor markets in which workers with different skills sort into jobs with different skill requirements. We leverage microdata on skill-based sorting together with an equilibrium model to quantify the role of worker-job matching in cross-country variation in aggregate outcomes. Methodologically, we innovate on the efficiency-units approach of traditional development accounting (e.g., Hall and Jones, 1999) in two important ways.[2] First, we model workers and jobs as production inputs that are each heterogeneous in multiple skill dimensions. Second, the matching pattern between workers and jobs matters for output and wages. This leads us to ask: Are workers better matched to jobs in higher-income countries? If so, why? And what are the aggregate consequences?

To address these questions, we combine theory and measurement. 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 directly 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 (e.g., 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 step, we document a series of facts about worker-job matching across countries. Our central starting observation is that workers' skills are more aligned with their jobs' skill requirements in higher-income countries. Skill-based sorting is greater in higher-income countries along the intensive margin (i.e., between employed workers

[1] 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). In China during the Sui dynasty, entry into the state bureaucracy was based on performance on the written Imperial Examinations, which were open to the public, rather than being based on nepotism and aristocratic influence. For the rulers of Greek city-states, it was thought that only a philosopher-king, or a ruler who is also a lover of wisdom, could guide the ship of state to its destination.

[2] The development-accounting literature has studied the contributions to aggregate output due to human capital (Jones, 2014; Lagakos et al., 2018b; Hendricks and Schoellman, 2018, 2023), physical capital (Young, 1995), technology (Caselli and Coleman II, 2006; Caselli, 2017; Comin and Mestieri, 2018; Caselli and Ciccone, 2019; Malmberg, 2022; Rossi, 2022; Bassi et al., 2022), labor market frictions (Poschke, 2023; Donovan et al., 2023), and misallocation of homogeneous labor and capital (Hsieh and Klenow, 2009; Buera et al., 2011; Midrigan and Xu, 2014; Bau and Matray, 2023).

and jobs) as well as along the extensive margin (i.e., selection into employment). We focus on three possible factors underpinning the relationship between worker-job matching patterns and economic development. The first factor comprises the endowments of worker skills and job skill requirements, which determine match feasibility. In a given country, the similarity between two-sided endowments governs the potential share of matches in which worker skills are aligned with job skill requirements. The second factor 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 a given worker-job match. If technology puts greater weight on the complementarities between certain worker skills and certain job skill requirements, then there are stronger incentives to match along those dimensions. The third factor relates to matching frictions, which guide the relative importance of workers' and jobs' idiosyncratic traits unrelated to productivity in the matching process, such as social networks, family wealth, corruption, and discrimination at the hiring stage. 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 inform country-specific deviations from the law of one price due to idiosyncratic matching frictions. We find that all three factors 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 both directions. In the spirit of development accounting, we quantify the contribution of the three factors that underpin 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 the micro evidence and the macro implications. Our model integrates the tools from matching theory (e.g., Becker, 1973; Choo and Siow, 2006) under multidimensional heterogeneity (Lindenlaub, 2017; Lindenlaub and Postel-Vinay, 2023) into a development accounting framework.[3]

In the model, each country's labor market is characterized by three fundamentals: 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 is comprised of two components: one part based on match output determined by the productive attributes of workers and jobs, and one part based on idiosyncratic factors unrelated to productivity, which we refer to as frictions in the sense that they lead to deviations from the output-maximizing allocation of workers across jobs. The importance of these frictions is indexed by a country-specific scale parameter guiding the distribution over

[3]Unlike our focus on economic development in a cross-section of countries, existing applications of matching models have been mostly confined to individual high-income countries (e.g., Jones et al., 2018; Bagger and Lentz, 2018; Lise and Postel-Vinay, 2020). Important exceptions are the Roy-Fréchet models of Lagakos and Waugh (2013), Young (2013), Bryan and Morten (2019), and Alvarez (2020), though they do not distinguish between endowments, technology, and matching frictions, given that worker skills and job skill requirements are unobserved in their contexts.

two-sided idiosyncratic matching wedges entering 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. Endowments of worker skills and job skill requirements determine 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 the effect on worker-job matching, these three fundamentals determine a country's aggregate outcomes, including the 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 have not only more productive worker skills and job skill requirements but also a 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, wage inequality, and skill returns.

In line with our empirical evidence, the estimated model implies a positive relation between the meritocracy index (i.e., the extent to which the worker-job allocation is output-maximizing) and economic development. For instance, Norway—the highest-income country in our sample—has a meritocracy index of 0.75, almost four times that of Ecuador—the lowest-income country in our sample. The worker-job matching patterns that we empirically documented, therefore, reflect greater misallocation in lower-income countries. To quantify the sources and consequences of variation in worker-job matching, we use the estimated model to simulate several counterfactuals in which we eliminate cross-country differences in one or more of the three fundamentals—endowments, technology, and matching frictions. In doing so, 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 variation in aggregate output across countries. 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 overlapping skill demands of jobs as in the frontier country, the cross-country variation in output would be 25 percent lower.[4] Jointly adopting the frontier endowments and technology explains the lion's share (i.e., 94 percent) of cross-country differences in output per worker, suggesting 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. Intuitively, improving the matching between workers and jobs—and thus narrowing the gap between actual and potential output—has limited returns in lower-income countries where inferior skill endowments and technology depress potential output.

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—e.g., due to more flexible labor laws or reduced nepotism in hiring—are unimportant. On the contrary, a large share of the gains from economic development are realized through improved sorting. We estimate that improvements in the worker-job allocation account for 36 percent of the cross-country convergence in output per worker due to the adoption of frontier endowments and technology, which boost the returns to sorting in poorer countries, leading to additional amplification of their effect on aggregate outcomes. This reflects our central finding that the available skill endowments and technology constrain the returns to better worker-job matching in low-income countries. Altogether, these findings suggest that meritocracy in the form of an 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 sorting by skills are more powerful than those designed to minimize idiosyncratic matching frictions in lower-income countries.

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—increase the average meritocracy index across countries, they each have

[4] This also provides an upper bound on the effect of meritocracy mediated by endowments. That is, by adopting the frontier levels of worker skills and job skill requirements in all countries, we effectively account for endogenous investments in human and physical capital based on prevailing degrees of meritocracy.

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 the past decades, there is still significant under-utilization 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 lower-income 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 integrating labor markets across countries. 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 an improved worker-job allocation relative to our baseline with national labor markets.

This paper advances our understanding of the role of worker-job matching in economic development. We study the micro sources and aggregate consequences of meritocracy in the labor market for a large set of countries that vary substantially in GDP per capita. To this end, we combine rich microdata on worker skills and job skill requirements with an equilibrium model to interpret worker-job sorting patterns across countries at different stages of development. We contribute to the growing evidence on the role of factor misallocation in development, which has mostly focused on homogeneous labor and capital (e.g., Hsieh and Klenow, 2009; Buera et al., 2011; Midrigan and Xu, 2014; Bau and Matray, 2023). Since labor accounts for around two-thirds of national income around the globe, understanding how worker-job matching affects aggregate outcomes across countries is of prime importance. This is the contribution of our paper.

Outline. The rest of this article is structured as follows. Section 2 provides an overview of the PIAAC data. Section 3 documents empirical facts pertaining to multidimensional worker skills, job skill requirements, and their matching patterns across countries. Section 4 develops an equilibrium model of worker-job matching. Section 5 proves that the model parameters are identified. Section 6 discusses model estimation, parameter estimates, and model fit. Section 7 simulates counterfactuals in order to shed light on the sources and consequences of meritocracy across countries. Finally, Section 8 concludes.

2 Data Description

2.1 The Survey of Adult Skills

Data Description. Our main data source is the OECD Survey of Adult Skills of the *Programme for the International Assessment of Adult Competencies (PIAAC)*, 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 skill measures in the areas of numeracy and literacy.[6] Importantly, skills are measured in incentivized tests rather than self-reported or inferred. The survey as a whole, including the assessments of skills and skill requirements, is designed to be comparable between countries. Using these harmonized skill measures, we do not need to rely on education-based metrics, like years of schooling, which may not be comparable across countries. The PIAAC data span 38 countries, 28 of which have all the information (e.g., continuous wages) required for our study—see Appendix A.1 for the complete country list.

Sample Selection. We restrict attention to individuals between the ages of 20 and 59 with non-missing information for key variables (i.e., numeracy and literacy skill scores, gender, employment status, and sampling weight) and continuous—as opposed to categorical—income reports when employed. We also drop the self-employed, for whom we do not have reliable wage information.[7]

2.2 Variable Definitions

Worker Skills. The PIAAC survey reports scores from incentivized numeracy and literacy skill tests on a scale from 0 to 500. While we observe raw test scores, it is instructive to consider the meaning of different ranges of them. The lowest range (i.e., scores below 176) of 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 (i.e., scores from 226 to 275) reflects the ability to "identify and act on mathematical information embedded in common contexts." The highest range (i.e., scores from 376 to 500) covers the top one 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 exercises, we use a discretized version of the skill distributions to ensure similar treatment in the data and in the model. To deal with the issue that skills and skill requirements are measured in different units but need to be made comparable for the analysis of 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 each skill dimension (e.g., numeracy), we first

[5]See OECD (2019) for a technical document with details on the PIAAC dataset.

[6]A subset of countries also report *Information and Communications Technology (ICT)* skills. Here, we focus on numeracy and literacy skills as these are available for most countries.

[7]In the top-left panel of Figure 27 (Appendix A.4), we demonstrate that in all countries of our sample, self-employment is not very common, especially when compared with the lowest-income countries in the world.

globally order all individuals across countries and give each individual a number between 0 and 1 that reflects their rank in the global distribution. We then take the mean over the global ranks across workers in the same country- and skill-specific quintile. This yields discrete distributions of numeracy and literacy skills for each country, which take values between 0 and 1 while preserving differences in skill levels across countries.[8]

The main advantage of the PIAAC skill measures compared to using education as a proxy for skills is that the tests were designed to be comparable across countries, whereas differences in unobservable quality of education make international comparisons difficult (Barro and Lee, 2013; Martellini et al., 2023). In line with this, in Figure 25 in Appendix A.3, we show that education explains only a small share of the variation in skills, especially in the lowest-income countries.

Job Skill Requirements. To measure skill requirements for a given job, defined by four-digit *International Standard Classification of Occupations (ISCO)* occupation codes, we look at all workers in a given country who report being employed in that occupation.[9] The survey asks workers to report whether they perform certain tasks pertaining to each skill. For instance, for numeracy, they are asked about tasks that use a calculator, algebra, make budgets, and so on. We sum the number of tasks that each worker completes in each area—numeracy and literacy—and weigh each performed task by its difficulty (see Appendix A.1.1 for more details). We then take the average of this measure across all workers in a given occupation in each country to arrive at country-specific skill requirements of numeracy and literacy for each job. To make the units of job skill requirements comparable to those of skills, we again transform them into *global quintiles*, as we did for worker skills above. As a result, both worker skills and job skill requirements take values between 0 and 1, while at the same time their distributions differ across countries as indicated by the raw measures.

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 two summary measures of worker-job matching that reflect this notion.[10] The PIAAC data allows us to differentiate skill bundles both "vertically" by ranking skills in a given dimension and "horizontally" by distinguishing between different types of skills. To empirically summarize the worker-job matching pattern based on multidimensional skills and skill requirements, we propose two measures. The first one is a categorical variable that splits the worker-job pairs into "perfect

[8]We use global quintiles to balance two objectives. On the one hand, we would like that the cells of the discretized distributions are not too sparsely populated, which is why we create quintiles *within* each country. On the other hand, we attach a number equal to the *global* rank to these country-specific quintiles to preserve cross-country differences in the skill distributions.

[9]The United States and Ireland only report ISCO-2 codes, whereas Estonia and Finland only report ISCO-1 codes. We use two- and one-digit ISCO codes for these countries, respectively. ISCO-4 codes are used for all other countries.

[10]What constitutes meritocratic worker-job matches, of course, depends on the available endowments, which determine the feasibility of matches, and the production function, which determines the returns to matching certain worker skills to certain job skill requirements. We have not defined or estimated either of these objects at this stage but we view our empirical facts as suggestive of corresponding model fundamentals, which we will introduce in the next section.

matches" (i.e., if a worker's skills match the skill requirements of their job in each dimension), "good matches" (i.e., if the worker's skills are within a narrow radius around their job's skill requirements), and "poor matches" (i.e., if the worker's skills are outside of a narrow radius around their job's skill requirements). Our 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 assign each worker skill and each job skill requirement to quintiles of their respective distributions within each country. As a result, each worker is characterized by a two-dimensional vector of numeracy and literacy skills, with each vector entry taking on values 1 to 5. Likewise, each job is characterized by a two-dimensional vector of numeracy and literacy skill requirements, with each entry taking on values 1 to 5. There are, thus, 25 possible worker types and 25 possible job types. We define a match to be "perfect" when the worker's skills and the job's skill requirements exactly match on both dimensions, "good" when each of the worker skills and the job skill requirements are at most one quintile away from the perfect match, 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 job skill requirements.

Therefore, we also build a second measure of worker-job matching with a cardinal interpretation. Based on the "global quintiles" of worker skills and job skill requirements explained above, we compute the average Euclidean distance between a worker's skill vector and their job's skill requirement vector, both contained in $[0,1]^2$. 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 $\sqrt{2} \approx 1.41$ 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 speak to this extensive margin by using the PIAAC data to measure the skill gap between employed versus nonemployed individuals, computed as the percentage difference in mean skill levels between the two groups.

2.3 Summary Statistics

Our sample consists of 120,448 observations, representing over 718.2 million individuals in 28 countries. Table 1 presents some key summary statistics.[11] Panel A shows general country characteristics. While the data cover middle- and high-income countries, it spans a substantial part of the development spectrum, with countries' GDP per capita ranging from Ecuador at 11,424 dollars (PPP) to Norway at 62,399 dollars (PPP)—a ratio of around 5.5. In terms of population sizes, our sample ranges from Estonia, with 0.7 million covered individuals, to the United States, with 285.4 million covered individuals. Women's population share and age are relatively homogeneous across countries. Hourly wages show a similar range to that of GDP per capita, with a factor of 5.2 between the lowest- and highest-wage countries. Finally, the dataset contains between 2,854 and

[11] Appendix A.3 contains additional summary statistics by country.

7,159 observations per country, which is sizable but also imposes practical limits on how much we can split the data in our analysis.

Panel B shows labor supply characteristics. There are marked cross-country differences in skills. The average respondent scores just above half of the available marks on each of the skill tests. In the top panels of Figure 24 in Appendix A.3, we show the distributions of skills within each country, highlighting the two lowest-income countries (i.e., Ecuador and Mexico) and the two highest-income countries (i.e., Norway and the United States). Average skills are greater in higher-income countries, but there is significant dispersion. Finally, years of schooling and employment shares vary widely across countries, the latter especially among women.

Panel C shows labor demand characteristics. In the bottom panels of Figure 24 in Appendix A.3, we show the distributions of skill requirements within each country, again highlighting the two lowest-income countries (i.e., Ecuador and Mexico) and the two highest-income countries (i.e., Norway and the United States). Similar to worker skills, job skill requirements are also greater in higher-income countries, with significant dispersion. Another notable fact is the scarcity of large firms with more than 50 workers in some countries, especially at lower incomes.

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)	25.53	0.67	2.57	6.94	25.92	284.86
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	0.63	0.37	0.55	0.69	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 across the 28 countries included in our analysis. Panel A shows basic country characteristics. Panel B shows statistics pertaining to labor supply. Panel C shows statistics pertaining to labor demand. Columns represent the mean, the minimum, the 25th percentile, the median, the 75th percentile, and the maximum of each variable at the country level. *Source:* PIAAC.

2.4 Context and Data Validation

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

A unique aspect of PIAAC is that it directly tests various dimensions of skills among the working-age population. To validate these measures, Figure A.5 in Appendix A.5 shows strong correlations between the skill scores of working-age respondents in PIAAC and the corresponding skill scores of 15-year-old students in the *Program for International Student Assessment (PISA)* along multiple skill dimensions. This suggests that, first, the PIAAC data capture meaningful skills, and second, the skills tested by PIAAC are persistent, motivating our assumption of treating them as fixed factors in our equilibrium model of the labor market.

Another distinct feature of PIAAC is its information on 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 because different countries may use different technologies to produce the same goods, implying that the skills required in a given job are not necessarily the same everywhere. As a result, worker-job matches may be misclassified if skill requirements from the U.S. O*NET were universally applied to all countries (Atencio-De-Leon et al., 2023; Caunedo et al., 2023). Figure 26 in Appendix A.3 plots the coefficient of determination (R^2) from a regression of skill requirements in PIAAC on the corresponding O*NET measures for the same job. We find that O*NET explains only around 20–60 percent of the variation in numeracy requirements and around 60–70 percent of the variation in literacy requirements in any given country, with the explained share being higher in higher-income countries.

To lend further credence to the representativeness of the PIAAC data, we compare our PIAAC survey data along important dimensions with data from the *Jobs of the World Database (JWD)* and the *Luxembourg Income Study (LIS)*, both within and across countries, with two main findings.[12] First, we confirm the representativeness within countries of the PIAAC data vis-à-vis national census data for important labor market outcomes such as the share of workers in paid jobs, education, labor force participation (Figure 27 in Appendix A.4), as well as the occupational composition (Figure 28 in Appendix A.4). Second, we compare the sample of countries covered by the PIAAC survey with other countries across the development spectrum. We find that the subset of PIAAC countries falls in the upper tercile of countries ranked by GDP per capita, as do their shares of workers in salaried jobs, average years of education, and women's relative labor force participation rates (Figure 27 in Appendix A.4).

[12] The JWD harmonizes census data from the *International Integrated Public Use Microdata Series (IPUMS-International)* as well as 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 factors behind worker-job matching in the data. The first factor comprises endowments of worker skills and job skill requirements, which determine match feasibility. The second factor pertains to technology—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 match. The third factor consists of matching frictions, which guide the relative importance of idiosyncratic as opposed to skill-related attributes in the matching process. Such frictions may reflect formal institutions (e.g., regulatory quality or anti-discrimination laws) as well as informal institutions (e.g., corruption or social norms) that give a role for agents' nonproductive attributes to affect their labor market outcomes.[13] In what follows, we document a sequence of 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?

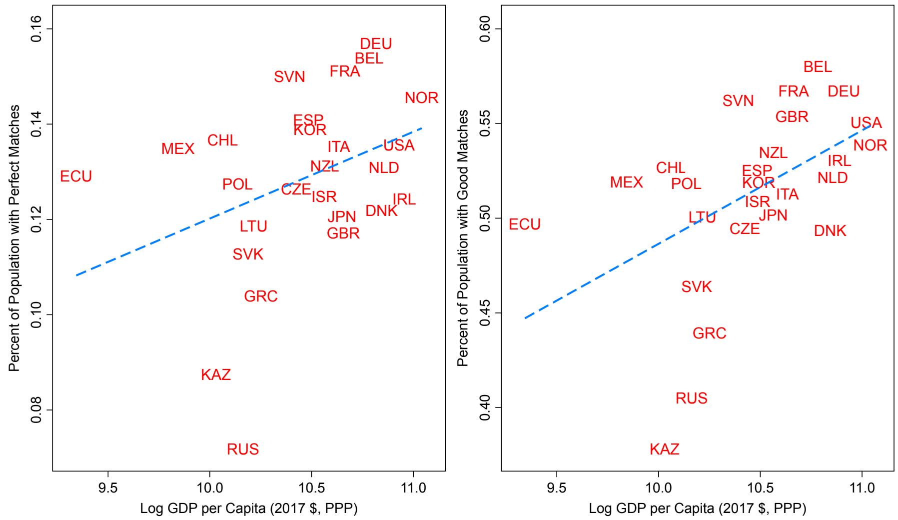
Intensive-Margin Matching. Figure 1 shows the country-specific shares of perfect and good matches between worker skills and job skill requirements, as defined in Section 2. The share of perfect worker-job matches (left panel) ranges from 7 percent to 16 percent across countries. The more generous definition of good worker-job matches is higher, ranging from 35 percent to 60 percent. Both measures reflect large cross-country differences in skill-based sorting. Importantly, the shares of perfect and good matches are increasing in GDP per capita. Figure 2 underscores this finding based on our continuous measure of worker-job mismatch, namely the average Euclidean distance between a worker's skills and their job's skill requirements, which is strongly decreasing in GDP per capita.[14] From this evidence, we conclude that in higher-income countries, workers are better matched to jobs in the sense that workers' skills are more closely 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. We are interested in the selection into employment based on skills. Figure 3 shows the skill gap between em-

[13] While the endowments of worker skills and job skill requirements, as well as technology, reflect past investments in human and physical capital affected by meritocracy in the labor market, we treat these as given in the data and our model-based accounting exercise below.

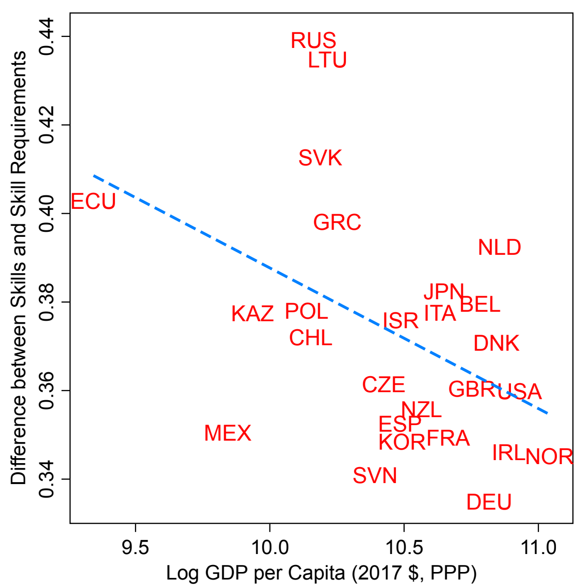
[14] Figure 32 in Appendix B.2 shows that these patterns are robust to using raw skill and job skill requirement scores to compute the Euclidean distance.

Figure 1: 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 numeracy and literacy 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 numeracy and literacy skill dimensions. *Source:* PIAAC.

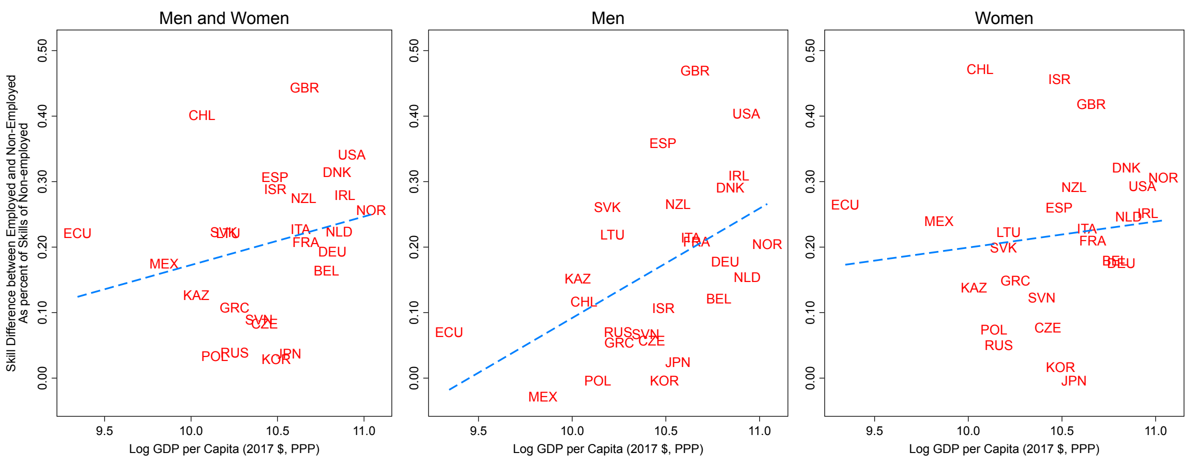
Figure 2: Intensive Margin: More Skill-Based Alignment of Worker-Job Matches in Higher-Income Countries



Notes: This figure plots the mean distance between workers' skills and the skill requirements of the job that they are employed in by country. Differences are 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.

ployed and nonemployed individuals across countries. Focusing on the overall population in the left panel, two observations emerge. First, the skill gap is positive in all sample countries, reflecting positive skill-based selection into employment. Second, there is a positive correlation between the skill gap and GDP per capita, with the gap increasing from around 10 percent to around 25 percent across the development spectrum.[15] 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 of these facts are consistent with women facing substantial barriers to labor market participation, especially 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.

