Meritocracy across Countries[*]

Oriana Bandiera[†]   Ananya Kotia[‡]   Ilse Lindenlaub[§]
Christian Moser[¶]   Andrea Prat[||]

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Abstract

Are labor markets more meritocratic in richer countries? If so, why? And what are the implications of greater meritocracy for cross-country income differences? We provide answers by comparing the extent to which workers with different skills are matched with jobs that require those skills, using individual-level data on a sample of 120k working-age people across 28 countries. We find a positive correlation between meritocracy and national income, and investigate three factors that underpin it: (i) technology, which determines the productivity of matches; (ii) endowments of worker skills and job skill requirements, which determine the feasibility of matches; (iii) idiosyncratic matching frictions that capture the importance of (non-productive) worker and job traits for the matching process. By estimating a structural model of equilibrium matching with multiple skill dimensions, we find that idiosyncratic frictions lead to a deviation from the meritocratic—i.e., output-maximizing—allocation of workers to jobs and thereby a gap between actual and potential output in all countries, particularly in the poorest ones. However, technology and endowment differences primarily explain the variation in meritocracy and national income across countries. Therefore, policies aimed at reducing idiosyncratic frictions to improve labor market matches will not be effective unless they are combined with interventions that enhance match productivity.

[†]Department of Economics, London School of Economics and Political Science. Email: o.bandiera@lse.ac.uk.

[‡]Department of Economics, London School of Economics and Political Science. Email: a.kotia1@lse.ac.uk.

[§]Department of Economics, Yale University. Email: ilse.lindenlaub@yale.edu.

[¶]Graduate School of Business, Columbia University. Email: c.moser@columbia.edu.

[||]Graduate School of Business, Columbia University. Email: andrea.prat@columbia.edu.

1   Introduction

The notion of meritocracy has an extensive background in political philosophy and the social sciences (Arrow et al., 2000). It is often seen as a rule for the selection and advancement of individuals within organizations, famously in the bureaucracy of large empires, but also as a general principle to allocate power and resources in society. While meritocracy is a concept that has been applied to many contexts (Sen, 2000), it fundamentally involves choosing an allocation rule based on merit rather than an individual's personal attributes. What exactly constitutes merit depends on what is being allocated and on the objective of the allocation.[1]

This paper is concerned with meritocracy in labor markets where individuals have different skills and jobs have different skill requirements. In a perfect meritocracy, the allocation of workers to jobs coincides with the competitive market equilibrium, in which workers' skills are matched with the jobs' skill requirements so that total output is maximized. The allocation is supported by prices (i.e., wages) that reflect skills, skill requirements, and the quality of their match. In practice, however, individual attributes, such as wealth and connections, also impact the jobs that workers find. This raises the question that we aim to address in this paper: Is meritocracy weaker in poorer countries? If so, why? And what are the consequences for aggregate outcomes?

This paper provides a measure of meritocracy and its correlation to national income, and analyzes the extent to which it is driven by differences (i) in technology that determine match productivity, (ii) in endowments of worker skills and job skill requirements that determine the feasibility of "good" matches between workers and jobs and (iii) in the extent to which idiosyncratic traits unrelated to worker and job productivity (i.e., what we refer to as "frictions") affect the matching process. The latter may reflect informal institutions, for instance social norms and the acceptance of corrupt behavior in hiring decisions, as well as formal institutions, such as the inadequate enforcement of anti-discrimination laws or labor contracts.

To measure meritocracy in the labor market, we need to assess the skills of workers and the skill requirements of their actual and potential jobs. We use the OECD Survey of Adult Skills from the Program for the International Assessment of Adult Competencies (PIAAC), which contains skills and job skill requirements of a representative sample of adults in 28 middle and high-income countries. Literacy and numeracy skills are measured by means of standardized tests, which are designed to be comparable across countries. This circumvents the long-standing issue of the incomparable quality of education in research on economic development (e.g., Martellini et al., 2023). In turn, to measure jobs' skill requirements, we use survey responses to questions that ask for the type and number of tasks done at work. We take the sum of skill-specific tasks weighted by the task difficulty for each worker, aggregated at the occupation-country level. This yields occupation-specific (or job-specific) skill requirements scores for numeracy and literacy.[2]

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[1]The idea of selecting the "best" men to run the State goes as far back as Confucius in the East and Plato in the West. For the rulers of Greek city states in 395BC, Plato chose truthfulness, temperance, justice, and a good memory. To become bureaucrats in Imperial China, applicants had to sit exams testing writing and literacy skills.