Figure 3: Extensive Margin: Greater Skill-Based Selection into Employment in Higher-Income Countries



Notes: This figure plots the employed-to-nonemployed skill differential and GDP per capita across countries. For each individual, we average their global quintiles of numeracy and literacy skills and then compute the difference in average skill quintiles of the employed and the nonemployed. A higher skill differential value indicates that workers with higher numeracy and literacy skills are more likely to self-select into employment as opposed to nonemployment. *Source:* PIAAC.

3.2 Three Factors Behind Worker-Job Matching

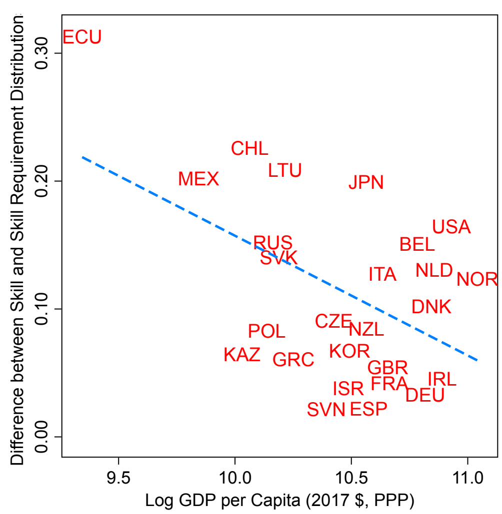
We now discuss three factors that can rationalize the documented worker-job matching patterns and how they vary across countries.

Factor 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 certain worker-job matches. We measure the alignment between a country's endow-

[15] In Figure 33 in Appendix B.2, we show that these patterns are robust to computing this statistic based on raw scores of worker skills and job skill requirements.

ments of worker skills and job skill requirements using a simple distance metric.[16] Specifically, we compute the average Euclidean distance between the intersection of global quintiles of worker skills and the intersection of 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, regardless of whether or not the worker is matched to that job. Conversely, it is maximized (i.e., $\sqrt{2} \approx 1.41$) when the economy's skill requirements are most misaligned with the skills workers possess. Importantly, this distance metric is independent of the actual worker-job matching patterns, which we focused on above, as it compares all available worker skills to all available job skill requirements in a country, regardless of who matches with whom. Figure 4 plots this distance metric against GDP per capita across countries. We find a smaller distance in higher-income countries, reflecting more aligned endowments of worker skills and job skill requirements in more developed economies. Intuitively, one expects that greater overlap in worker and job endowments in higher-income countries makes it easier for meritocracy—in the form of better worker-job matches—to materialize.

Figure 4: Endowments: More Aligned Worker Skills and Job Skill Requirements in Higher-Income Countries



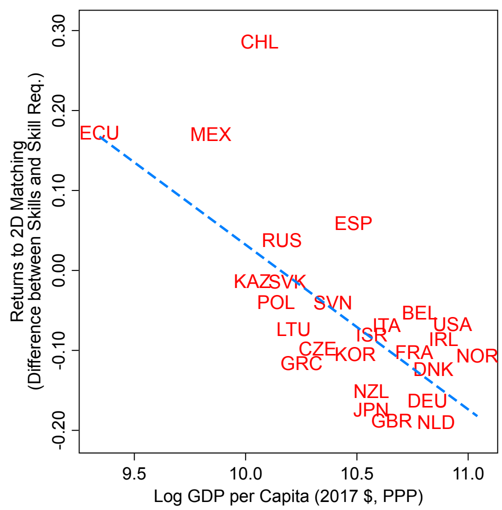
Notes: This figure shows the distance between the distributions of worker skills and that of job skill requirements against GDP per capita across countries. Unlike in the analysis of worker-job matches surrounding Figure 2, here we do not restrict the skill distribution to only employed individuals. In each country, the distance is computed as the weighted average Euclidean distance between the vector containing the global quintiles of all workers' numeracy and literacy skills (i.e., irrespective of workers' employment status) and the vector containing the global quintiles of all jobs' numeracy and literacy skill requirements. These differences are weighted by the probability mass of workers in each cell defined by the intersection of worker skills and job skill requirements. *Source:* PIAAC.

Factor 2: Technology. A country's production technology determines the payoff from matching different worker skills with different job skill requirements. Differences in technology will lead to greater skill-based sorting in higher-income countries if they produce more complex products, use

[16] Figures 30 and 31 in Appendix B.1 illustrate differences between the endowments of multidimensional worker skills and job skill requirements in each country in our sample.

more elaborate machines or organize firms with deeper hierarchies, all of which renders worker-job complementarities stronger. While we do not observe technology or match output directly, in a decentralized market economy, output and thus technology will be reflected in wages that induce workers choose jobs based on their relative returns. Thus, to capture differences in technology across countries, Figure 5 plots the wage penalty from worker-job skill mismatch, which we estimate as the coefficient on the Euclidean distance between worker skills and job skill requirements in a Mincerian wage regression[17].We find a strong negative relationship between the estimated mismatch penalty and GDP per capita, suggesting that technology puts a relatively greater reward on worker-job sorting in higher-income countries. This fact suggests that high-income countries have greater economic gains from skill-based sorting, which pushes them toward greater meritocracy in the labor market.

Figure 5: Technology: Greater Penalty for Worker-Job Skill Mismatch in Higher-Income Countries



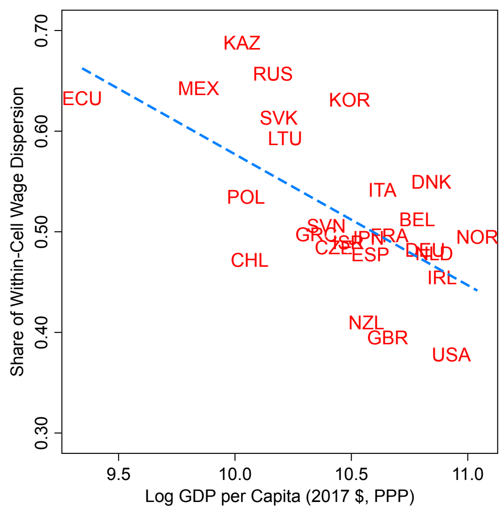
Notes: This figure shows that higher-income economies offer greater rewards for better matches (i.e., those with lower differences between worker and corresponding job attributes). The vertical axis plots estimates of the coefficient β from the following regression: $\ln(w_i) = \alpha + \beta \text{Diff}_i + \gamma X_i + \varepsilon_i$, where Diff_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. A lower value of Diff_i indicates a closer match between a worker's skills and their job's skill requirements. X_i is a vector of Mincerian controls for education, experience, and the square of experience. *Source:* PIAAC.

Factor 3: Idiosyncratic Matching Frictions. The third factor that can shape a country's labor market sorting patterns are frictions that constrain the matching process. In a frictionless labor market, the law of one price commands that individuals with the same skills in jobs with the same skill requirements earn the same wage. For this reason, residual wage dispersion 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

[17]Figure 35 in Appendix B.3 shows robustness of this fact to a specification where we exclude mincer controls from the wage regressions

extent to which they affect the matching process might do. For example, the enforcement of antidiscrimination laws might be weaker or corruption might be more tolerated in poorer countries. If such frictions are systematically more important in lower-income countries, they could lead to less skill-based matching in lower-income countries. To gauge the relative importance of idiosyncratic matching reasons in the data, Figure 6 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.[18] We find a strong negative relationship between residual wage dispersion and GDP per capita across countries. This suggests a lower degree of matching frictions, consistent with a more meritocratic worker-job assignment in higher-income countries.

Figure 6: Matching Frictions: Lower Residual Wage Dispersion in Higher-Income Countries



Notes: This figure plots the share of dispersion in log wages not explained by skills, skills requirements, and the match between the two. We first construct quintiles for each dimension of skills and skill requirements. We then allocate each worker i into country-specific cells formed by the intersection of quintiles of their numeracy and literacy skills, $Num_i, Lit_i \in \{1, \ldots, 5\}$ and their job's quintiles of numeracy and literacy skill requirements $NumReq_i, LitReq_i \in \{1, \ldots, 5\}$. The vertical axis plots the ratio of within-cell wage dispersion to overall wage dispersion, estimated as the ratio of the residual sum of squares over the total sum of squares from 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 and literacy skill quintile k' and numeracy skill-requirement quintile k'' and literacy skill-requirement quintile k''', and X_i is a vector of Mincerian controls for education, experience, and the square of experience. *Source:* PIAAC.

3.3 Interpreting the Empirical Evidence

We started with the central observation that in higher-income countries, workers' skills are more aligned with their jobs' skill requirements, and employed workers are more positively selected. We interpreted this as evidence that meritocracy in the labor market is positively correlated with economic development. We inspected three potential factors behind this pattern. The first was a 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

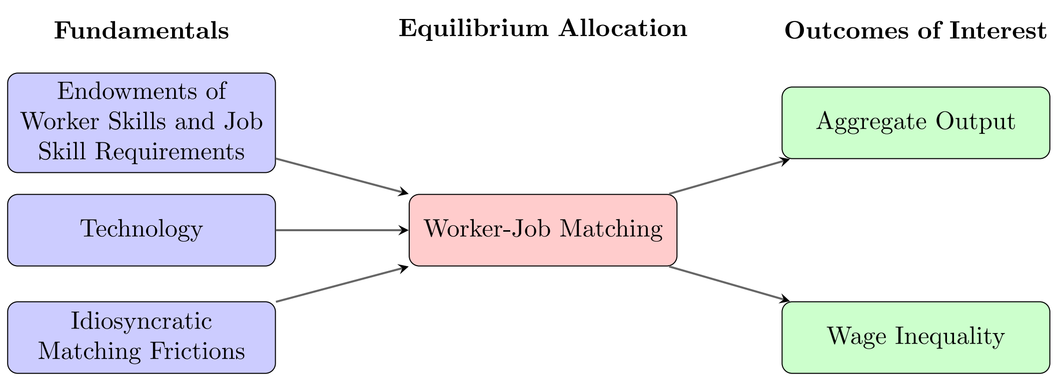
[18] The pattern is robust to (i) alternative discretizations of worker and job types, (ii) the omission of Mincerian controls, (iii) the inclusion of occupation fixed effects, and (iv) the additional inclusion or omission of worker and job skill measures in the wage regression—see Figure 34 in Appendix B.2, Figure 36 in Appendix B.4, and 37 in Appendix B.5.

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 will rationalize this through differences in technology that determine the economic output from matching up certain bundles of worker skills with bundles of job skill requirements. The third factor was a lower share of residual wage dispersion in higher-income countries. In our model, this corresponds to differences in idiosyncratic matching frictions affecting the worker-job matching process. Together, these facts inform our equilibrium model, in which countries differ in their endowments, technology, and idiosyncratic matching frictions, which together shape worker-job matching—and thus meritocracy—in the labor market.

4 An Equilibrium Model of Meritocracy in Worker-Job Matching

Motivated by the empirical facts documented in the previous section, 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) into the seminal matching framework of Choo and Siow (2006) to study the matching between workers and jobs as determined by three fundamental factors: endowments, technology, and idiosyncratic matching frictions. In each country, *endowments* of worker types and job types, together with *technology* determining the output of a worker-job pair, guide the feasibility and returns to matching. However, the output-maximizing worker-job allocation is impeded by *idiosyncratic matching frictions*, the strength of which follows a country-specific scale parameter.[19] We are interested in how each of these three factors shapes worker-job matching and, thereby, aggregate output and wage inequality across countries. Figure 7 provides a schematic model overview.

Figure 7: Model Overview



[19]While we refer to this fundamental as a "friction" in the sense that it reduces output, we do not attach any normative meaning to it. That is, what we term "frictions" is a stand-in for either malignant or benevolent reasons behind deviations from the output-maximizing worker-job allocation.

4.1 Environment

The world consists of N^C of countries, each with its own labor market.[20] Each labor market is characterized by a country-specific skill distribution among workers, a country-specific skill requirement distribution among jobs, a relative measure of jobs, a production function that combines worker and job attributes with country-specific parameters, and country-specific idiosyncratic matching frictions. 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.[21] 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 accruing to the worker and profits accruing to the job.

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) $(g_x)_{x \in \mathcal{X}}$ 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 numerical 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 $(h_y)_{y \in \mathcal{Y}}$ and relative measure $m^J \in \mathbb{R}^+$.

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. That workers' outside options depend on both skills and gender allows for gender-specific comparative advantage in home production. From here on, we assume $f_{\emptyset y}(y) = 0$.[22]

Idiosyncratic Matching Frictions. Idiosyncratic matching frictions lead to deviations from the output-maximizing worker-job allocation, both along the intensive margin (i.e., which worker matches with which job) and along the extensive margin (i.e., selection into employment). Specif-

[20] For simplicity, there is no interaction between different countries' labor markets in our baseline analysis. We allow for regional or global labor markets in an extension in Section 7.4.

[21] 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.

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

ically, matching is guided not only by systematic reasons relating to output but also by matching frictions, which we model as wedges entering individual workers' and jobs' match preferences. 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:

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

where the scale parameter $\sigma \in \mathbb{R}^+$ guides the extent of idiosyncratic matching frictions: $\sigma \to 0$ results in output-maximizing matching guided by the relative strengths of worker-job complementarities in production, while $\sigma \to \infty$ 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—i.e., a source of *misallocation* of worker skills to job skill requirements. These frictions may reflect malignant reasons for mismatch, such as information asymmetries (Stigler, 1961), corruption (Weaver, 2021), or nepotism (Akcigit et al., 2021), but they may also reflect more benign reasons such as a desire to live close to one's parents (Chan and Ermisch, 2015). Regardless of the specific interpretation, these matching wedges are separate from forces that affect the allocation and transfers based on output alone. Our interest lies in the dispersion of these matching wedges, guided by scale parameter σ, that rationalizes the observed matching patterns between workers and jobs in a given country. In this sense, our methodology allows us to conduct an accounting exercise within an equilibrium matching 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; Jones et al., 2018; Birinci et al., 2024).

4.2 Matching

A labor market matching results from a process in which workers choose which job to work in or to remain nonnemployed, 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 extreme-value shocks (e.g., McFadden, 1973), the *conditional choice probabilities* associated with optimizing behavior of worker type x are

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

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

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

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

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

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

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

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

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

4.3 Equilibrium Definition and Properties

In equilibrium, workers and jobs choose their payoff-maximizing matches in a way such 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 $\mu(x,\varnothing) := \mu^W(x,\varnothing)$ and $\mu(\varnothing,y) := \mu^J(\varnothing,y)$ denote the equilibrium frequencies of unmatched workers and firms, respectively. We can now define an equilibrium.

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

- *jobs and workers maximize their respective payoffs, resulting in conditional choice probabilities* (3)–(4) *for jobs and* (1)–(2) *for workers; and*

- *labor market clearing* (5) *holds.*

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 $f_{x\varnothing}(x)$ and $f_{\varnothing y}(y)$, and *idiosyncratic match surplus*, which comprises agents' idiosyncratic matching wedges δ_{xk} and δ_{iy}:

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

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

Equilibrium Properties. We now state a number of useful equilibrium properties, the derivations of which are in Appendix C. We combine the relative choice probabilities $\mu^J(x,y)/\mu^J(\varnothing,y)$ for jobs of type y, and $\mu^W(x,y)/\mu^W(x,\varnothing)$ for workers of type x with labor market clearing (5) to obtain the following expression for the *systematic match surplus* of match (x,y):

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

We call the match surplus in (7) 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, systematic match surplus 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 $\mu(x,y)/\mu(x,\varnothing)$, market clearing, and matching frequencies $\mu(x,y)$ from equation (7):

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

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, as well as the availability of type y jobs relative to that of type x workers, captured by the ratio of idle jobs relative to nonemployed workers, $\mu(\varnothing,y)/\mu(x,\varnothing)$.

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

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

In addition, we obtain *idiosyncratic wages*, $\tilde{w}(x_i,y_k)$, which 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}—and thus generate 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 effectively 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, $w(x, y)$, pertaining to any match between a type x worker with 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] Similarly, job k of type y receives the residual surplus in the form of *idiosyncratic profits* from matching with worker i of type x, given by $\tilde{v}(x_i, y_k)$.

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

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

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

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

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

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 *Iterative Projective Fitting Procedure (IPFP)*, provides a computationally efficient solution to high-dimensional matching

[23] Two additional remarks are worth noting at this point: 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}. Second, equilibrium wages in our model additively incorporate the worker's preference over a given job type represented by δ_{iy}, in contrast to the standard logic of compensating differentials under which jobs will reduce their wage payment by the same amount (Rosen, 1986).

[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 extreme-value distribution.

problems.[25] 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 extreme-value 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 the problems stemming 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, are essentially continuously distributed. This makes 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. This demonstrates that the equilibrium is unique.

4.4 Meritocracy

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. Denote a country's parameter vector by $\theta := \big(G(\cdot),H(\cdot),m^J,f(\cdot),f_{x\emptyset}(\cdot),\sigma\big)$, the actual frequencies of worker-job matches by $\mu(x,y)$, and the hypothetical frequencies of worker-job matches in the frictionless case with $\sigma\to 0$ by $\mu^*(x,y)$. The following index makes precise the notion of meritocracy in the labor market, based on matching productive attributes of workers with productive traits of jobs.

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,*

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

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.

Less pronounced idiosyncratic matching frictions (i.e., lower levels of σ) are associated with more output-based worker-job sorting guided by the technological returns to productive attributes (x,y). This pushes $\mu(x,y)$ closer to $\mu^*(x,y)$, thereby narrowing the gap between actual and potential output and increasing the meritocracy index, $\mathcal{M}(\theta)$. The meritocracy index is maximized

[25] For economic applications of IPFP algorithms, see Galichon et al. (2019) and Chen et al. (2021).

(i.e., $\mathcal{M}(\theta) = 1$) in a frictionless economy (i.e., $\sigma \to 0$), which we interpret as the perfectly meritocratic labor market.[26] 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 have a role to differentially affect actual versus potential output and thus $\mathcal{M}(\theta)$.

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

Better-aligned endowments of worker skills, $G(\cdot)$, and job skill requirements, $(H(\cdot), m^J)$, facilitate output-based sorting. For any given level of friction, $\sigma > 0$, a good fit between skill supply and demand tends to enable the formation of productive matches and incentivizes workers to seek matches that better fit their skills simply because more suitable jobs are available. Once more, this pushes $\mu(x, y)$ closer to $\mu^*(x, y)$, thereby narrowing the gap between actual and potential output and increasing the meritocracy index $\mathcal{M}(\theta)$.[27]

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. In this formalization of meritocracy, frictions play a central role because a meritocratic labor market is one in which only productive worker and job attributes shape their matching, regardless of idiosyncratic traits unrelated to productivity.

5 Identification

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

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

where $G(\cdot)$ is the distribution of worker types, $H(\cdot)$ is the distribution of job types, m^J is the relative mass of jobs, $f(\cdot)$ is the production function, $f_{x\varnothing}(\cdot)$ 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 neither appear in θ. For the purpose of our identification result only, we normalize the output of matches involving the lowest worker skill type $(\underline{x_n}, \underline{x_\ell})$, where $\underline{x_n} := \min x_n$ and $\underline{x_\ell} := \min x_\ell$, to $f(\underline{x}, y) = 0$ for all job types $y = (y_n, y_\ell, y_s)$.[28]

[26] In a frictionless economy (i.e., $\sigma \to 0$), the equilibrium is unique in terms of match surplus, which is what matters here, but not necessarily in terms of wages.

[27] Note that greater technological returns or more aligned endowments increase both actual and potential output. However, we find that the increase in actual output in the numerator dominates the increase in potential output in the denominator of the meritocracy index in all of our simulations below.

[28] 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.

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. $\square$

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

First, regarding endowments, $G(\cdot)$ and $H(\cdot)$ are distributions over observable worker and job types, so they are identified based on the empirical shares of worker skills and job skill requirements.[29] In turn, the relative job mass, m^J, is identified based on the aggregate profit share.[30]

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. In a frictionless world (i.e., $\sigma \to 0$), the law of one price implies 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 (Mortensen, 2003). 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 workers of type x who match with jobs of type y. As a result, there is wage dispersion within a given (x,y) match, which is strictly increasing in σ and unaffected by all other model parameters.[31] Therefore, the empirical within-(x,y)-cell wage dispersion identifies σ.

Third, technology $(f(\cdot), f_{x\emptyset}(\cdot))$ is identified based on observed matching patterns. Consider the outside option of workers. It 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 wage in a match (observed), the degree of idiosyncratic matching frictions (identified above), and the worker's outside option, we can identify $f_{x\emptyset}(\cdot)$. In turn, given endowments $(G(\cdot), H(\cdot), m^J)$ and idiosyncratic matching frictions σ, we can identify the production function $f(\cdot)$ 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 $(\underline{x_n}, \underline{x_\ell})$ 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 productive worker depends only on match output $f(x,y)$, wage $w(x,y)$ (observed) and idiosyncratic matching frictions σ (identified above), so we can identify $f(x,y)$ for each worker-job pair $(x,y) \in \mathcal{X} \times \mathcal{Y}$.

[29] Note that we identify $H(\cdot)$ 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.

[30] 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.

[31] To see this, note that (10) implies $Var(\tilde{w}(x_i, y_k)|x,y) = Var(\delta_{iy}) = \pi^2\sigma^2/6$ by virtue of the EV Type I distribution.

6 Estimation

We estimate our model separately on each of $N^C = 28$ countries, for which we have microdata from the PIAAC survey. In doing so, we allow all model parameters—corresponding to endowments, technology, and idiosyncratic matching frictions—to flexibly differ across countries. We first introduce the parameterization of the model and then discuss our estimation procedure, which is directly informed by the identification arguments spelled out in the previous section.

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. To operationalize the model, we discretize the distributions of worker skills and job skill requirements from the 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) by first partitioning their marginal distributions in each country into 5 country-specific quantiles and then assigning each of these quantiles a value that corresponds to its global rank in that dimension. We also 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' corresponds to more than 50 employees.[32] For workers, since we observe both nonemployed and employed individuals in the PIAAC survey, we can directly infer the population distribution of worker 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., idle and filled) job types is congruent to the observed distribution of filled jobs in a given country, which we observe in the PIAAC survey.[33] As a result, we obtain probability mass functions over 50 worker types, $(g_x)_{x \in \mathcal{X}}$, and 50 job types, $(h_y)_{y \in \mathcal{Y}}$.

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

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

[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 patterns of worker and job heterogeneity in the PIAAC data. On the other hand, we want a small enough number of grid points to keep the number of observations within (x, y) matches sufficiently large so that we can construct reliable measures of within-(x, y)-cell wage dispersion, which our estimation strategy relies 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.

The production function interacts both worker skills (x_n, x_ℓ) with all three job attributes (y_n, y_ℓ, y_s). A worker's gender x_g does not directly affect output.[34] 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 the equilibrium matching patterns. Equation (15) allows us to define *total factor productivity (TFP)* as $A := \alpha_{nn}$, leaving us with five complementarity parameters $(\hat{\alpha}_{n\ell}, \hat{\alpha}_{ns}, \hat{\alpha}_{\ell\ell}, \hat{\alpha}_{\ell n}, \hat{\alpha}_{\ell s})$, all relative to A.

We allow for flexible workers' outside options, $f^{kg}_{x\varnothing}$, nonparametrically estimated across 6 groups of workers, consisting of 3 broad skill groups indexed by $k \in \{\text{low}, \text{medium}, \text{high}\}$ interacted with 2 gender groups indexed by $g \in \{\text{female}, \text{male}\}$.[35] On the job side, we set the value from being idle identically to zero, $f_{\varnothing y}(y_n, y_\ell, y_s) = 0$. This restriction circumvents the need to identify this object based on our data.[36]

6.2 Estimation Procedure

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

$$\theta = \left((g_x)_{x \in \mathcal{X}}, (h_y)_{y \in \mathcal{Y}}, m^J, \alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s}, (f^{kg}_{x\varnothing})_{k \in \{\text{low,medium,high}\}, x_g \in \{\text{female,male}\}}, \sigma \right).$$

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 the distributions g_x across worker types x and h_y across job types y outside the model. In the second step, we use the model to estimate the remaining 14 parameters based on the *simulated methods of moments (SMM)*. This involves finding parameter vector θ, which for a given vector of model-based moments $\mathcal{S}^m(\theta)$ and the corresponding vector of data-based moments $\mathcal{S}^d$ minimizes objective function $\Omega(\mathcal{S}^m(\theta), \mathcal{S}^d)$. Here, $\mathcal{S}^m(\theta)$ and $\mathcal{S}^d$ are two column vectors of moments, each with 15 entries based on the parameterized model and the data, respectively. The moments we target in the SMM are tightly linked to our identification argument in Proposition 1.

Guided by our identification argument, 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 PPP dollars as an additional moment that is sensitive to levels, not just relative magnitudes, to separately determine TFP, A, and the scale parameter, σ.[37] We choose 6 skill- and gender-specific nonemployment rates to pin down workers' outside options $f^{kg}_{x\varnothing}$ across 3 broad skill groups k and 2 genders g, 6 moments reflecting the worker-job matching patterns to pin down the parameters

[34] Gender enters match surplus, however, because we allow for gender-specific outside options. That is, the model allows for the possibility of both gender- and skill-group-specific comparative advantages in home production.

[35] Assigning worker types to broad skill groups significantly reduces the dimensionality of the estimation routine while retaining sufficient heterogeneity. Specifically, we add each worker's numeracy and literacy scores, which range from quintiles 1–5 after discretizing, and then classify workers as "low-skilled" if the sum of their scores is 2–4, as "medium-skilled" if it is 5–7, and as "high-skilled" if it is 8–10.

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

[37] Proposition 2 in Appendix E.1 states an important homogeneity property of our model, which implies that target moments comprising 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 idiosyncratic matching frictions relative to TFP, σ/A.

of the production technology, $f(\cdot)$, and 1 moment reflecting the aggregate profit share to pin down the relative job mass m^J.[38]

In summary, our estimation procedure solves for the parameter vector

$$\theta^* = \arg\min_{\theta\in\Theta} \Omega\left(\mathcal{S}^m(\theta), \mathcal{S}^d\right). \tag{16}$$

We take as the objective function 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 the symbol $\oslash$.[39] 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 (16) by using a global optimization algorithm, followed by a local optimization algorithm that refines the global solution. See Appendix E.4 for details of the numerical solution 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, this sharp identification result—especially as far as σ is concerned—might not carry over to our practical implementation in estimation.

The first issue concerns the accuracy of the PIAAC data. If wages are reported with noise, then 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 measurement error.[40] If this measurement error is uniform across countries, we expect some bias in the *level* of the estimated σ in each country, but are not overly concerned with mismeasuring the differences in idiosyncratic matching frictions across countries—for the formal argument, see Appendix E.5. If, in turn, measurement error in wages were more pronounced in lower-income countries, then we would mistakenly estimate a negative relationship between σ and GDP, which implies that the true effect of σ on development is less than what we currently estimate. For this reason, one should treat our number for the quantitative effect of σ on development as an upper bound.

A second issue concerns 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. We think this issue is minor for two reasons. On one hand, to the extent that the bias in the estimated σ induced by our discretization is constant across countries, a similar argument to that on measurement error applies. On the other hand,

[38]Details of the construction of model and data moments are provided in Appendix E.2.

[39]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 ij).

[40]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, harmonized across countries, as part of the PIAAC data collection.

we verify that our choice of discretization is not essential for any subsequent results by trying alternative, either more or less coarse, groupings—see Figures 32 and 34 in Appendix B.2.

A third issue concerns 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 similar logic to that above, this is not a major threat if such unobserved attributes are distributed similarly across countries. Of greater concern is the possibility that unobserved productive heterogeneity is more dispersed in less developed countries. Two related insights alleviate this concern. First, we see observable skills being less (i.e., not more) dispersed in lower-income countries. Second, when we include in our analysis additional skill measures also reported in the PIAAC data (e.g., problem-solving skills), or indeed subtract some of the existing ones, we find very similar results—see Figure 37 in Appendix B.5 for details.

6.3 Estimation Results

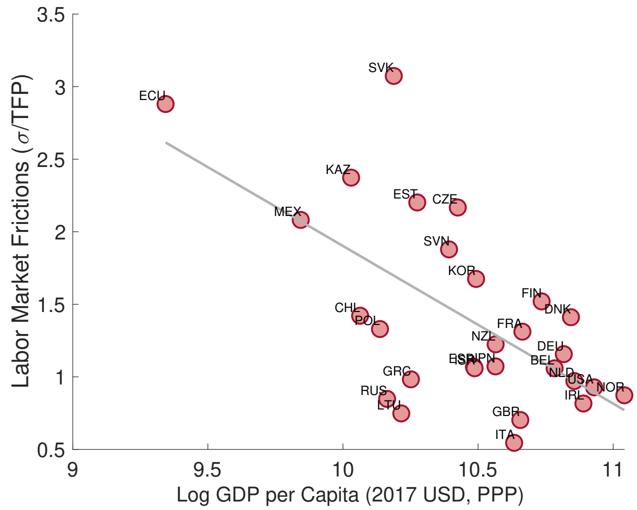
We now present the parameter estimates, model fit based on targeted moments, and model validation based on untargeted data moments across countries.

Parameter Estimates. Figure 8 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 lower-income countries. For example, the estimated σ/A in Ecuador, which is the lowest-income country in the PIAAC data, is around three times higher than in Norway, which is the highest-income country in the PIAAC data. These estimates directly reflect the empirical within-cell wage dispersion across countries, which is higher in lower-income countries—see Figure 6 in Section 3. Through the lens of our model, this suggests that worker-job matching is closer to random in lower-income countries. A descriptive analysis relating 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, and lack of regulatory quality across countries—see Appendix E.7 for details.

Figure 9 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 higher-income countries. This is particularly true for the coefficients 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 higher-income countries—see Figures 1 and 2 in Section 3.

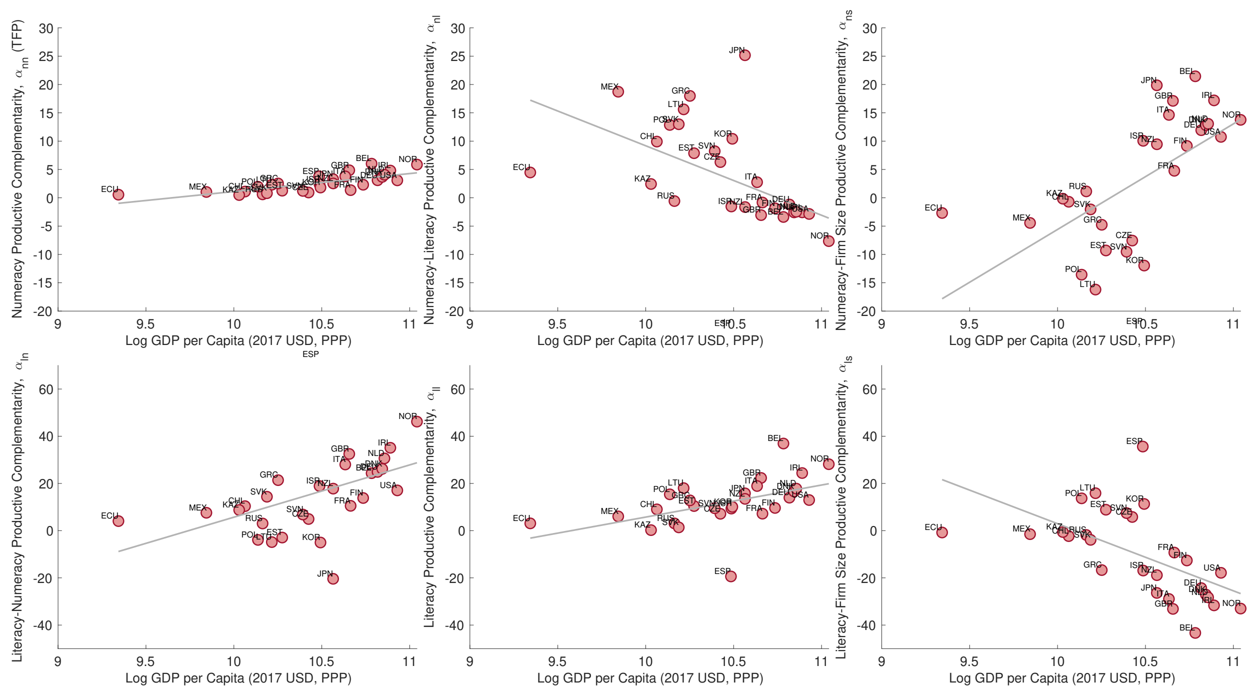
The left panel of Figure 10 shows how the relative value of home production, measured as the payoff from nonemployment relative to the mean value of market production, varies across the development spectrum for workers of different broad skill groups and genders. We find that

Figure 8: Estimated Relative Importance of Idiosyncratic 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 gray solid line represents the linear best fit. *Source:* Model estimates.

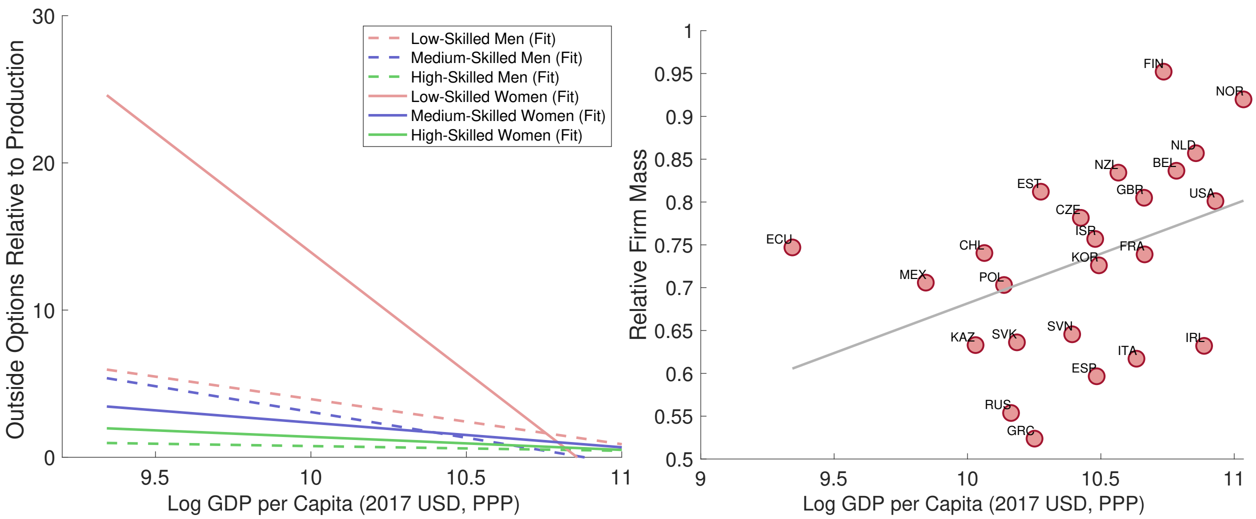
Figure 9: Estimated Production Function Parameters across Countries



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. The gray solid lines indicate the linear best fit. *Source:* Model estimates.

the relative value of home production tends to be higher for all skills in lower-income countries, which reflects their higher nonemployment rates. Strikingly, the negative cross-country pattern is considerably more pronounced for low-skilled women (solid red line) compared to low-skilled men (dashed red line), consistent with the high nonemployment rates among low-skilled women in low-income countries (Ngai et al., 2022; Doss et al., 2023). The right panel of Figure 10 shows that the relative mass of firms is lower in lower-income countries, which suggests that their labor markets are less competitive or subject to higher entry costs. These estimates are informed both by higher nonemployment rates and higher aggregate profit shares (i.e., lower labor shares) in lower-income countries—see Figure 38 in Appendix B.6.

Figure 10: Estimated Outside Options and Relative Firm Masses across Countries



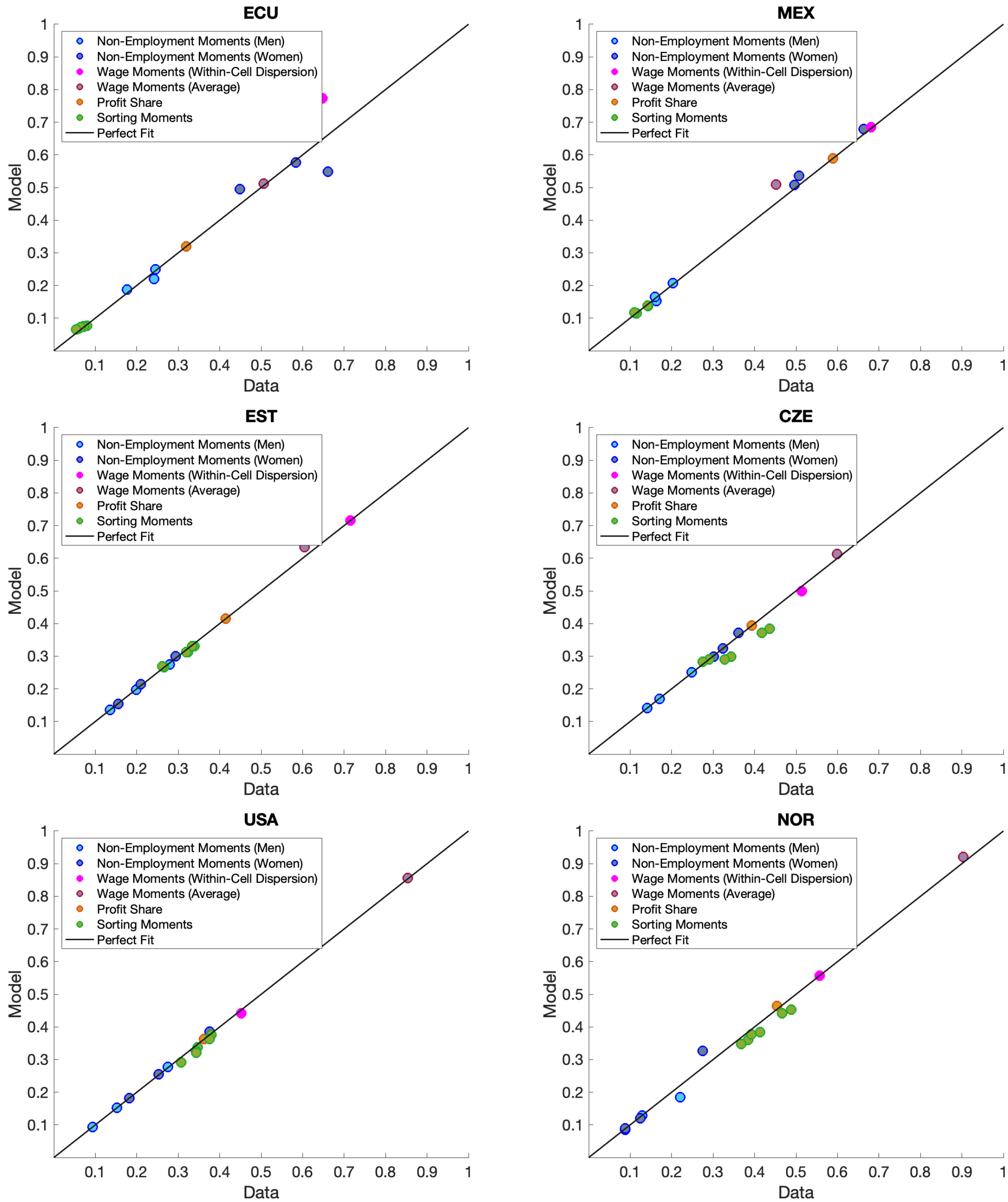
Notes: This figure plots estimates of the model parameters guiding broad worker groups' relative outside options $f^{kg}_{x\varnothing}$ (left panel) and the relative firm mass m^J (right panel) against log GDP per capita across countries. Each line in the left panel represents the linear best fit for 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 gray solid line indicates the linear best fit. *Source:* Model estimates.

Model Fit Based on Targeted Moments. To showcase the model fit based on targeted moments, Figure 11 focuses on the model fit for two low-income countries (i.e., Ecuador and Mexico), two middle-income countries (i.e., Estonia and the Czech Republic), and two high-income countries (i.e., the United States and Norway) from our set of 28 countries. The model fit for all countries is reported in Appendix E.6. Each panel plots the model-based moments against targeted data moments, where the 15 moments are split into six categories, indicated 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 Proposition 1 works well in practice, suggesting that the distributional and functional-form assumptions we imposed are not overly restrictive. Several features of the model fit are worth highlighting. First, both in the data and in the model, the moments pertaining to sorting patterns (green markers) are increasing in GDP per capita, consistent with our empirical fact that there is stronger worker-job sorting in higher-income countries—see Figures 1 and 2 in Section 3.1. Second, 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. Through the lens of our model, this moment informs the degree of idiosyncratic matching frictions across countries. Finally, our model matches the fact that average wages (purple marker) are increasing in GDP.

Model Validation Based on Untargeted Moments. We are interested in the extent to which the estimated model—through the channel of varying worker-job mismatch across countries—can account for the empirical cross-country heterogeneity in untargeted moments, including aggregate output, wage inequality, and skill returns. The top panels of Figure 12 show the model reproducing the stark differences in hourly output per worker or capita seen in the data. In our model, higher-income countries produce more output due to superior technology, a more skilled workforce, more demanding jobs, as well as lower idiosyncratic matching frictions. Whereas the first three factors directly boost productivity, they also indirectly boost productivity by reducing worker-job mismatch. The middle panels of Figure 12 show the model reproducing greater wage inequality in lower-income countries, both in terms of overall wage inequality measured by the 90–10 log wage gap and in terms of lower-tail inequality measured by the 50–10 log wage gap. In our model, the workforce in lower-income 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 greater idiosyncratic matching frictions in lower-income countries, which give rise to wage dispersion across identical workers and jobs, thus increasing overall wage inequality. Finally, the bottom panels of Figure 12 show the model reproducing greater numeracy returns (conditional on literacy skills) but slightly decreasing literacy returns (conditional on numeracy skills) across GDP per capita. Overall, while our model misses some of the levels of these untargeted moments in the data, it generally matches well the cross-country gradients.

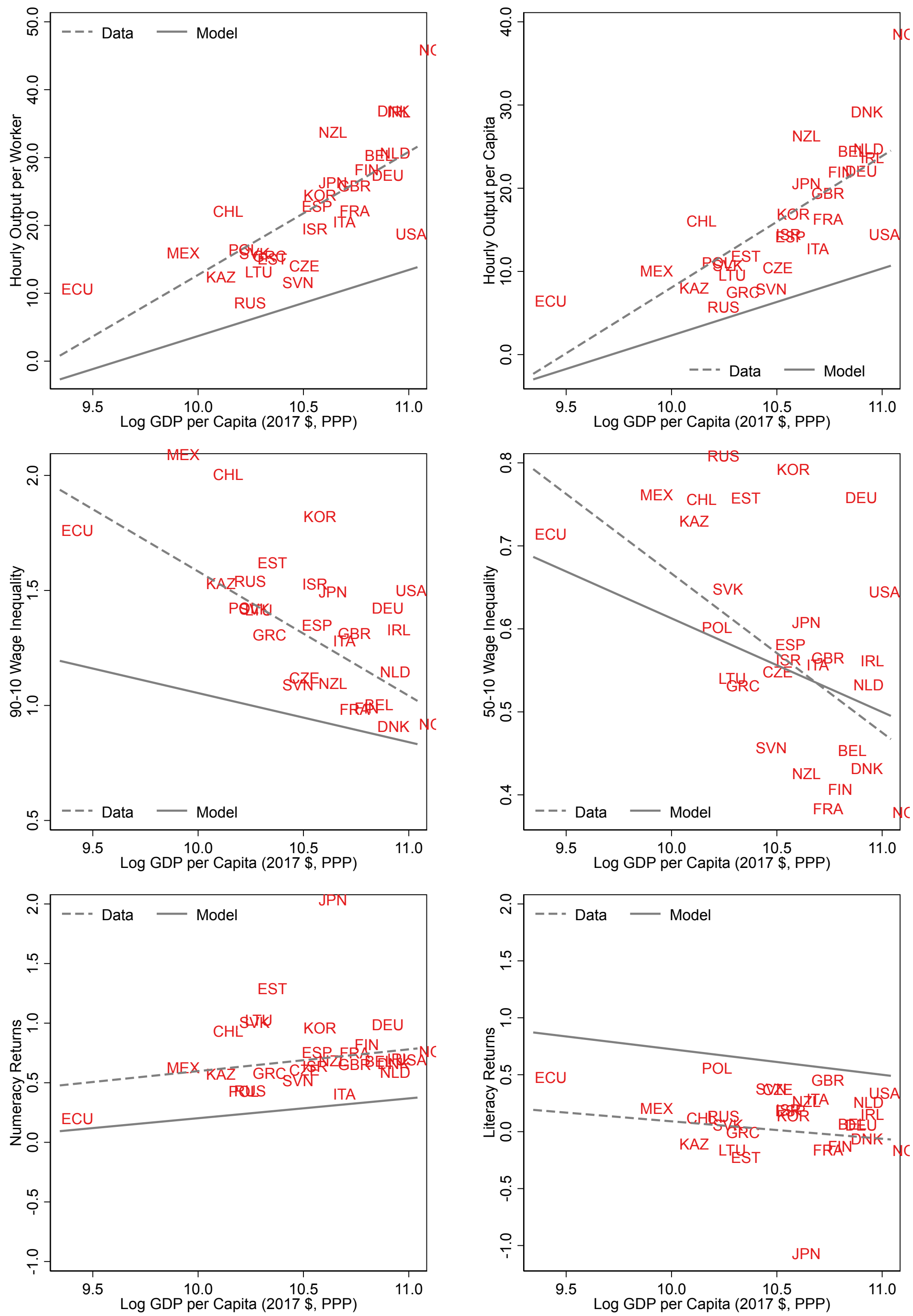
Cross-Country Differences in Worker-Job Matching. Our estimated model predicts important differences in worker-job matching patterns—and thus meritocracy in the labor market—across the development spectrum. On the intensive margin, the left panel of Figure 13 captures the output losses from the misallocation of workers across jobs by use of the above-defined meritocracy index $\mathcal{M}(\theta)$, which reflects the ratio of actual to potential output. The mean meritocracy index in our sample is around 0.55, reflecting substantial misallocation of workers across jobs in general. Furthermore, meritocracy indices tend to be increasing in GDP per capita. For instance, Norway—the highest-income country in our sample—has a meritocracy index of 0.75, almost four times that of Ecuador—the lowest-income country in our sample. That is, Norway could increase its output by around one-third, while Ecuador could increase its output by around five-fold. Importantly, Ecuador loses around 80 percent of its potential output due to a lack of incentives to sort based on misaligned endowments, inferior technology, and a high degree of idiosyncratic matching fric-

Figure 11: Model Fit for Selected Low-, Middle-, and High-Income Countries



Notes: This figure illustrates the model fit by plotting model moments against data moments for selected low-income countries (Ecuador and Mexico, top panels), middle-income countries (Estonia and the Czech Republic, middle panels), and high-income countries (the United States and Norway, bottom panels). The 45-degree line indicates a perfect fit between the model and the data. See Appendix E.2 for how the moments are constructed. The mean log wage (purple markers) is scaled by a factor of 1/3.5 to fit it into the same figure with the other moments. *Source:* PIAAC, OECD, and model estimates.

Figure 12: Model Validation Based on Untargeted Moments across Countries

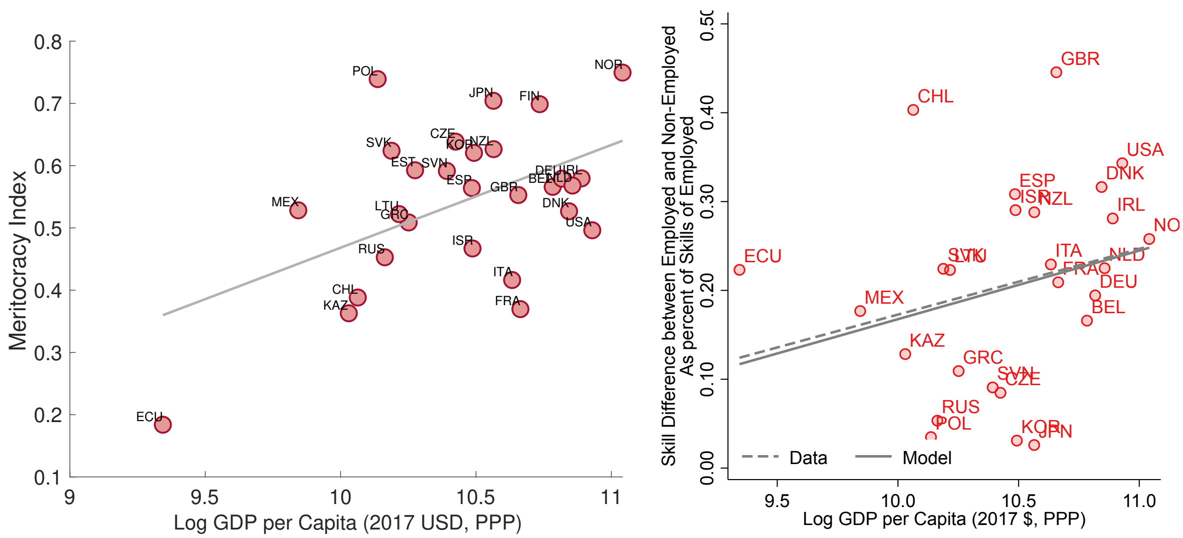


Notes: This figure shows the fit of the model vis-à-vis the data based on a set of untargeted moments against GDP per capita across countries. See Appendix E.2 for details on how the untargeted moments are constructed. Each red marker represents one country in the data. Dashed lines indicate the linear best fit to the data, while solid lines indicate the linear best fit to the model. *Source:* PIAAC, World Bank, and model estimates.

tions.