[2]Our measure is task-based like the U.S.-based O*NET, but it allows the same job to require a different combination

In our empirical analysis, we combine these measures of skills and skill requirements to compute the meritocracy gap as the Euclidean distance between skills and skill requirements on both dimensions, literacy and numeracy. Our first finding is that richer countries are more meritocratic, that is the distance between workers' skills and the skill requirements of their jobs increases as GDP per capita decreases. Our second finding is that the difference in skills between individuals in the labor force and those outside is positive everywhere and increasing in country income. To the extent that the tasks performed out of the labor force (for instance, childcare or home-keeping) require fewer skills than those performed in the labor force, this finding indicates that people also sort meritocratically on the extensive margin, and more so in richer countries.

We focus on three possible reasons underpinning the relationship between meritocracy and national income and thereby provide a unified framework of the factors highlighted predominantly in subsets or in isolation within the development accounting literature.[3] The first, technology—broadly defined to include not only machinery and equipment but also the organization of labor—captures the returns to sorting meritocratically. The second factor, the economy's endowments of worker skills and job skill requirements and especially their similarity, determines whether a tight fit between workers' skills and their jobs' skill requirements is feasible. That is, it governs the best possible matching a country can achieve, given the endowments of workers and jobs. The third factor, which we refer to as matching frictions, is the extent to which idiosyncratic (non-productive) traits of workers and jobs matter for their allocation.

We find evidence that all three factors are sources of meritocracy and impact how it varies with countries' income. We first show that in poorer countries, skills, skill requirements, and the match between the two, explain a smaller share of the observed variation of wages within the country. This indicates that idiosyncratic factors must be more relevant for how workers select into jobs, indicative of larger matching frictions. Second, we show that the Mincerian returns to matching with a job of the right skill level are lower in poorer countries. This indicates that, to the extent that wages are proportional to the marginal product of labor, the production technology of richer countries rewards meritocratic matches more. Finally, we show that the overlap between the distributions of skills and skill requirements in the economy as a whole is greater in richer countries. This indicates that workers in higher-income countries can choose from a wider set of jobs that match their skills well.

The correlation between meritocracy and GDP is an equilibrium relationship, and in the absence of an exogenous shock to either national income or meritocracy, it is impossible to ascertain whether national income increases the returns to meritocracy or whether meritocracy leads to higher income. What we can do, however, is to quantify the empirical relevance of the three channels that support this feedback loop. We do so by developing an equilibrium matching model that

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of skills in different countries.

[3]This literature has studied the role of workers' human capital (Jones, 2014, 2019; Lagakos et al., 2018b; Hendricks and Schoellman, 2018, 2023; Martellini et al., 2023), technology (Caselli and Coleman II, 2006; Caselli, 2017; Comin and Mestieri, 2018; Caselli and Ciccone, 2019; Malmberg, 2022; Rossi, 2022; Bassi et al., 2022; Porzio, 2023), the task intensity of occupations (Lewandowski et al., 2022; Caunedo et al., 2023), and matching frictions (Girsberger and Meango, 2022; Poschke, 2023; Donovan et al., 2023) in economic development.

we estimate separately in each country of our sample. The theoretical underpinnings lie in the literature on matching and sorting (Becker, 1973), especially under multi-dimensional heterogeneity (Lindenlaub, 2017; Lindenlaub and Postel-Vinay, 2023), which has informed many applications to high-income countries (e.g., Jones et al., 2018; Bagger and Lentz, 2018; Lise and Postel-Vinay, 2020).

In the model, we treat different countries' labor markets separately. In each national labor market, workers who differ in multi-dimensional skills and gender match with jobs that differ in multiple skill requirements and firm size (our proxy for job productivity) to produce output. Workers may choose to remain nonemployed and jobs may choose to remain idle. Workers and jobs match to maximize total match surplus, which is comprised of two components: systematic match output based on the productive attributes of both parties; and stochastic factors that derive from idiosyncratic wedges, which lead to deviations from the output-maximizing worker-job allocation. Workers' and jobs' payoffs—i.e., wages and profits—are shares of total match surplus. Countries can differ in the three dimensions discussed above, which we take as given as part of the model environment: technology, which encompasses the match production function and workers' home production function; matching frictions, which put weight on idiosyncratic factors in the matching process of workers and jobs; and the agents' endowments of skills and skill requirements.

We prove that these three model primitives of each country are identified based on individual-level data from the PIAAC. The main challenge is to separately identify a country's technology and its 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 from wage dispersion conditional on worker skills and job skill requirements. Having pinned down these matching frictions—and given that we identify the distributions of workers' skills and jobs' skill requirements directly from the PIAAC micro data—a country's technology is then identified from 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 sorting and conditional wage inequality that are informed by our identification argument. Our estimates suggest large differences in model primitives across countries: Richer countries are characterized by less severe labor market frictions; stronger complementarities between worker skills and job skill requirements in production; and not only more productive skills and skill requirements but also a better alignment between these endowments. 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, such as output per worker, wage inequality, and skill returns.