On the extensive margin, the right panel of Figure 13 shows that our model predicts stronger skill-based selection into employment in higher-income countries. When jobs are scarce—i.e., with a relative job mass below unity, as in our estimates in the right panel of Figure 10—actual output is greater when higher-skilled workers select into employment, while lower-skilled workers remain in nonemployment.[41] All else equal, skill-based selection into employment is more important for output in lower-income countries where jobs are relatively more scarce. However, our estimates in the right panel of Figure 13 suggest that selection is less positive (i.e., not more positive) in lower-income countries. Both in the data and the model, the average skill advantage of employed over nonemployed workers is around 10 percentage points larger in higher-income countries. Altogether, these findings suggest that labor markets in lower-income countries are less meritocratic.

Figure 13: 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 in the estimated model. Each red dot represents one country in the estimated model. The gray solid line indicates the linear best fit. The right panel plots the percentage difference between the average skill of employed workers and unemployed workers against GDP per capita across countries in the estimated model and in the data. See Figure 3 for more details. Each red dot represents one country in the data. The gray dashed line indicates the linear best data fit. The gray 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 and its consequences for economic development, our analysis proceeds in two steps. In the first step, we focus on the sources by asking: Why are some countries more meritocratic—i.e., with a meritocracy index closer to unity in the left panel

[41] This is especially true if the outside option of low-skilled workers is higher than that of high-skilled workers, as indicated by our estimates in the left panel of Figure 10.

of Figure 13? We consider three determinants: endowments, technology, and 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?

To understand whether the lack of meritocracy is a quantitatively important hurdle for development depends on the combination of idiosyncratic matching frictions along with endowments and technology. A reduction in frictions in lower-income countries (i.e., $\sigma \to 0$)—while keeping their technology and endowments fixed—increases aggregate output toward its potential and thus their meritocracy index. However, if potential output in these countries is relatively low, either due to their backward technology or inferior endowments of worker skills and job skill requirements, then the gains from more meritocracy are limited. In this case, unlocking greater gains requires upgrades to their technology and endowments, which increase the returns to worker-job sorting and thereby narrow the gap between their actual and now-increased potential output.[42]

7.1 Accounting for Aggregate Output and Cross-Country Inequality

We now use our estimated model for an equilibrium development accounting exercise by decomposing aggregate output and how it varies across countries into contributions due to endowments, technology, and idiosyncratic matching frictions.[43]

The Role of Endowments. We first turn to the contribution of heterogeneity in endowments toward cross-country income differences. To this end, we recompute equilibrium after counterfactually assigning each country the worker skill and job skill distributions of Norway, the highest-income country in our sample.[44] This has two distinct effects on most countries, especially those with initially low incomes. First, it directly increases output because high-skilled workers and jobs become more abundant. Second, it indirectly increases output by improving the worker-job allocation due to a better alignment of skill and skill requirement distributions.

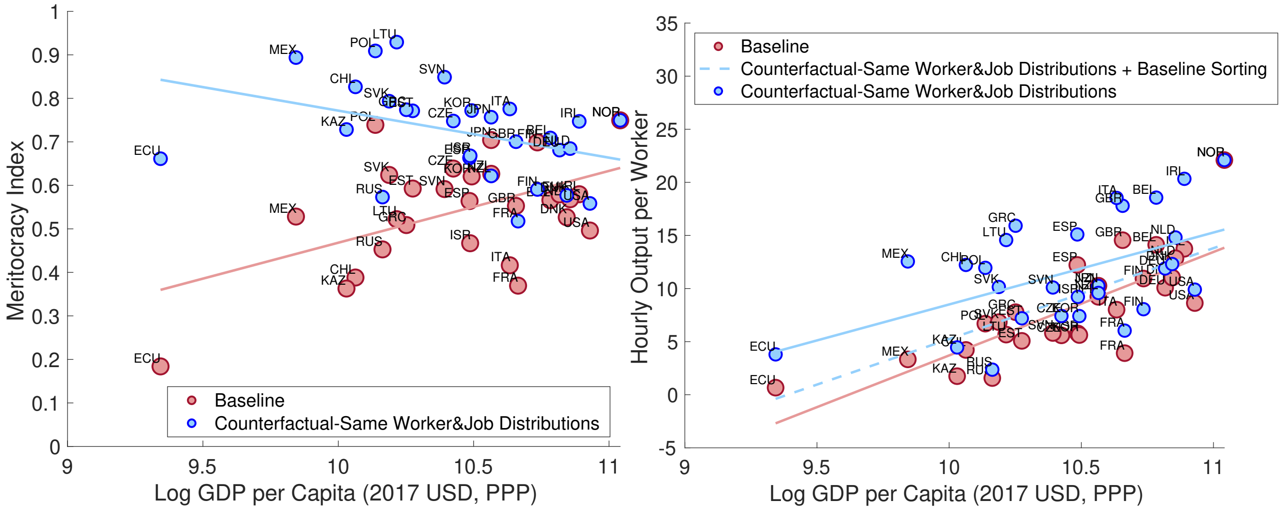
Figure 14 shows the results of this experiment. The left panel shows a pronounced increase in meritocracy in lower-income countries, reflecting the fact that a better alignment of skill supply and demand incentivizes more sorting for any given level of idiosyncratic matching frictions $\sigma > 0$. In fact, the effects are so large that the sign of the slope of the meritocracy index across countries flips from positive to negative. The right panel shows this leads to sizable output gains, especially in lower-income countries, leading to 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 shown by the dashed blue line in the right panel, which shows the output per worker when adopting Norway's endowments but with each country's meritocracy index fixed at baseline.

[42] That is, upgrades in technology and endowments not only cause the numerator of the meritocracy index to increase but also the denominator in a way that reduces the ratio between them.

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

[44] We have repeated the same exercise using the United States as the reference country, with very similar results.

Figure 14: Counterfactual Imposing Norway's Worker Skills and Job Skill Requirements across Countries

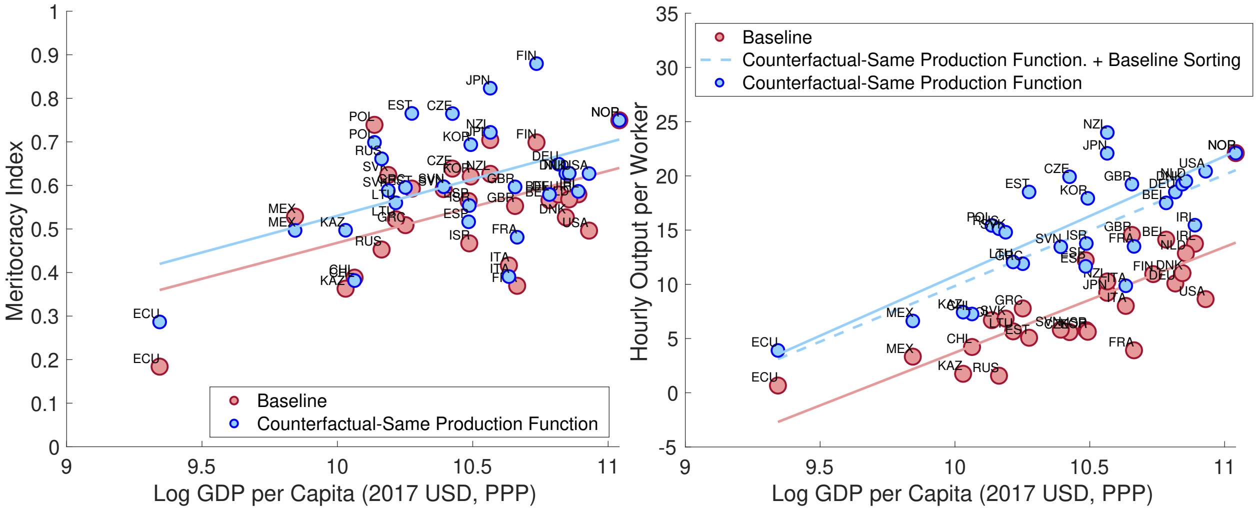


Notes: This figure shows the model-based counterfactual effects of implementing Norway's distributions of worker skills and job skill requirements in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates for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

The Role of Technology. To assess the role of cross-country differences in technology, we recompute equilibrium worker-job matching patterns and aggregate output after assigning all countries the production function of Norway, the highest-income country in our sample. Figure 15 shows the results of this counterfactual compared to the baseline. In the left panel, we see improvements in worker-job matching patterns across most countries. Intuitively, adopting Norway's frontier technology with stronger worker-job complementarities—for a given level of idiosyncratic matching frictions $\sigma > 0$—increases the returns to labor market sorting, thus reducing misallocation of worker skills across job skill requirements. The right panel shows that, as a result, hourly output per worker increases by a roughly constant amount across countries. This implies a large reduction in cross-country inequality, as evidenced by the 35 percent reduction in the coefficient of variation—see the right panel of Figure 18. Interestingly, most of these changes are due to the direct effect of technology improvements rather than the indirect effect through improvements in worker-job matching. To illustrate this, the dashed blue line in the right panel indicates the counterfactual output that would be obtained if Norway's technology was adopted everywhere but holding fixed each country's baseline meritocracy index and thus worker-job assignment.

The Role of Idiosyncratic Matching Frictions. We now assess the role of idiosyncratic matching frictions in explaining cross-country income differences. Figure 16 shows the results from a counterfactually adopting Norway's comparatively low degree of idiosyncratic matching frictions. The left panel shows that this results in a relative improvement in worker-job matching

Figure 15: Counterfactual Imposing Norway's Production Function across Countries



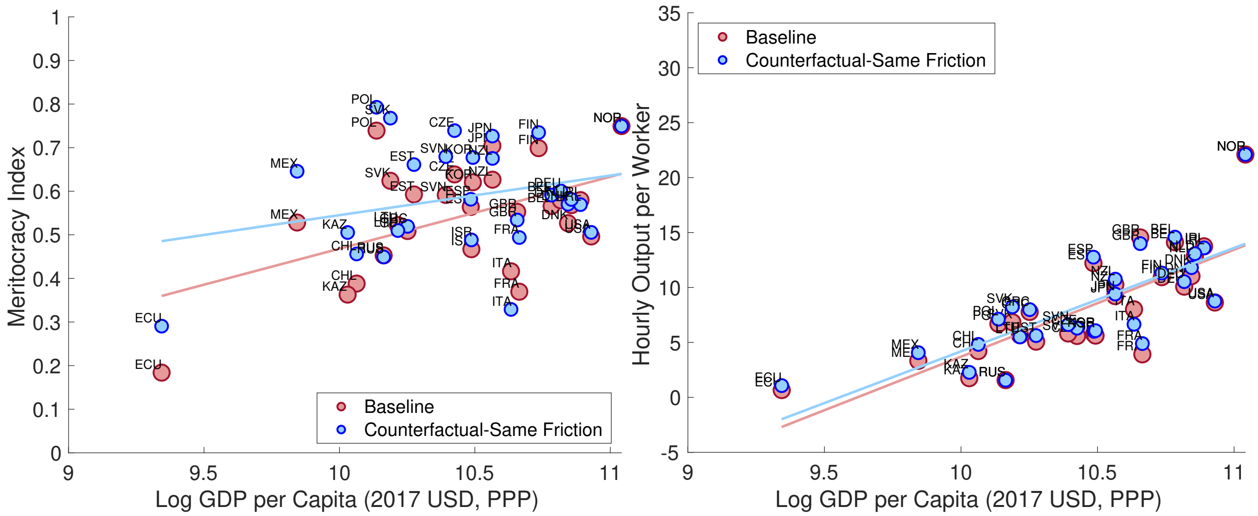
Notes: This figure shows the model-based counterfactual effects of implementing Norway's production technology in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates for each country, with the red solid line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

in lower-income countries. For instance, the meritocracy index increases between 20 and 80 percent among our four lowest-income countries but remains relatively constant among the highest-income countries. However, the right panel shows that the relative narrowing of the gap between actual and potential output in lower-income countries has only modest effects on aggregate output differences across countries. This finding reflects the important fact that low-income countries are constrained by other factors—i.e., their inefficient technologies and scarcity of high-skilled workers and jobs—which render their potential output levels low compared to 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 modest. This is because strengthening worker-jobs 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 primitive—endowments, technology, and idiosyncratic matching frictions. While each of the three primitives in isolation shaped aggregate outcomes, we have thus far ignored any complementarities between them. In this section, we show that the returns to improving the worker-job allocation depend on the other fundamentals of a country. Thus, incremental reforms targeting one primitive at a time fail to realize the potential gains from moving multiple primitives simultaneously.

Here, we highlight the complementarity that is quantitatively most important, namely that between endowments and technology. Appendix F.2 presents all remaining complementarities between model primitives. Figure 17 shows the results of counterfactually adopting Norway's

Figure 16: Counterfactual Imposing Norway's Idiosyncratic Matching Frictions across Countries



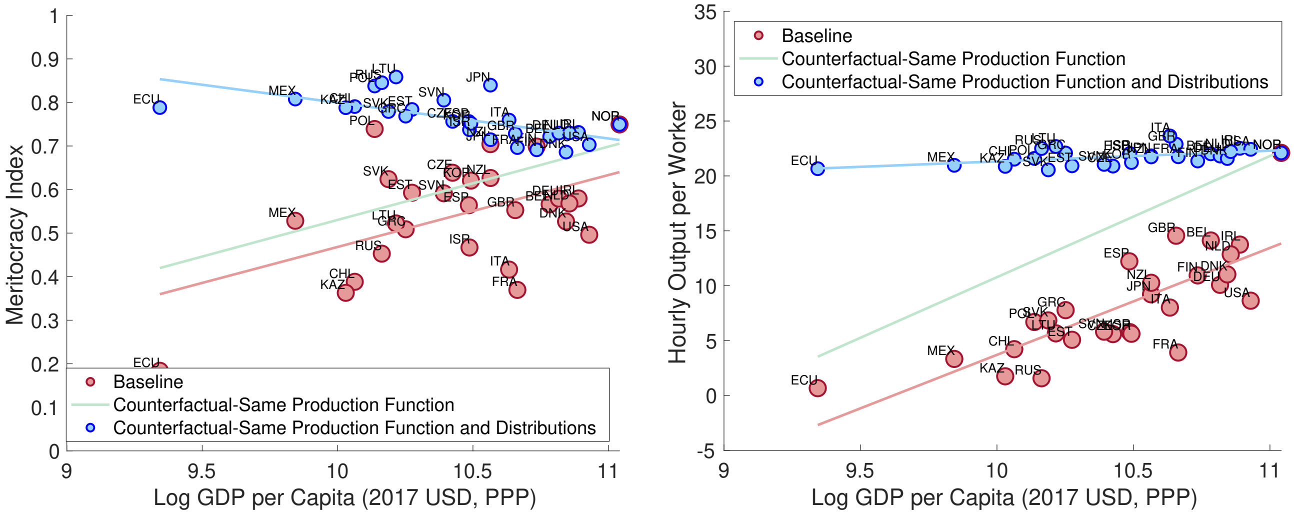
Notes: This figure shows the model-based counterfactual effects of implementing Norway's idiosyncratic matching frictions in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates for each country, with the red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

worker skills, job skill requirements, and production technology in all countries. Worker-job matching, measured by the meritocracy index in the left panel, improves markedly, and more so among lower-income countries. As a consequence, output per worker in the right panel increases overall and more so among lower-income countries. Importantly, the increase in output among low-income countries is significantly greater than the sum of the two counterfactuals in isolation. These synergies arise due to the disproportional increase in the returns to sorting in lower-income countries, which induces improvements in worker-job matching and pushes actual output toward a now-increased potential output. As a result, this dual counterfactual closes 94 percent of the cross-country gap in output per worker. We find that almost 40 percent of this convergence is due to improvements in worker-job sorting—see the middle panel of Figure 44 in Appendix F.2. The strong complementarities between improving skill endowments and technology also lead to a disproportional increase in global output per worker, which rises by 167 percent in this counterfactual.

Summary of Counterfactual Effects on Aggregate Output and Cross-Country Inequality. Figure 18 summarizes the counterfactual effects on aggregate output in the left panel and on cross-country inequality in the right panel. For each counterfactual, the figure shows two bars: the broad dark-blue bars represent the overall equilibrium effect, while the narrow light-blue bars represent the partial-equilibrium effect holding fixed the baseline worker-job matching patterns as summarized by a given country's meritocracy index.

Starting with aggregate output in the left panel, a few observations are worth highlighting. First, the largest global output gains from the individual counterfactuals are realized when adopt-

Figure 17: Counterfactual Imposing Norway's Endowments and Technology across Countries



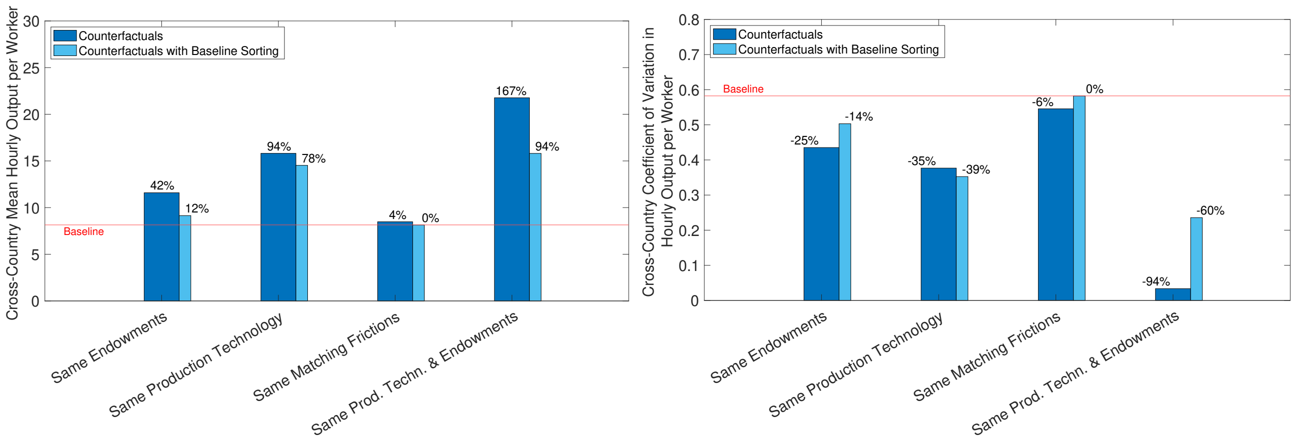
Notes: This figure shows the model-based counterfactual effects of assigning Norway's endowments of worker skills and job skill requirements as well as their production technology simultaneously to all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles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

ing Norway's frontier technology (+94 percent), compared to the effects of equalizing idiosyncratic matching frictions (+4 percent) and endowments (+42 percent). Second, the complementarities between endowments and technology are large: The effects of simultaneously adopting the frontier endowments and technology are around 23 percent larger (+167 percent) compared to 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., +167 percent compared to +94 in the case of simultaneously adopting the frontier endowments and technology).

Moving on, we highlight several results pertaining to cross-country inequality, measured by the coefficient of variation of hourly output per worker across countries. First, the most important single factor explaining cross-country inequality is technology (−35 percent), followed by endowments (−25 percent) and idiosyncratic matching frictions (−6 percent). Second, while the effect of technology on cross-country inequality is mostly direct, an improved worker-job allocation is key to explaining the convergence due to equalized endowments (−25 percent versus −14 percent) and drives all of the effects due to lower frictions (−6 percent versus 0 percent). Third, there are also strong complementarities between endowments and technology. Simultaneously adopting the frontier endowments and technology closes 94 percent of the cross-country income gap, which is around 57 percent greater than the sum of the two counterfactuals in isolation (−60 percent). Importantly, a significant share of the effects under this combined counterfactual is driven by improved worker-job sorting (−94 percent versus −60 percent).

In sum, our equilibrium model shows that improved worker-job matching is crucial for harvesting the gains from improved endowments and technology: Investments that better align countries' endowments of worker skills and job skill requirements or improve their technology, increase the returns to worker-job sorting and thereby narrow the gap between actual output and a new, higher potential output. Conversely, the gains from lowering idiosyncratic matching frictions and the resulting improvements in worker-job sorting are limited in economies where inferior skill 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 higher-income countries is mostly a consequence, rather than a source, of economic development that can be brought about by investing in the workforce, upgrading jobs, and adopting frontier technology.

Figure 18: Summary of Counterfactual Effects on Aggregate Output and Cross-Country Inequality



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). The broad dark-blue bars represent outcomes based on the baseline scenario or the counterfactual exercises. The narrow light-blue bars represent the counterfactual while keeping each country's meritocracy index at its baseline level by adjusting actual output. The numbers on top of the bars indicate the percentage change relative to the baseline. *Source:* Model simulations.

7.2 Accounting for Differences in Wage Inequality across Countries

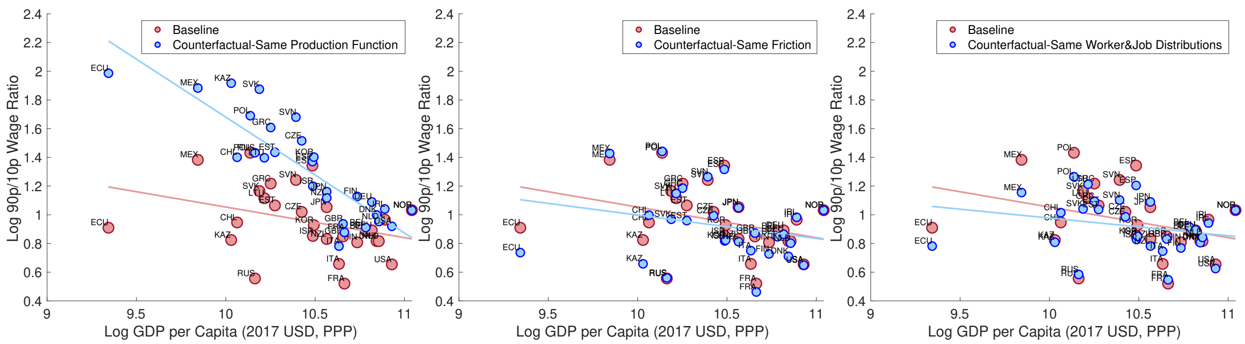
So far, our emphasis has been on average output. However, changes in worker-job matching also have distributional consequences within labor markets. In this section, we use a sequence of counterfactuals to account for wage inequality in different countries across the development spectrum.

Adopting the frontier technology in all countries leads to significantly greater wage inequality across the board, and more so in lower-income countries— see the left panel of Figure 19. This is because both the direct effects of stronger worker-job complementarities and the indirect effects of improved worker-job sorting increase wage inequality. Within countries, the main beneficiaries of technological improvements are high-skilled workers, who are a particularly scarce resource in low-income countries, thus contributing to greater inequality.

In contrast, the middle panel of Figure 19 shows that equalizing idiosyncratic matching frictions tends to reduce wage inequality overall and disproportionally so in lower-income countries. This is because the indirect effect of increased wage inequality through improved worker-job matching is more than offset by the direct effect of decreased wage inequality through a reduction in idiosyncratic heterogeneity in wages within a (x, y) match. Intuitively, these effects are larger in lower-income countries, where idiosyncratic matching frictions are more pronounced to begin with.

Finally, the right panel of Figure 19 shows that equalizing endowments reduces wage inequality disproportionally in lower-income countries. In spite of the ensuing improvements in worker-job matching, the reduction in wage inequality largely stems from the direct effect of increasing the supply of high-skilled workers in lower-income countries, which pushes down skill returns.

Figure 19: Counterfactual Effects on Wage Inequality from Adopting either Norway's Endowments, Technology, or Idiosyncratic Matching Frictions across Countries



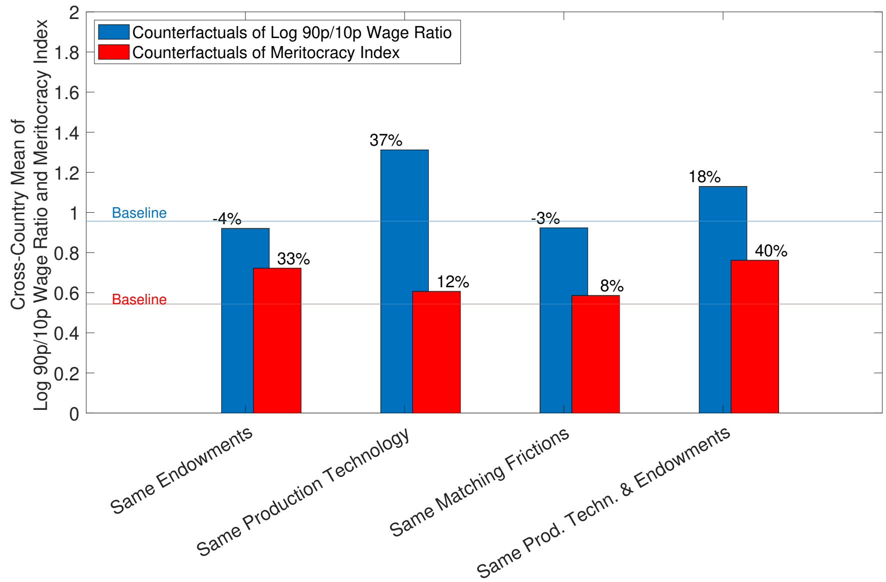
Notes: This figure shows the model-based counterfactual effects of implementing Norway's production technology in all countries on the meritocracy index (left panel), hourly output per worker (middle panel), and wage inequality (right panel). Red circles represent the baseline model estimates for each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

Figure 20 summarizes the effects of various counterfactuals on wage inequality. An important takeaway is that wage inequality can either increase or decrease (blue bars) under improved worker-job matching, as measured by an increase in the meritocracy index (red bars), depending on what caused this improvement.

7.3 Gender Gaps in Employment and Pay across Countries

Our framework naturally lends itself to studying the misallocation of workers across jobs, not only along the intensive margin (i.e., worker-job matching) we have emphasized so far but also along the extensive margin (i.e., employment versus nonemployment). In this section, we study a particularly salient dimension of misallocation, namely gender differences in labor market outcomes in relation to economic development. Despite universal increases in female labor force participation over the past decades, most countries are still characterized by significant gender imbalances in employment and skill utilization. Reasons include both supply-side factors (e.g., fertility, marriage, child-rearing, and social norms that limit women's labor force attachment) and demand-side factors (e.g., discrimination at the hiring stage and in promotion decisions). Figure

Figure 20: Summary of Counterfactual Effects on Worker-Job Matching and Wage Inequality



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 (red bars) and wage inequality, as measured by the log 90-10 wage ratio (blue bars). The numbers at the top of each counterfactual bar indicate the percentage change relative to the baseline meritocracy index (red horizontal line) and the baseline log 90-10 wage ratio (blue horizontal line), respectively. *Source:* Model simulations.

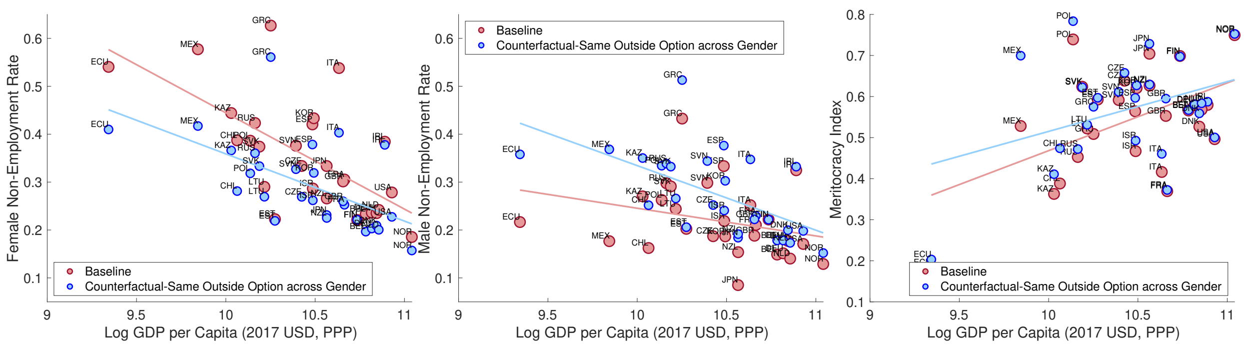
46 in Appendix F.3 shows that skills are relatively similar across genders in most countries. Thus, the underqualification of women is likely not the main driver of gender differences in labor market outcomes. Our model captures a mix of possible supply- and demand-side barriers through differences in women's outside options. Our estimated home production technology in the left panel of Figure 10 in Section 6.3 reveals sizeable gender differences, which suggests that this may be an important source behind the observed gender gaps in employment and pay.

Although women are similarly skilled as men, Figure 21 shows that female nonemployment rates are up to 30 percentage points higher than male nonemployment rates in the lowest-income countries, while this gap is around 5 percentage points in the highest-income countries (red dots and lines in the left and center panels). Turning to the intensive margin, Figure 47 in Appendix F.3 shows that high-skilled women are more underrepresented in high-skilled jobs within lower-income countries. In turn, these patterns are reversed for low-skilled women who are more over-represented in low-skilled jobs within lower-income countries. Compared to gender differences on the extensive margin, however, these intensive-margin differences are comparatively small.

We relate gender differences on the extensive and intensive margins to aggregate outcomes by considering two counterfactuals. First, we assign all women the male outside option $f_{x\emptyset}^{k,\text{male}}$. On the extensive margin, the left and center panels of Figure 21 show that this counterfactual pushes a large number of women from nonemployment into employment, particularly in lower-income countries where gender differences in outside options are higher, to begin with. However, given the fixed number of available jobs, this counterfactual leads to an almost one-for-one crowding out of male employment. Thus, the effect of changes in the gender composition of the workforce depends on changes in the average skills among employed workers. That is, the effect depends on whether the women who enter employment are more skilled than the men they replace (Ashraf et al., 2023; Jones et al., 2018).

On the intensive margin, the right panel of Figure 21 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 lower-income countries, where worker-job mismatch was more severe to begin with. As a result, there is more similar worker-job matching, as measured by a flattening of the meritocracy index, across countries.

Figure 21: Misallocation of Women and Men on the Extensive and Intensive Margin



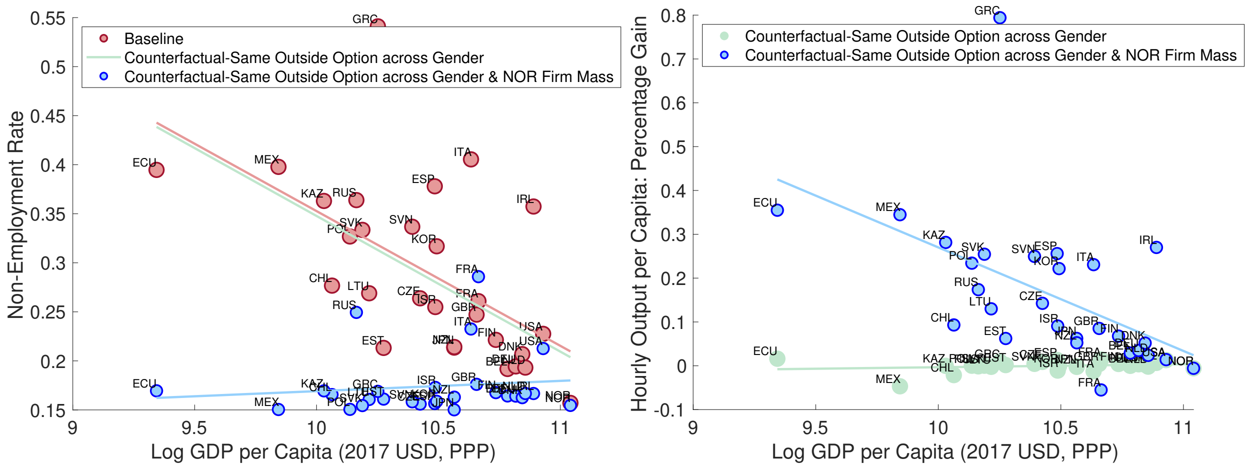
Notes: This figure shows the model-based counterfactual effects of giving women in each country the same outside options as that of men on women's nonemployment rates (left panel), men's nonemployment rates (middle panel), and the worker-job sorting measured by the meritocracy index (right panel). The red circles and solid red best-fit line show the baseline simulation results against GDP per capita across countries and their best linear fit. The blue circles and solid blue best-fit line show the counterfactual results plotted against GDP per capita across countries and their best linear fit. *Source:* Model simulations.

Figure 22 shows that, by itself, this counterfactual has little aggregate effects on nonemployment (left panel) and aggregate output (right panel), which reflects the fact there is large crowding-out and small gender skill differentials. This can be reconciled with the findings of Ashraf et al. (2023) and Jones et al. (2018) by noting that the labor force participation rates in our sample of countries are higher than in the countries for which those previous studies found that women are more positively selected. In contrast, if we also increase countries' job masses to match Norway's Norway in a second counterfactual, we find a sharp drop in nonemployment rates in lower-income countries (blue circles and solid line in the left panel), yielding an almost constant nonemployment rate of around 17 percent across countries. Associated with this are substantial gains in hourly output per worker (blue circles and solid line in the right panel), especially for the lowest-income countries. We conclude that 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 the worker-job allocation. In our baseline model, the assignment of workers to jobs happened within each country's labor market. In reality, though most workers remain attached

Figure 22: The Role of Female Labor Force Participation in Development with and without Fixed Distribution of Jobs

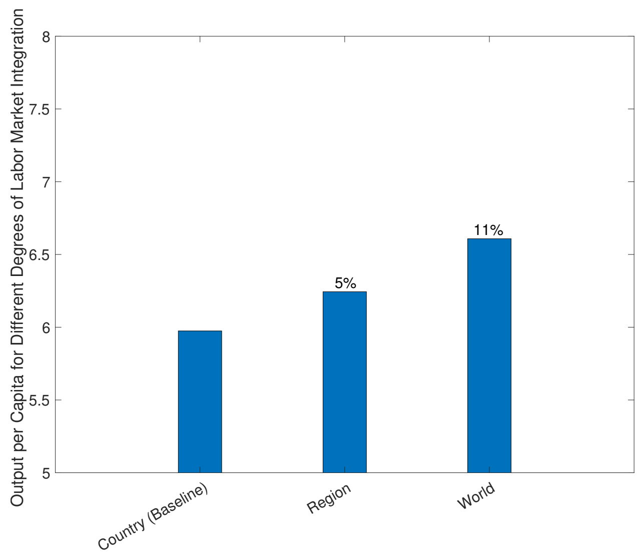


Notes: This figure shows the model-based counterfactual effects of giving women in each country the same outside options as that of men on aggregate nonemployment rates (left panel) and aggregate output per worker (right panel). The red circles and solid line show the baseline simulation results against GDP per capita across countries and their best linear fit. The green solid line shows the best linear fit of the counterfactual equating women's outside options to those of men. The blue circles and solid line show the counterfactual that additionally adopts Norway's mass of firms, plotted against GDP per capita across countries and their best linear fit. *Source:* Model simulations.

to their country of birth, international migration is often associated with large output and welfare gains for migrants (Borjas, 1999; Hendricks and Schoellman, 2018; Lagakos et al., 2018a; Dustmann and Preston, 2019). To investigate the gains from labor market integration, we allow for free worker flows across country borders in two counterfactuals. First, we simulate regional labor market integration, allowing for free mobility within labor markets defined by seven regions: Continental Europe plus Great Britain, Scandinavia, Southern Europe, Ex-USSR countries, Asia plus New Zealand, North America, and South America. Second, we simulate global labor market integration, allowing for free mobility across all countries. In each of these scenarios, we assume that the set of worker skills in an integrated labor market consists of the union of the respective sets in the member countries. Moreover, we assume that workers in an integrated labor market have access to the technology and skill requirements of the country in which they are employed and to the average degree of idiosyncratic matching frictions in the region. By allowing for labor mobility between countries while keeping job skill requirements and technology constant, this counterfactual highlights the gains from trade in worker skills and job skill requirements across countries.

Figure 23 presents the simulated effects on aggregate output from increasingly integrated labor markets. Compared to the baseline scenario with country-specific labor markets, output per capita increases by around 5 percent under regional integration. The gains from labor mobility are more than twice as high when moving to a single integrated world labor market, in which case output per capita increases by around 11 percent over baseline. It is worth noting that, by design, these gains arise primarily due to improved worker-job matching. Our simulations neglect 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 mobility of workers that results in improved worker-job matching—the central mechanism highlighted in this paper.

Figure 23: Global Output per Capita for Different Levels of Labor Market Integration



Notes: This figure shows output per capita in the model for four scenarios representing different levels of labor market integration: (i) our baseline of 28 countries, (ii) seven regions consisting of Asia and New Zealand, Ex-USSR, North America, Northern Europe excluding Scandinavia, Scandinavia, Southern Europe, and South America, and (iii) the world consisting of a single integrated 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 as well as to the average degree of idiosyncratic matching frictions in the region. The numbers at the top of each counterfactual bar indicate the percentage change relative to the baseline. *Source:* Model simulations.

8 Conclusion

Are labor markets in higher-income countries more meritocratic, in the sense that workers are matched to jobs in which they are the most productive? If so, why? And what are the aggregate consequences? To answer these questions, we use internationally comparable microdata on worker skills and job skill requirements from over 120,000 individuals in 28 countries. We empirically show that, in labor markets of higher-income countries, workers' skills better match the requirements of their jobs. To interpret this fact, we develop an equilibrium model of matching with multidimensional skills, in which the worker-job allocation depends on three factors: endowments of worker skills and job skill requirements, technology, and idiosyncratic matching frictions. We show that the model is identified. We separately estimate it for each country and use it for a sequence of counterfactual exercises to highlight the importance of worker-job matching across countries for development.

We find that worker-job matching patterns in higher-income countries are closer to the output-maximizing allocation. Furthermore, differences in the skill endowments of workers and jobs, as well as differences in technology, account for most cross-country income differences. In turn, idiosyncratic matching frictions play a relatively modest role, which demonstrates that the available endowments and technology in poor countries constrain the gains from a better worker-job allocation. At the same time, a large share of the gains from adopting better skill endowments and technology are realized through improved worker-job sorting. These findings suggest that greater meritocracy in higher-income countries is mostly a consequence, rather than a source, of economic development. As a result, policies aimed at improving worker-job matching by reducing idiosyncratic matching frictions alone will not effectively eradicate cross-country income differences unless combined with interventions that enhance match productivity.

We further use our model for two natural applications. First, we show that the misallocation of women's skills on the extensive margin is decreasing in development. However, unleashing the gains from a higher female labor force participation in low-income countries hinges on a larger availability of jobs. Second, we show that regional labor market integration significantly boosts global output by improving the worker-job allocation across borders.

To conclude, understanding the process of matching workers to jobs in labor markets across countries has important implications for important issues related to economic development, including cross-country income differences, wage inequality, gender disparities, and migration.

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Appendix for
"Meritocracy across Countries"

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Christian Moser Andrea Prat

March 18, 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 main paper. Appendix B presents additional materials pertaining to the facts presented in Section 3 of the main paper. Appendix C contains derivations of key expressions from the equilibrium model in Section 4 of the main paper. Appendix D states the formal identification proof as well as the formal proof of the homogeneity property of the model in Section 5 of the main paper. Appendix E describes further details of the numerical estimation procedure introduced in Section 6 of the main paper. Finally, Appendix F shows additional results relating to the counterfactual analysis in Section 7 of the main paper.

A Data Appendix

A.1 Survey of Adult Skills of the *Programme for the International Assessment of Adult Competencies (PIAAC)*

Our main data source is the OECD Survey of Adult Skills of the *Programme for the International Assessment of Adult Competencies (PIAAC)*, which aims to obtain a nationally representative sample of the target 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 OECD (2019). Of these, 28 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. The raw PIAAC microdata are publicly available for download via OECD (2024).

A.1.1 Key variables

Data on skills and skill requirements. PIAAC formally assesses three cognitive skill domains: literacy, numeracy, and problem-solving in technology-rich environments or *Information and Communications 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. The PIAAC data report scores from incentivized tests for numeracy and literacy skills on a scale from 0 to 500. 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, they are asked whether workers perform tasks that use a calculator, algebra, make budgets, and so on. We sum the number of tasks that each worker completes in each area—numeracy and literacy—and weigh each task performed by its difficulty. PIAAC categorizes numeracy and literacy tasks into five proficiency levels based on task difficulty. We use these proficiency levels—where level 1 is the lowest skill proficiency and level 5 is the highest—to weigh each task 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 by OECD (2019). For example, using a calculator is assigned the lowest weight of 1. Working with fractions and preparing charts and tables span proficiency levels 2 and 3, 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 each literacy task's skill proficiency level. 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 made comparable for analyzing worker-job sorting, we transform both raw measures using "global percentiles." Specifically, regarding skills, we globally rank all workers across countries by each skill and give them a score that equals their position (i.e., percentile) in the global skill distribution. In most of our exercises, we use a discretized version of the resulting skill distributions to ensure a similar treatment in data and model. To do so, we average the global skill scores among all workers in the same country-specific quintile. This renders a well-defined skill distribution of numeracy and literacy skills for each country between the values of 0 and 1 while preserving differences in skill distributions across countries. We transform our raw skill requirement measures in a similar way.

Data on 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, to classify workers into small and large firms, we use data on the size of the firm a worker reports working in. 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.

Sample Selection. We restrict attention to all individuals in our data who are between the ages of 20 and 59, have non-missing values for the following variables: numeracy and literacy skill scores, gender, employment status, and sampling weight, and also report a continuous (as opposed to categorical) income measure when employed. We also drop self-employed individuals for whom we do not have reliable wage information.[45]

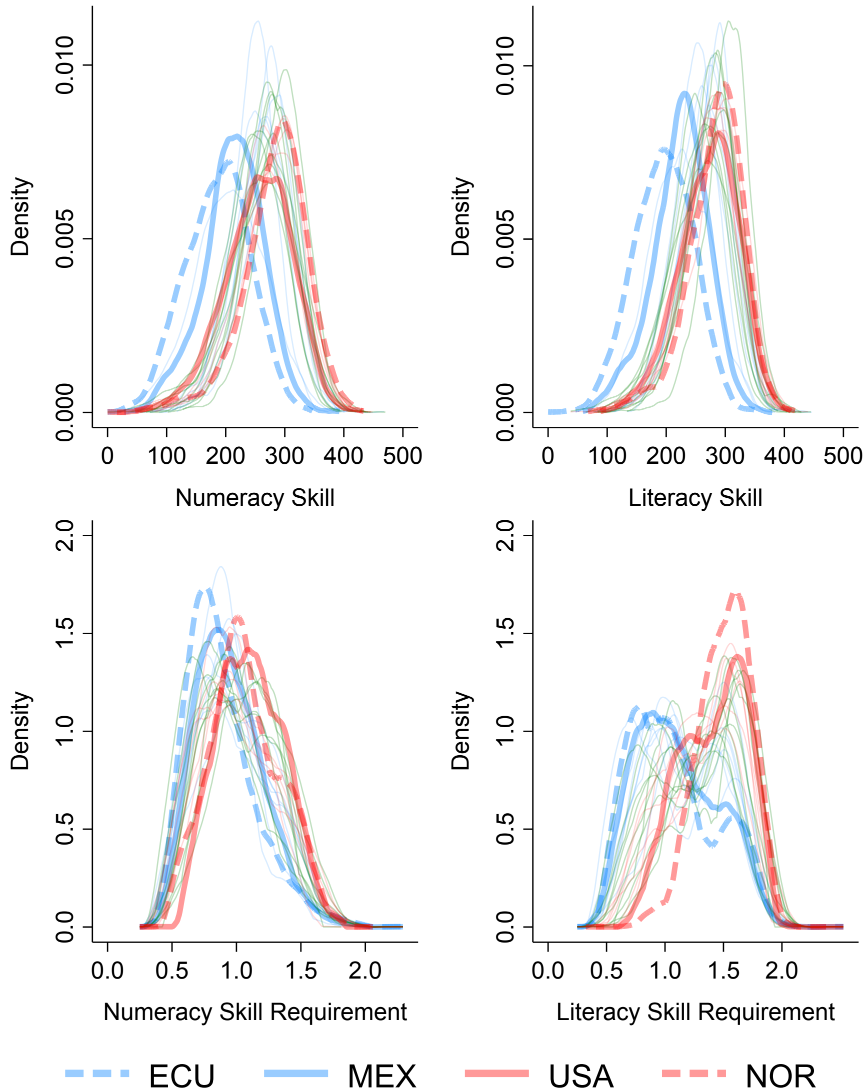
A.2 Other Data Sources

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

[45] Below, in Appendix 27, we demonstrate that self-employment is relatively less common in our sample of countries compared to a larger set of countries across the development spectrum.

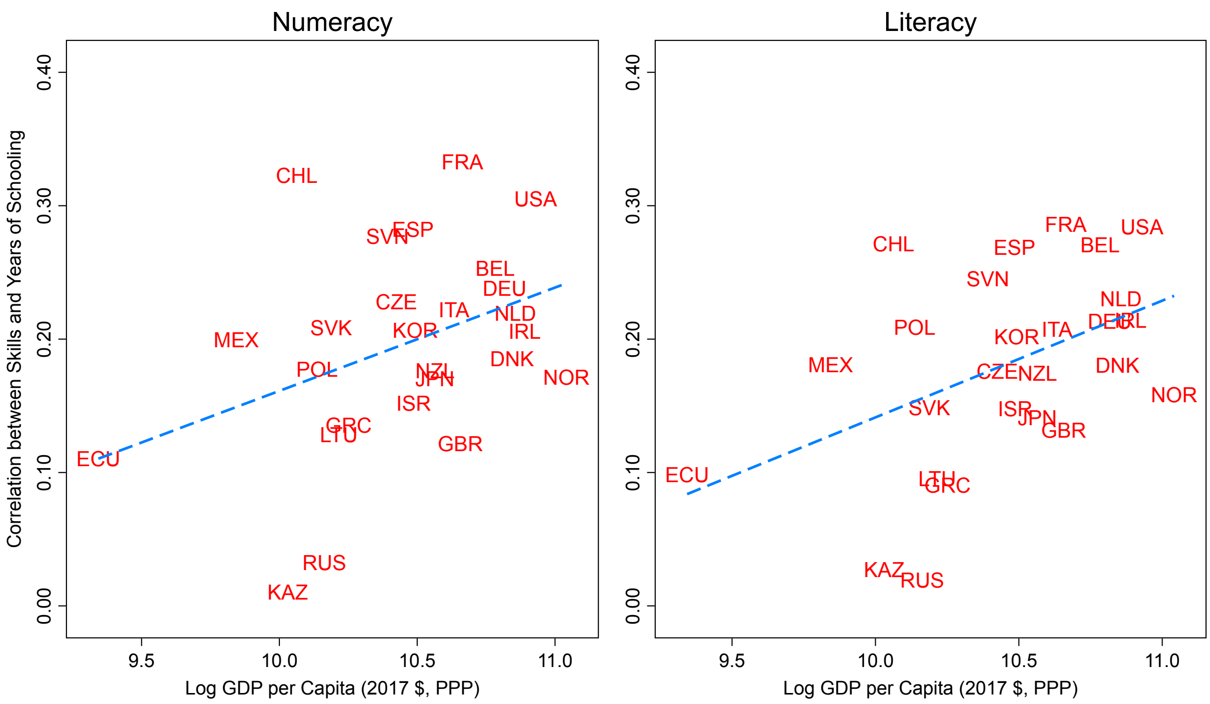
A.3 Summary Statistics

Figure 24: Distributions of Worker Skills and Job Skill Requirements across Countries



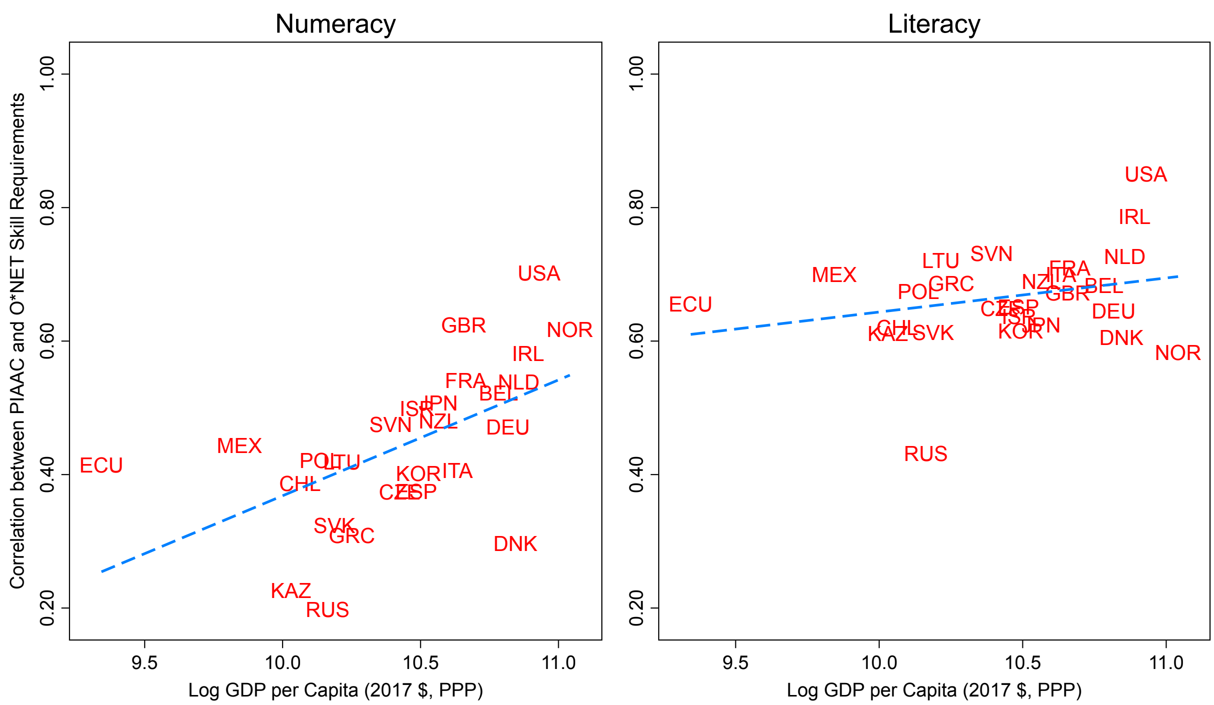
Notes: This figure shows the empirical distributions of worker skills (top panels) and job skill requirements (bottom panels) for numeracy (left panels) and literacy (right panels). The black solid line indicates the global distribution obtained by pooling all countries. Each thin solid line represents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

Figure 25: Correlation between Skills and Education



Notes: Both panels report the 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 26: Correlation between PIAAC and O*NET Measures of Skill Requirements

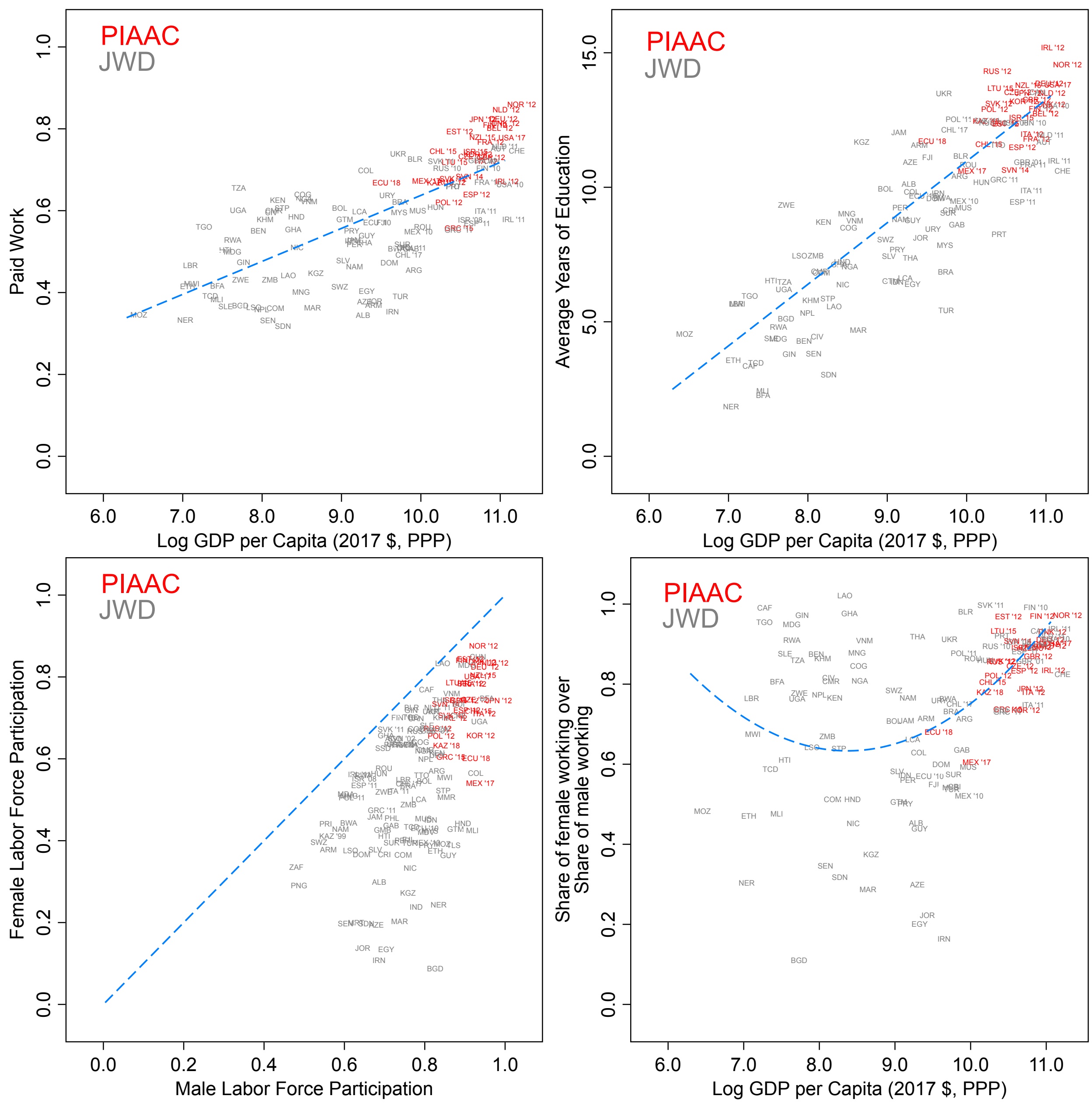


Notes: Both panels report the R^2 of a regression of the PIAAC skill requirement measures on the O*NET measures, the left panel for numeracy skill requirements and the right panel for literacy skill requirements. Skill requirement scores from O*NET data are computed as follows. We use three modules of 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 2008 occupation codes, we are able to assign a skill requirement score to 441 4-digit ISCO 2008 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 three 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 so that they lie in $[0, 1]$ by subtracting the minimum value and dividing by the range of values. *Sources:* PIAAC and O*NET.

A.4 Labor Market and Educational Outcomes across the Development Spectrum

The top-left panel of Figure 27 below plots the share of paid workers against log GDP per capita. Red labels denote countries in our PIAAC survey, while gray labels denote countries in the JWD. Reassuringly, the two sets of countries closely align, suggesting that the PIAAC survey is representative within countries. At the same time, it is worth noting that countries in the PIAAC survey constitute the top third of all countries in the JWD. There is a positive relationship between the share of paid workers and development, both in the PIAAC and more broadly. This suggests that there are more jobs in higher-income countries. The top-right panel shows the average years of education, which vary between 2.0 and 15.0 worldwide. Again, the PIAAC sample is representative within countries and constitutes the top third of all countries in terms of educational attainment. The bottom-left panel plots the labor force participation rate of women against that of men. In all countries, the participation rate of women in the labor force is lower than that of men. There is significant heterogeneity in female labor force participation rates across PIAAC countries and, to a lesser extent, in male labor force participation rates. The bottom-right panel shows the ratio between women's labor force participation rate and men's across the development spectrum. We see a well-known U-shaped curve, indicating that women's relative labor force participation rate is higher at very low and very high levels of development. The PIAAC countries all fall to the right of the inflection point of this curve.

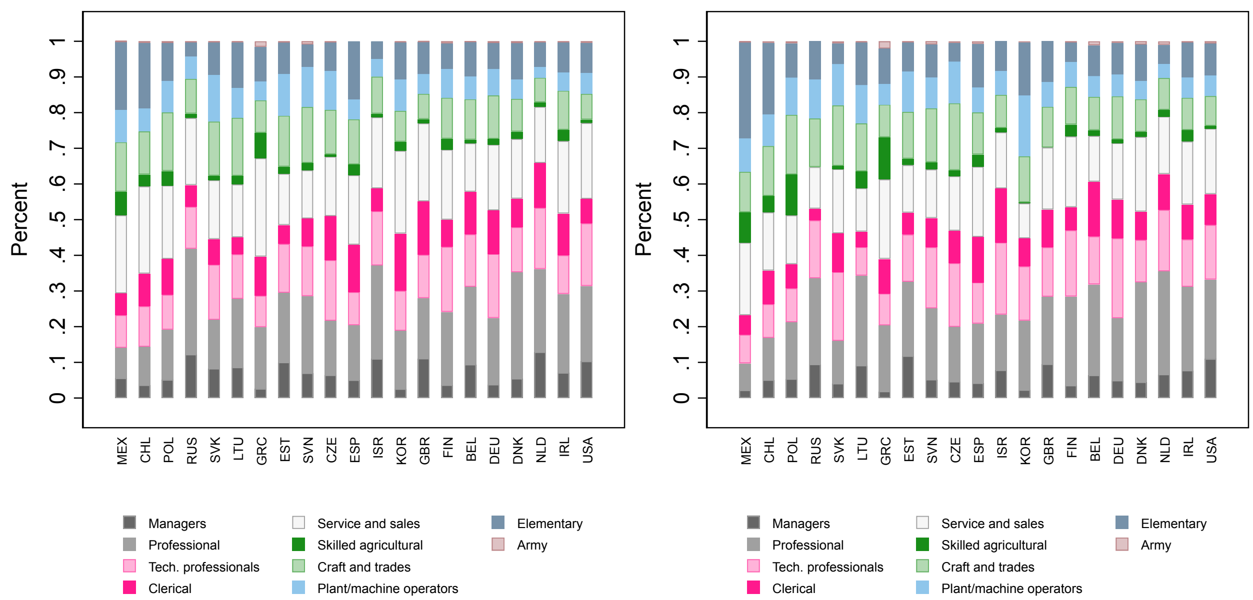
Figure 27: Comparison between PIAAC and JWD Data



Notes: These graphs pool cross-country data from PIAAC and The Jobs of The World (JWD). The Jobs of the World Dataset harmonizes census data from national census data from IPUMS and the Demographic and Health Surveys (DHS) to retrieve labor market outcomes. The top-left panel plots the share of workers in paid employment as a share of the total population against the log GDP per capita in purchasing power parity. The top-right panel plots the average years of education of the population against the log GDP per capita. The bottom-left panel plots women's labor force participation rate against men's labor force participation rate. The labor force participation rate is calculated as the share of individuals either employed or currently seeking employment as a share of the total population. Lastly, the bottom-right panel plots the share of women's to men's labor force participation rates against log GDP per capita. *Source:* PIAAC and JWD.

Figure 28: Comparison between PIAAC and LIS Data

(A) PIAAC (B) LIS

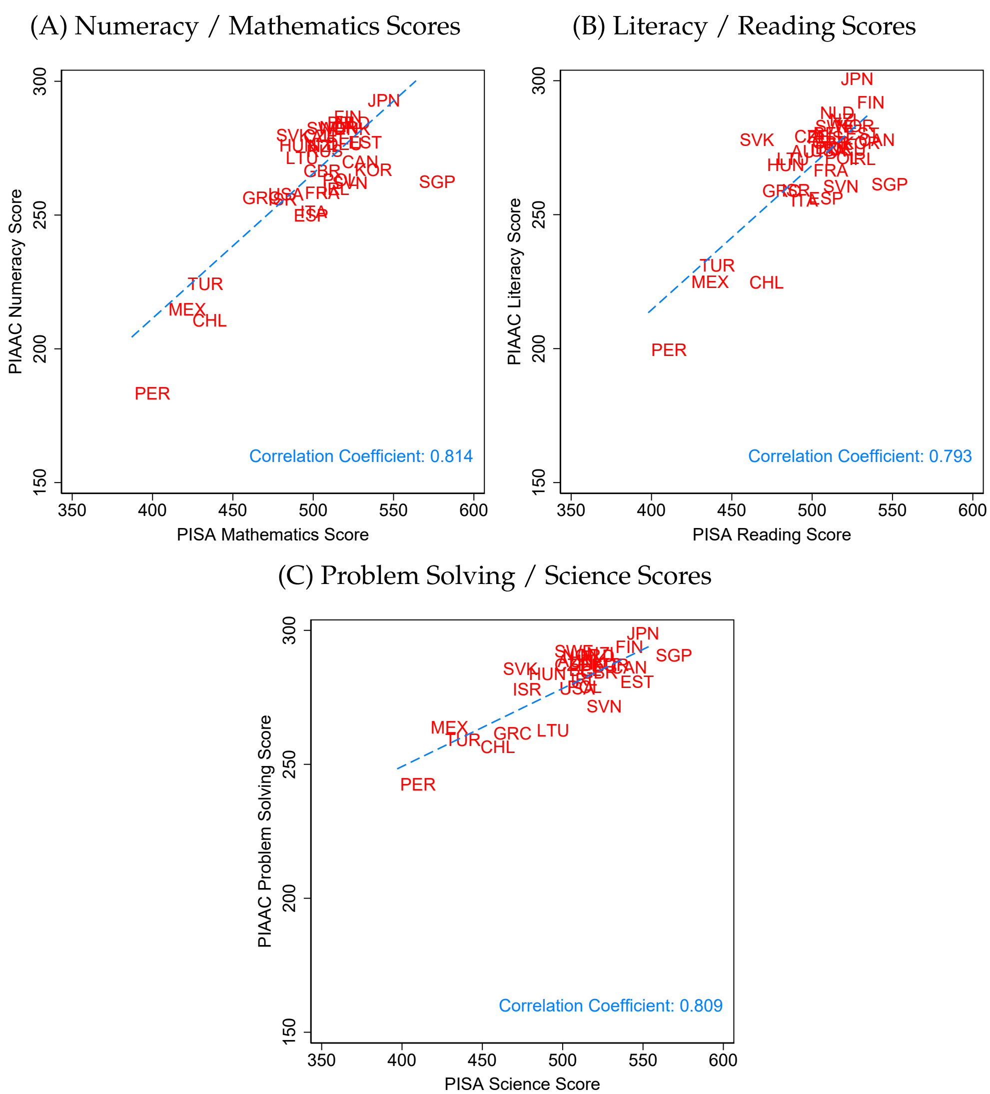


Notes: This figure shows the occupational structure in the PIAAC data (panel A) and the LIS data (panel B) for 21 countries, for which the two datasets overlap. Occupations are structured into ten categories according to ISCO-1 occupation codes. *Source:* PIAAC and LIS.

A.5 Comparison between Childhood and Working-Age Skill Measures

Figure 29 shows the country-level correlations between test scores in various skill dimensions of the PIAAC completed by working-age adults and the corresponding skill dimensions in the PISA completed by 15-year-old students in the same countries. In all three skill dimensions—i.e., numeracy, literacy, and problem-solving —the data show a strong positive correlation between childhood and adult measures of skill proficiency across countries. We conclude from this that (i) our PIAAC skill measures have meaningful content and (ii) that skills tend to be quite persistent, motivating our assumption of treating them as fixed factors in our equilibrium model of the labor market.

Figure 29: 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 PIAAC completed by working-age adults and the corresponding skill dimensions in the PISA completed by 15-year-old students in the same countries for numeracy / mathematics skills (panel A), literacy / reading skills (panel B), and problem solving / science scores (panel C). *Source:* PIAAC and PISA.

B Facts Appendix

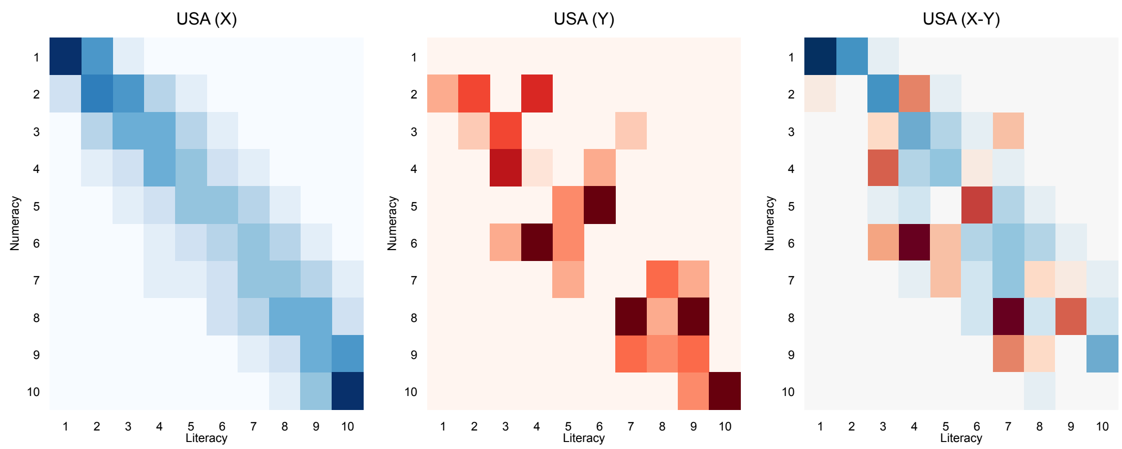
B.1 Endowments of Worker Skills and Job Skill Requirements across Countries

To compare the distributions of skill supply and demand, we first compute deciles of both numeracy and literacy skills of all workers (i.e., not just matched workers) and also of skill requirements of all jobs and form 10×10 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 30 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 31 below reports the difference for every country and shows that 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 indicates that upskilling the workforce of low-income countries may benefit them since it would render a tighter matching between worker skills and job skill requirements feasible and thus boost meritocracy.

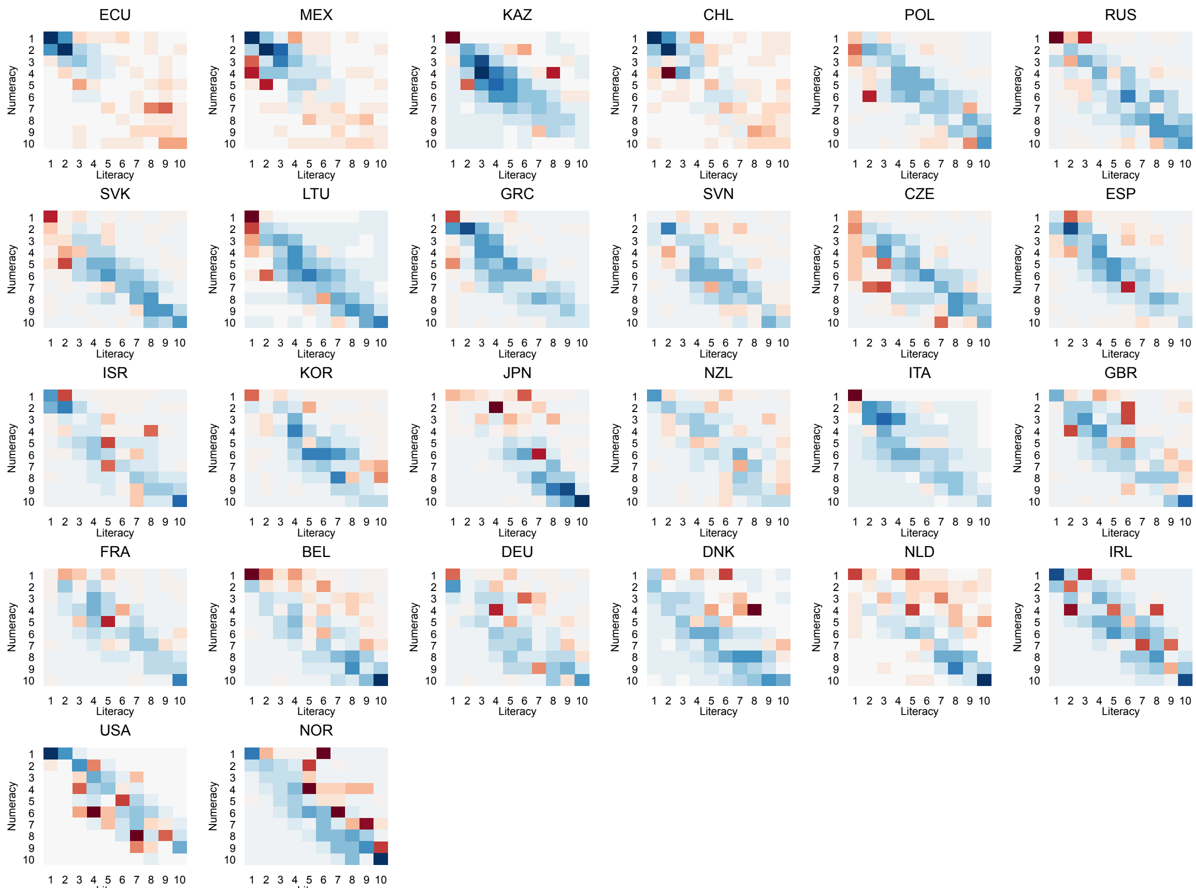
The following Figure 31 shows the difference heatmaps separately for each country in our sample.

Figure 30: Endowments of Worker Skills, Job Skill Requirements, and their Difference in the United States



Notes: This figure shows skill cells (first panel) and skill requirement cells (second panel) based on country-specific deciles in each skill dimension. The first panel shows every combination of numeracy and literacy skills, where the color intensity is proportional to the size of the group that has that combination. The second panel shows every combination of numeracy and literacy skills requirements, color-coded in the same way. The third 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 third 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.

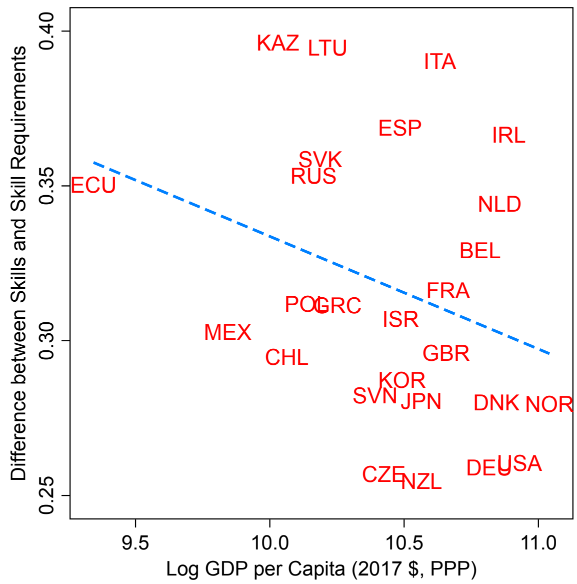
Figure 31: Differences between Endowments of Worker Skills and Job Skill Requirements across Countries



Notes: This figure replicates the third panel of Figure 30 for 26 countries in our sample—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 10 ×10 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 deciles in two dimensions: numeracy and literacy. 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. Please see the note below Figure 30 for more details. *Source:* PIAAC.

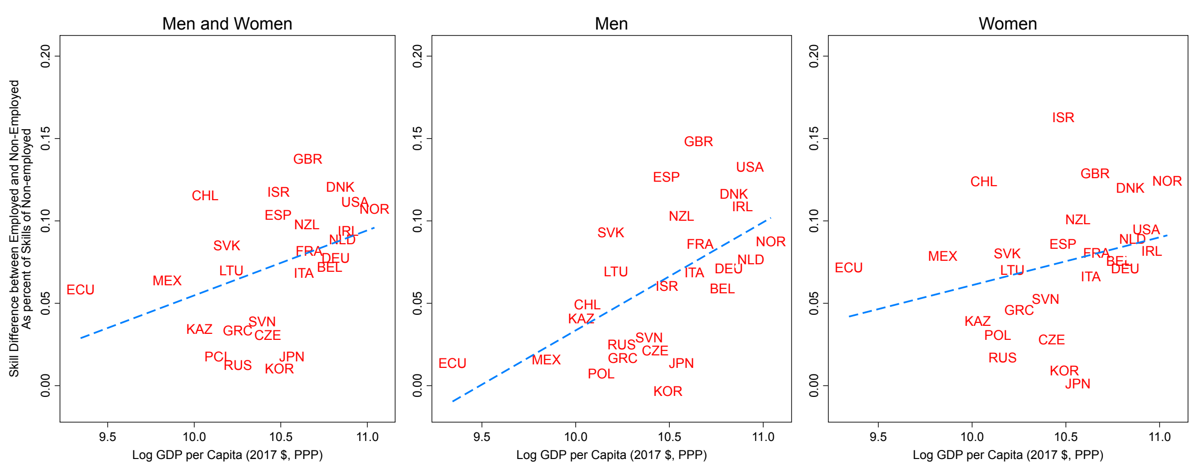
B.2 Robustness of Skill-Based Worker-Job Matching to Choice of Discretization

Figure 32: Smaller Distance between Workers' Skills and their Jobs' Skill Requirements in Higher-Income Countries using Raw Skill and Skill-Requirement Scores (Robustness)



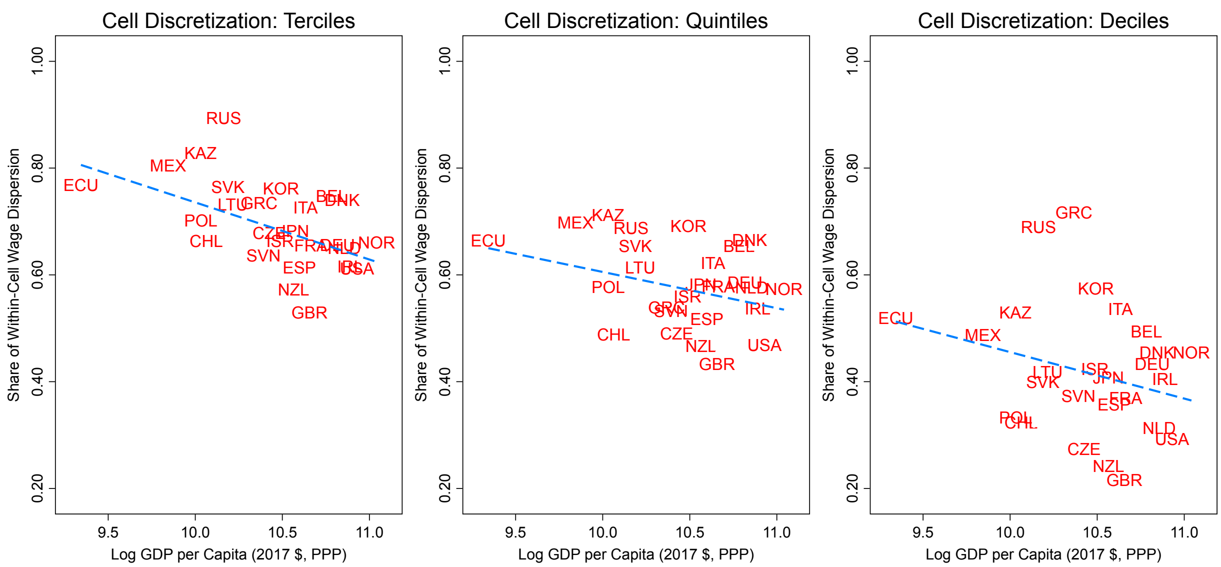
Notes: The figure plots the mean distance between workers' skills and the skill requirements of the job that they are employed in by country. Distances are computed as the Euclidean distance between the 2×1 vector containing the raw worker skill scores, each normalized to lie between 0 and 1 by subtracting 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 33: More Positive Skill-Based Selection into Employment in Higher-Income Countries using Raw Skill Scores (Robustness)



Notes: This figure plots the employed-to-nonemployed skill differential and GDP per capita across countries. For each individual, we average their raw literacy and numeracy skill scores and then compute the difference in average skill scores of the employed and the nonemployed. A higher skill differential value indicates that workers with higher numeracy and literacy skills are more likely to self-select into employment as opposed to nonemployment. *Source:* PIAAC.

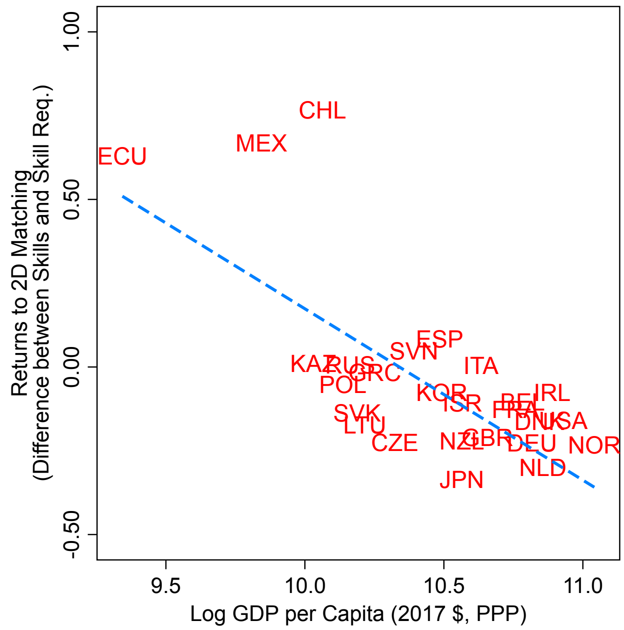
Figure 34: Lower Residual Wage Dispersion in Higher-Income Countries using Alternative Cell Discretizations (Robustness)



Note: The figure plots the share of wage dispersion not explained by dummies for cells defined as the interaction between worker skills and job skill requirements, as in Figure 6, 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 note below Figure 6 for further details. *Source:* PIAAC.

B.3 Robustness of Penalty for Worker-Job Skill Mismatch to Omitting Mincerian Controls

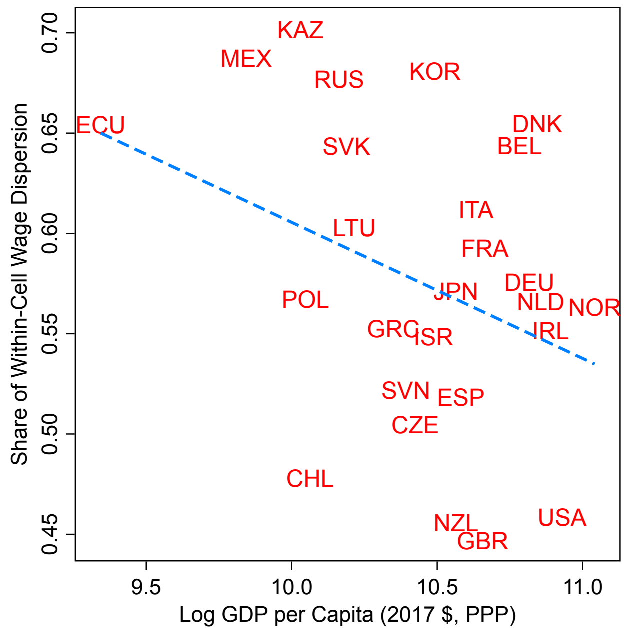
Figure 35: Greater Penalty for Worker-Job Skill Mismatch in Higher-Income Countries without Mincer Controls (Robustness)



Notes: This figure shows that higher-income economies offer greater rewards for better matches (i.e., those with lower differences between worker and corresponding job attributes). The vertical axis plots estimates of the coefficient β from the following regression: $\ln(w_i) = \alpha + \beta \text{Diff}_i + \varepsilon_i$, where Diff_i is computed as the average Euclidean distance between the 2×1 vector containing the global quintiles of a worker's numeracy and literacy skills and the 2×1 vector containing the global quintiles of their job's numeracy and literacy skill requirements. A lower value of Diff_i indicates a closer match between a worker's skills and their job's skill requirements. *Source:* PIAAC.

B.4 Robustness of Residual Wage Dispersion to Omitting Mincerian Controls

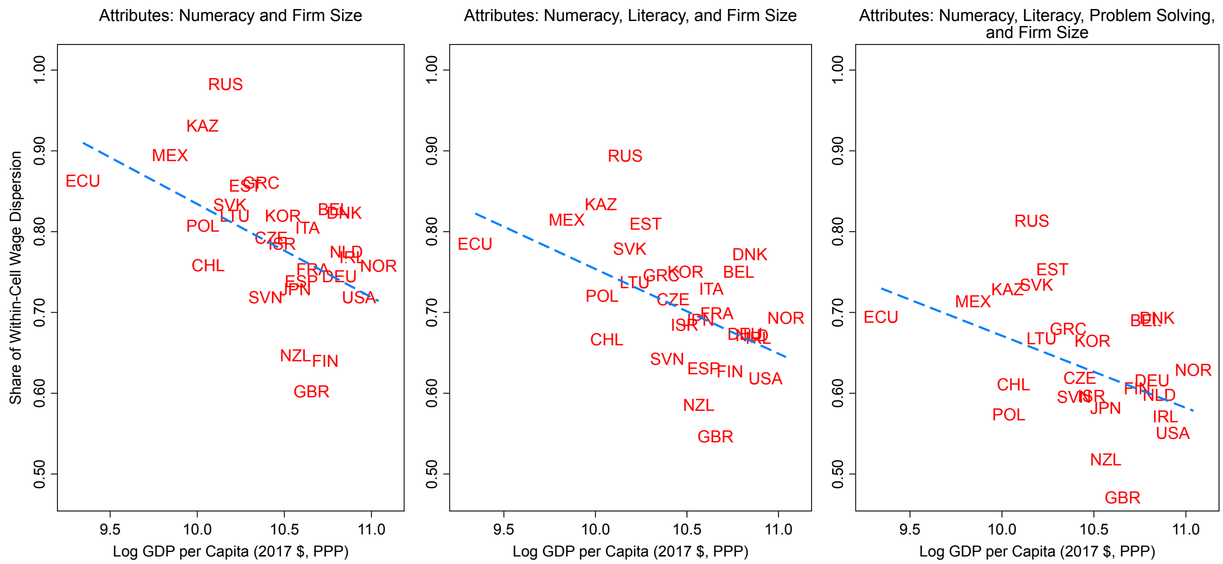
Figure 36: Lower Residual Wage Dispersion in Higher-Income Countries without Mincerian Controls (Robustness)



Notes: This figure plots the share of dispersion in log wages not explained by skills, skills requirements, and the match between the two. We first construct quintiles for each dimension of skills and skill requirements. We then allocate each worker i into country-specific cells formed by the intersection of their skill quintiles $x_{i,j} \in \{1, \dots, 5\}$ and their job's skill-requirement quintiles $y_{i,j} \in \{1, \dots, 5\}$, for $j \in \{\text{numeracy}, \text{literacy}\}$. The vertical axis plots the ratio of within-cell wage dispersion to overall wage dispersion, estimated as the ratio of the residual sum of squares over the total sum of squares from the following regression: $\ln(w_i) = \sum_{k,k',k'',k'''} \beta_{k,k',k'',k'''} \mathbb{1}[(Num_i, Lit_i, NumReq_i, LitReq_i) = (k, k', k'', k''')] + \varepsilon_i$, 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 and literacy skill quintile k' and numeracy skill-requirement quintile k'' and literacy skill-requirement quintile k'''. *Source:* PIAAC.

B.5 Robustness of Residual Wage Dispersion to Inclusion of Unobserved Attributes

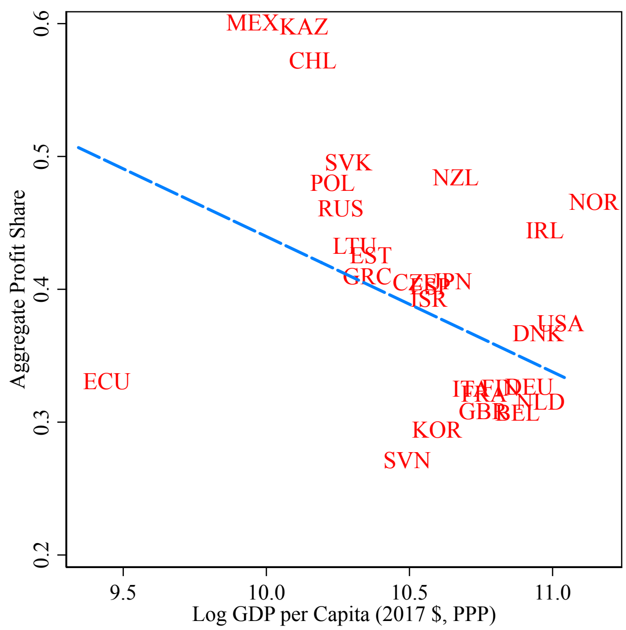
Figure 37: Lower Residual Wage Dispersion in Higher-Income Countries under Different Skill and Skill Requirement Attributes (Robustness)



Note: The figure plots the share of wage dispersion not explained by skill × skill requirement cells, as in Figure 6, 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 skills and skill requirements to our baseline specification. Note that data on problem-solving skills is not available for Italy, France, and Spain, and these countries are omitted from the last panel. Note also that we use terciles to define cells for this robustness graph (as opposed to our baseline specification of quintiles). This is so because with quintiles, adding additional attributes (such as problem-solving in the last panel) causes the cells to be too sparse. See also the note below Figure 6. *Source:* PIAAC.

B.6 Aggregate Profit Shares across Countries

Figure 38: Aggregate Profit Shares across Countries



Notes: This figure shows the aggregate profit shares across countries. For each country, the profit share is computed as 1 − labor share.
Source: FRED and OECD.

C Model Appendix

In this appendix, we derive a number of key equilibrium properties of the model presented 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

$$\log\left(\frac{\mu_{x|y}}{\mu_{\emptyset|y}}\right) = \log\left(\frac{\mu^J(x,y)}{\mu^J(\emptyset,y)}\right) = \frac{f(x,y) - w(x,y) - f_{\emptyset y}(y)}{\sigma}, \tag{17}$$

$$\log\left(\frac{\mu_{y|x}}{\mu_{\emptyset|x}}\right) = \log\left(\frac{\mu^W(x,y)}{\mu^W(x,\emptyset)}\right) = \frac{w(x,y) - f_{x\emptyset}(x)}{\sigma}. \tag{18}$$

Combining equations (17)–(18) by substituting out the wage function $w(x,y)$ and imposing labor market clearing (5), we obtain

$$\sigma \log\left(\frac{\mu(x,y)}{\mu(\emptyset,y)}\right) = f(x,y) - \left(\sigma \log\left(\frac{\mu(x,y)}{\mu(x,\emptyset)}\right) + f_{x\emptyset}(x)\right) - f_{\emptyset y}(y). \tag{19}$$

We solve (19) for $s(x,y) := f(x,y) - f_{x\emptyset}(x) - f_{\emptyset y}(y)$ to obtain the expression for systematic surplus $s(x,y)$ in (7).

Systematic Wages. Solving (18) for the wage function, w, and imposing labor market clearing (5), we obtain

$$w(x,y) = \sigma \log\left(\frac{\mu(x,y)}{\mu(x,\emptyset)}\right) + f_{x\emptyset}(x) \tag{20}$$

Now plug in the matching frequency $\mu(x,y)$ from (11) into (20) to obtain the expression for the wage, $w(x,y)$, 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

$$f(x,y) - f_{\emptyset y}(y) + \delta_{i\to k,y} + \delta_{x,k\to k} - \tilde{w}(x_i,y_k) = f(x,y) - f_{\emptyset y}(y) - w(x,y) + \delta_{xk}, \tag{21}$$

$$\tilde{w}(x_i,y_k) - f_{x\emptyset}(x) + \delta_{i\to i,y} + \delta_{x,k\to i} = -f_{x\emptyset}(x) + w(x,y) + \delta_{iy}, \tag{22}$$

where (21) corresponds to jobs and (22) to workers. Specifically, (21) is the post-transfer surplus of job k of type y and (22) 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 (21) or (22) 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 Salanié (2015), we now impose the following restrictions on the pre-transfer split of the idiosyncratic surplus components:

$$\delta_{x,k\to i} = 0 \quad \Longrightarrow \quad \delta_{xk} = \delta_{x,k\to k}, \tag{23}$$

$$\delta_{i\to i,y} = 0 \quad \Longrightarrow \quad \delta_{iy} = \delta_{i\to k,y}. \tag{24}$$

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 the restrictions (23)–(24), we obtain the expression for idiosyncratic wages $\tilde{w}(x_i, y_k)$ in (10).

D Identification Appendix

D.1 Proof of Proposition 1

Proof. Our goal is to identify the parameter vector, $\theta := \big(G(\cdot), H(\cdot), m^J, f(\cdot), f_{x\emptyset}(\cdot), \sigma\big)$. As stated in the text, we normalize the output of matches involving workers of the lowest skill type $(\underline{x_n}, \underline{x_\ell})$, 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 $H(\cdot)$. The proof proceeds in five steps.

Step 1: Identifying the worker type distribution $G(\cdot)$ and the job type distribution $H(\cdot)$.
Since $G(\cdot)$ and $H(\cdot)$ are distributions over observable worker and job attributes, they are identified and 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 the argument in Salanié (2015), the wage dispersion within (x, y) matches is given by that of an EV Type I distribution with scale parameter σ:

$$Var\left(\tilde{w}(x_i, y_k) | x, y\right) = \frac{\pi^2 \sigma^2}{6}. \tag{25}$$

Thus, we can invert (25) for *any* match type (x, y) to uniquely pin down the scale parameter of the distribution of matching wedges, σ.

Step 3: Identifying workers' nonemployment value $f_{x\emptyset}(\cdot)$.
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

$$\log\left(\frac{\mu(x, \emptyset)}{\mu(x, y)}\right) = \frac{f_{x\emptyset}(x) - w(x, y)}{\sigma}. \tag{26}$$

On the left-hand side of (26), both the share of nonemployed workers $\mu(x, \emptyset)$ 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 $w(x, y)$ is observed. Thus, we can solve (26) for the outside option $f_{x\emptyset}$ for each worker type x.

Step 4: Identifying the production function $f(\cdot)$.
Consider the log relative choice probabilities of job type y matching with any arbitrary 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 $f(\underline{x}, y) = 0, \forall y$, we can write

$$\log\left(\frac{\mu(x, y)}{\mu(\underline{x}, y)}\right) = \frac{f(x, y) - w(x, y) + w(\underline{x}, y)}{\sigma}. \tag{27}$$

On the left-hand side of (27), 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 above and the corresponding wages $w(x, y)$ and $w(\underline{x}, y)$ are observed. Thus, we can solve (27) 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 a match type (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 in

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

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 $\mu(\varnothing, y)$:

$$\widehat{\mu}(x,\varnothing) := \frac{\mu(x,\varnothing)}{m^W} = h_x \frac{\exp(f_{x\varnothing}(x)/\sigma)}{\exp(f_{x\varnothing}(x)/\sigma) + \sum_{\tilde{y}\in\mathcal{Y}} \exp(w(x,\tilde{y}))/\sigma)}, \tag{28}$$
$$\widehat{\mu}(\varnothing,y) := \frac{\mu(\varnothing,y)}{m^J} = g_y \frac{\exp(f_{\varnothing y}(y)/\sigma)}{\exp(f_{\varnothing y}(y)/\sigma) + \sum_{\tilde{x}\in\mathcal{X}} \exp(f(\tilde{x},y) - w(\tilde{x},y))/\sigma)}. \tag{29}$$

Note that $\widehat{\mu}(x, \varnothing)$ in (28) 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 (29) are already identified. Then, we can express the profit share in match (x, y) as

$$\frac{f(x,y) - w(x,y)}{f(x,y)} = \frac{\sigma \left[\log\left(\frac{\widehat{\mu}(x,\varnothing)}{\widehat{\mu}(\varnothing,y)}\right) - \log\left(m^J\right)\right] + s(x,y)}{2f(x,y)}. \tag{30}$$

Taking expectations over worker types x and firm types y, separately in the numerator and the denominator on each side of equation (30), 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 (30) for the relative mass of firms m^J.

To summarize all model parameters $\theta = \left(G(\cdot), H(\cdot), m^J, f(\cdot), f_{x\varnothing}(\cdot), \sigma\right)$ are identified. □

E Estimation Appendix

E.1 Homogeneity Properties

Proposition 2. *Systematic wages $w(x,y)$, idiosyncratic wages $\tilde{w}(x_i, y_k)$, 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 choice probabilities $(\mu(x,y), \mu(\emptyset, y), \mu(x, \emptyset))$, 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 $(\mu(x,y), \mu(\emptyset, y), \mu(x, \emptyset))$ is homogeneous of degree 0 in $\mathcal{P}$. We will verify this property below.

Indexing the wage function by the set of parameters $\mathcal{P}$, $w(\cdot, \cdot; \mathcal{P})$, 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 wage function w is homogeneous of degree 1 in $\mathcal{P}$.

Similarly, for the profit function, $\nu(\cdot, \cdot; \mathcal{P})$, 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 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, $\tilde{w}(\cdot, \cdot; \mathcal{P})$, 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 $\tilde{w}(\cdot,\cdot;\mathcal{P})$ 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 $s(\cdot,\cdot;\mathcal{P})$ is homogeneous of degree 1 in $\mathcal{P}$.

To summarize, we have shown that systematic wages $w(x,y)$, idiosyncratic wages $\tilde{w}(x_i,y_k)$, 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 (3)–(2) that the conditional choice probabilities of jobs and workers are all homogeneous of degree 0 in $\mathcal{P}$, which verifies the claim made at the beginning of this proof.

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

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

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 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) are 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 (30) 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 $f(\cdot,\cdot;\mathcal{P})$ is homogeneous of degree 1 in $\mathcal{P}$. □

E.2 Targeted Moments

In this section, we describe how each of the targeted moments used in estimation is constructed in the model and the data. 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 its global rank in that dimension. 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 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. While 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 unemployment rates by broad skill group (see above on how they 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 groups 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 explain the details underlying 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:

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

where $\boldsymbol{\lambda} \in \mathbb{R}^N$ is the parameter vector to be estimated and $\tilde{\phi} := (\phi_1, \ldots, \phi_N)$ are N known linearly independent basis surplus vectors. In our case, $\boldsymbol{\lambda} = \{\alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell n}, \alpha_{\ell\ell}, \alpha_{\ell s}\}$ and $N = 6$ with $\tilde{\phi} = \{x_n y_n, x_n y_\ell, x_n y_s, x_\ell y_n, x_\ell y_\ell, x_\ell y_s\}$.

We then compute the joint moments of any feasible matching $\boldsymbol{\mu}$ as the average values of the basis output vectors:

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

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

$$C_n(\hat{\boldsymbol{\mu}}) = C_n\left(\boldsymbol{\mu}^{\boldsymbol{\lambda}}\right) \quad \forall n.$$

E.3 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 7 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.4 Solution Algorithm

For a given parameter vector, we use the Iterative Projective Fitting Procedure (see Section 4.3) to compute the equilibrium in each country. To find the parameter vector that minimizes the distance between model-implied moments and data moments given by equation (16), we repeatedly solve the model for a set of parameter vectors. Because this equation describes 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.5 Details of Identification Threats

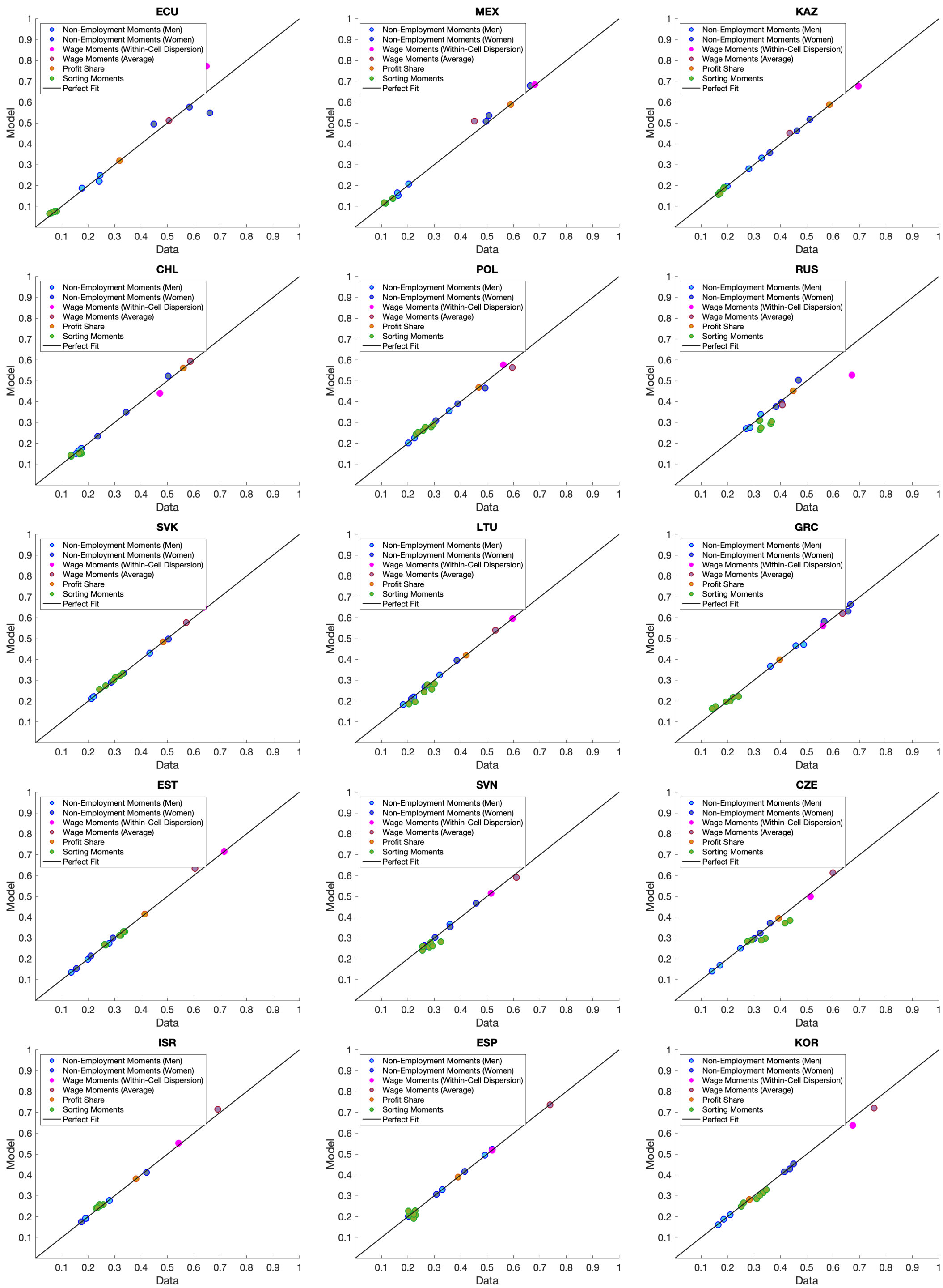
Here, we provide additional details of the identification threats discussed in Section 6.2 of the main paper. Specifically, we formalize the argument concerning measurement error in wages. Suppose we observe wages with measurement error $\varepsilon_c \sim F(\cdot; \mu_\varepsilon, \sigma_\varepsilon^2)$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

$$Var\left(\tilde{w}(x_i, y_k)|x, y\right) = Var\left(\delta_{iy}\right) + Var\left(\varepsilon_c\right) = \frac{\pi^2}{6}\sigma^2 + \sigma_\varepsilon^2. \tag{31}$$

Equation (31) 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 would infer $\hat{\sigma}^2 = Var(\tilde{w}(x_i, y_k)|x, y)$, whereas the true value is $\sigma^2 = 6[Var(\tilde{w}(x_i, y_k)|x, y) - \sigma_\varepsilon^2]/\pi^2$. Note that the two are related through an affine transformation, so any cross-country relationship involving the estimated $\hat{\sigma}$ would closely mirror 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 exactly 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 were more pronounced in lower-income countries, then we would mistakenly estimate a negative relationship between σ and GDP, which implies that the true effect of σ on development is less than what we currently estimate. For this reason, one should treat our number for the quantitative effect of σ on development as an upper bound.

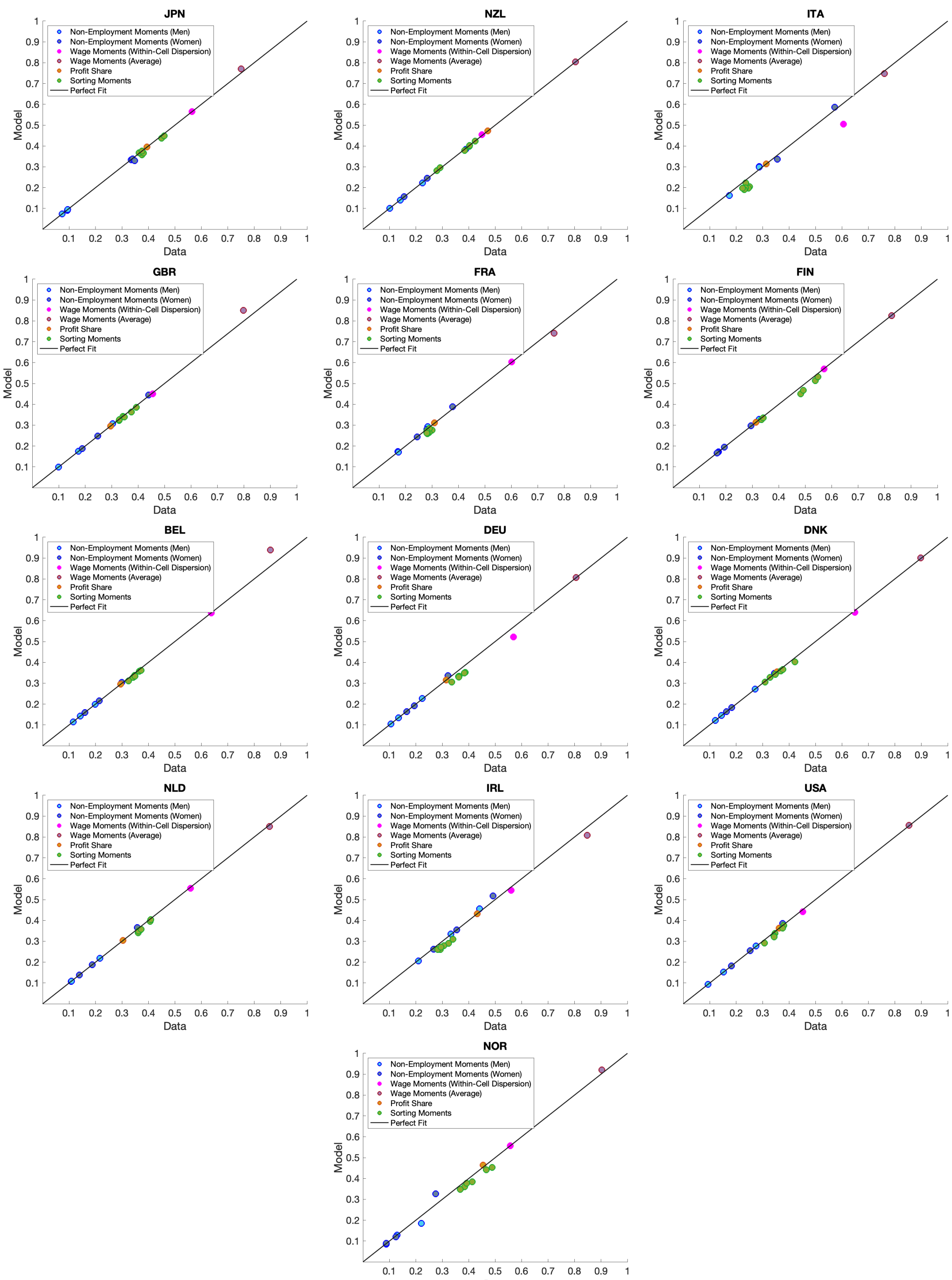
E.6 Details of Model Fit

Figure 39: Model Fit for Middle-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. For details, see Figure 11. *Source:* PIAAC, OECD, and model simulations.

Figure 40: Model Fit for High-Income Countries

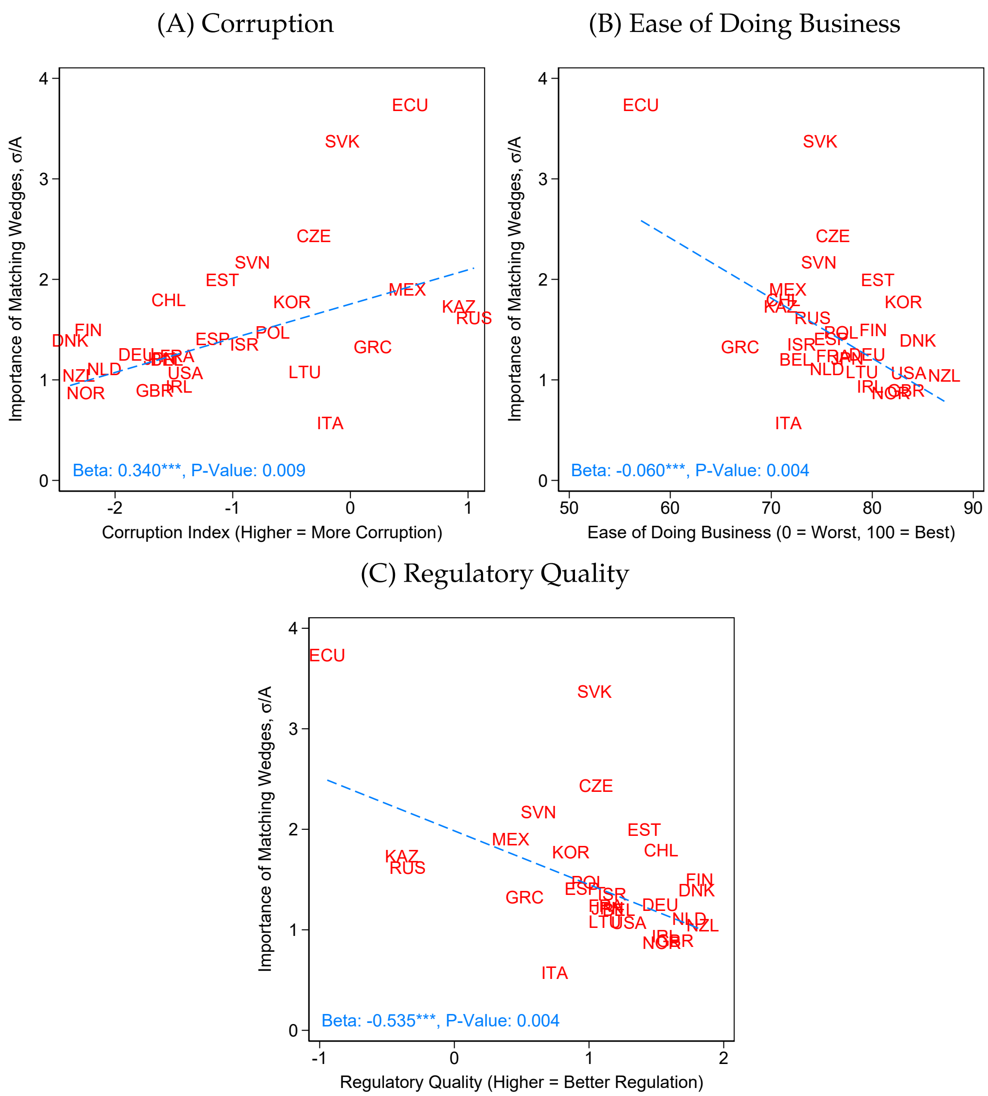


Notes: This figure illustrates the model fit by plotting model moments against data moments for high-income countries of the PIAAC sample. For details, see Figure 11. *Source:* PIAAC, OECD, and model simulations.

E.7 Correlates of Model Estimates

Figure 41 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, and a regulatory-quality index. All three projections show statistically significant correlations, suggesting that our estimates of the relative importance of idiosyncratic matching frictions reflect the quality of institutions and the business environment.

Figure 41: 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 three explanatory variables: a corruption index (panel A), an ease-of-doing-business index (panel B), and a regulatory-quality index (panel C). 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 and model simulations.

F Counterfactuals Appendix

F.1 Implementation of Counterfactuals

In this section, we describe in detail the implementation of our counterfactual simulations.

1. **Same Production Function.** We implement Norway's production function f^{Norway} in all countries while keeping the extent of relative matching frictions σ / A at each country's baseline level. That is, we compute for each country c the counterfactual level of frictions to achieve this as $\sigma^c_{counter} = A^{Norway} \times \sigma^c / A^c$.

2. **Same Matching Frictions.** We implement Norway's matching frictions in all countries, i.e., each country c faces $\sigma^c_{counter} = A^c \times \sigma^{Norway} / A^{Norway}$.

3. **Same Endowments.** We implement Norway's skill distribution H, skill requirement distribution J and job mass M^J in each country c.

4. **Same Production Function and Endowments.** This counterfactual combines 1. and 3.

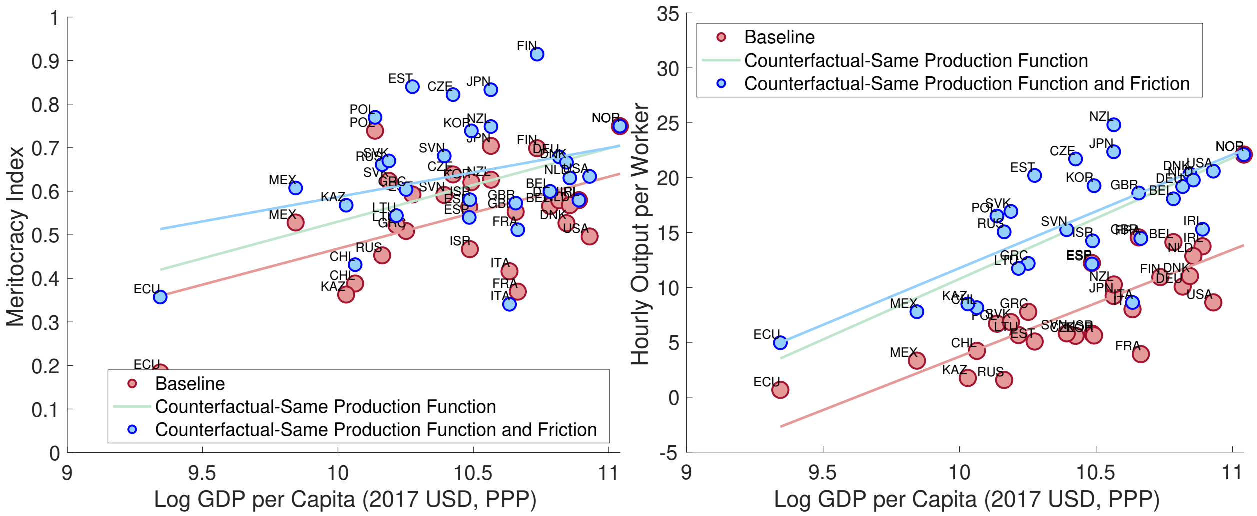
5. **Same Production Function and Matching Frictions.** This counterfactual combines 1. and 2.

6. **Same Matching Frictions and Endowments.** This counterfactual combines 2. and 3.

7. **Counterfactuals with Fixed Meritocracy.** To compute output per worker in counterfactuals 1. to 5. while keeping the level of meritocracy at each country c's baseline level, we compute $output^c_{\text{fixed merit}} = output(potential)^c_{counter} \times output(actual)^c / output(potential)^c$.

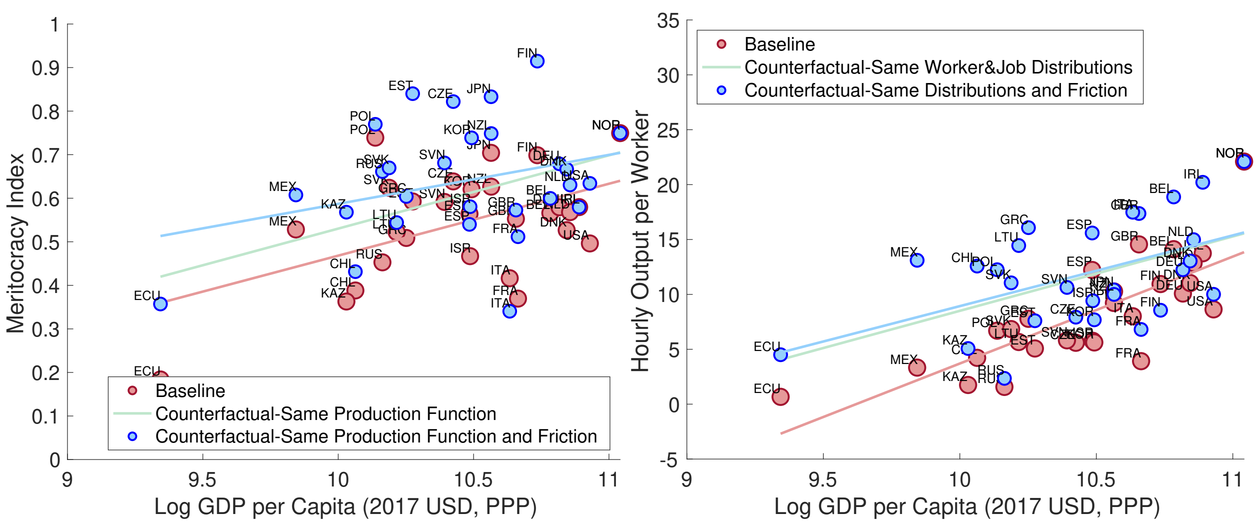
F.2 Additional Counterfactual Simulations

Figure 42: Counterfactual Imposing Norway's Production Function and Frictions across Countries



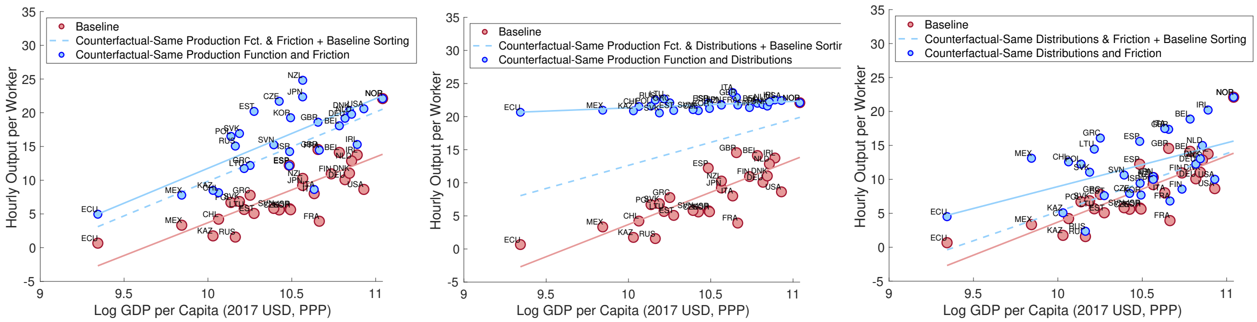
Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian production technology and matching frictions simultaneously in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates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

Figure 43: Counterfactual Imposing Norway's Distributions and Frictions across Countries



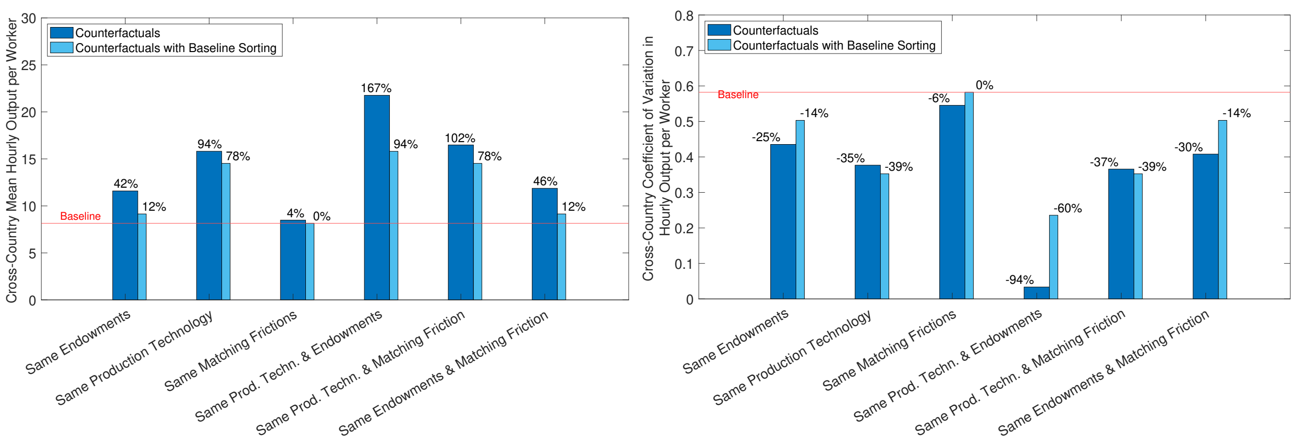
Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian distributions and matching frictions simultaneously in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates for each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

Figure 44: Counterfactual Imposing Norway's Production Function, Frictions and Distributions across Countries: The Role of Worker-Job Sorting



Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian production technology and matching frictions (left panel), the effects of implementing the Norwegian production technology as well as distributions of worker skills and job skill requirements (middle panel), and the effects of implementing the Norwegian distributions of worker skills and job skill requirements and matching frictions (right panel) simultaneously in all countries. Red dots represent the baseline model estimates for each country, with the red solid line indicating the linear best fit across GDP per capita. Blue dots represent the counterfactual results for each country, with the blue solid line indicating the linear best fit across GDP per capita. The blue dashed line in each panel indicates the linear best fit across GDP per capita in the respective counterfactual while keeping each country's worker-job sorting patterns (i.e., its meritocracy index) at its baseline. *Source:* Model simulations.

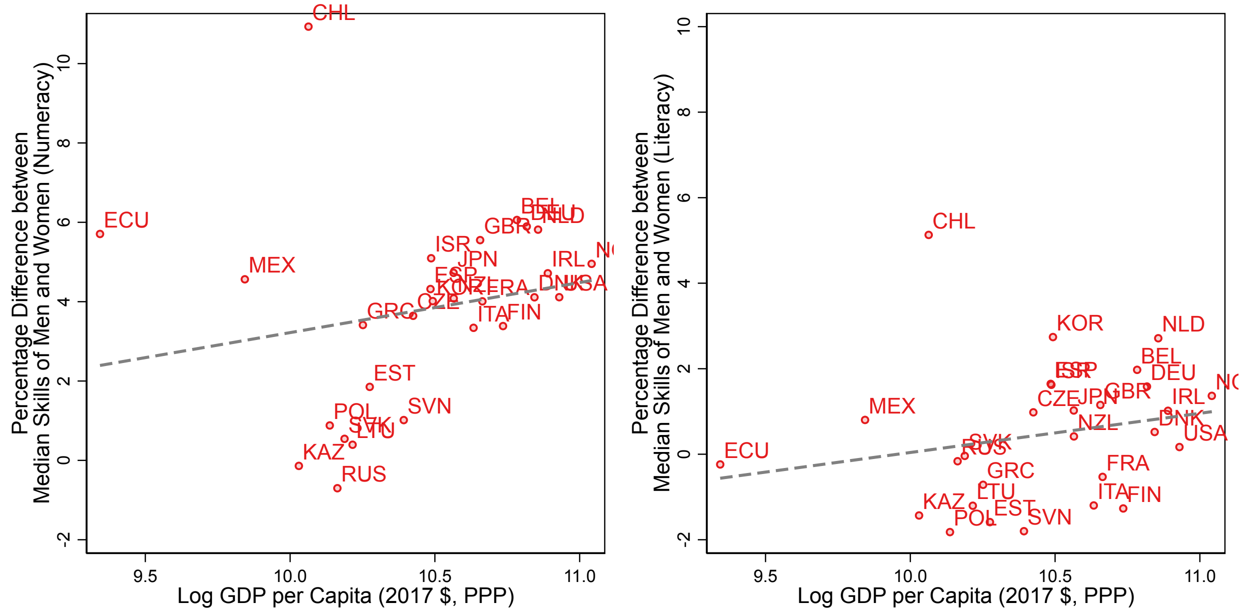
Figure 45: Detailed Summary of Counterfactuals: Global Mean and Coefficient of Variation of Output per Worker



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 18, we here report the interactions between all model primitives. The dark blue broad bars indicate outcomes based on the baseline scenario or the counterfactual exercises. The light blue narrow bars indicate outcomes in the counterfactual exercises while keeping each country's meritocracy index at its baseline level by adjusting actual output. The numbers at the top of each counterfactual bar indicate the percentage change relative to the baseline. *Source:* Model simulations.

F.3 Skill Misallocation by Gender in the Data

Figure 46: Gender Differences in Skills across Countries



Notes: We report the percentage difference between the median skill of men and that of women in each country as a function of their log GDP per capita. The dashed line indicates the linear best fit. The left panel shows numeracy skills, while the right panel shows literacy skills. *Source:* PIAAC.

Figure 47: 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.