We use the estimated model to build a meritocracy index, defined as the ratio of actual output over potential output absent matching frictions. Importantly, the estimated model reproduces our central fact that high-income countries are more meritocratic. Norway—the richest coun-

try in our sample—has a meritocracy index of around 0.61, more than three times as large as that of Ecuador—the poorest country in our sample. That is, Ecuador loses about twice as much output—80% of its potential output—due to its lack of meritocracy in the labor market and resulting mismatch compared to Norway, whose output would be 40% higher in a frictionless world. It is noteworthy that the ratio of the meritocracy index between the richest and the poorest countries in our sample (3) is about half of the ratio of GDP per capita for the same pair of countries (5.5), which is indicative of meritocracy accounting for a sizeable share of the observed cross-country variation in income but, at the same time, suggests that other factors matter as well. For a proper quantitative assessment of what drives cross-country-differences in meritocracy and their role in national income, we build counterfactual scenarios in which we eliminate cross-country differences in one or more of the three factors—technology, endowments, and frictions—by universally imposing the values of the richest country in our sample (Norway).

We find that differences in endowments and production technology account for most of the cross-country heterogeneity in outcomes: Giving all countries access to Norway's advanced technology reduces the cross-country variation in GDP per worker by 41%. In turn, if all countries had access to Norway's highly productive workforce that meets the skill demands of their productive jobs, it would bring down GDP differences by 30%. This also provides an upper bound on the effect of meritocracy on investment in human capital, that is, by assigning the same, high, level of skills we effectively mute the potential discouragement effects of meritocracy on the accumulation of skills.

In contrast, idiosyncratic factors that create deviations from perfect meritocracy play a relatively modest role: When all countries are characterized by Norway's relatively low labor market frictions, cross-country income differences drop by only 8%. Intuitively, eliminating these idiosyncratic factors in the matching process improves the alignment between skills and skill requirements in the worker-job pairs that form. But if productivity and thus potential output is low, even a large improvement will not have much impact on aggregate income in the international comparison.

This is not to say that the ability of workers to sort—e.g. due to flexible labor laws or a reduction in nepotism—is unimportant for development. To the contrary, a large share of the gains from adopting better and more aligned worker and job endowments, as well as a more advanced technology, are achieved through improved worker-job sorting: We estimate that this improved worker-job allocation accounts for 27% of the gains in global output and 38% of the cross-country convergence in incomes. This reflects our central finding that the available skill endowments and technology constrain the returns to meritocracy.

Advances in technology and more aligned worker-job endowments enhance labor market sorting in poor countries because these changes boost the rewards that are associated with good matches, thereby amplifying the direct effect of these shifts on national income. Therefore, the lack of meritocratic labor markets is a consequence of economic underdevelopment—i.e., the limited access to advanced technology and productive worker/job endowments that make sorting

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little worthwhile—rather than its source.

We conclude that individual idiosyncratic factors that create a wedge between the actual and the optimal allocation of workers to jobs are similar across countries. Their effect on output is, however, much more muted in richer countries because, due to their frontier technology that rewards good matches and more overlap between the endowments of workers and jobs, incentives to sort optimally are much stronger. This echoes evidence that financial incentives mute the negative effect of social connections on productivity within organisations (Bandiera et al., 2009; Beaman and Magruder, 2012; Hjort, 2014). Our findings imply that policy interventions designed to increase the returns to sorting by skills are more powerful than those designed to minimize only idiosyncratic frictions in worker-job matches.

We finish with two natural applications of our model.[4] First, we study the misallocation of women's skills on the extensive margin and its role in countries' aggregate outcomes. Despite the universal increase in female labor force participation over the past decades, there is still significant under-utilization and misallocation of women's skills, especially in low-income countries. To speak to this issue, we counterfactually set women's home production equal to that of men— capturing supply-side factors that impact their lack of participation—and find a large surge in female employment, particularly in lower-income countries. However, because jobs are relatively scarce there, the rise in female employment rates is offset by an almost one-for-one decline in employment among men, which highlights the importance of studying this issue in an equilibrium model. On the contrary, if we allow the number of jobs also to adjust, we not only find large gains in (female) employment but also in output. Second, we study the effect of regional labor market integration on global output through its effect on sorting patterns. To this end, we simulate the resulting worker-job matching in an economy where worker and job types are pooled across countries. With this counterfactual, we have in mind a scenario in which workers and firms can freely flow across space, possibly induced by reforms to immigration and international-investment policies. Our analysis suggests large potential output gains from moving to regional, continental, or even global labor markets. These gains are partly due to the improved allocation of workers to jobs, which was constrained by the boundaries of national labor markets in our baseline setting.

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 income per capita. We do so both empirically and using an equilibrium labor market model, which allows us to interpret the rich patterns of worker-job sorting 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 capital, either on its own or in combination with homogeneous labor (e.g., Hsieh and Klenow, 2009; Buera et al., 2011; Midrigan and Xu, 2014; Bau and Matray, 2023). Since labor

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[4]Our applications—the role of gender in economic development and the gains from cross-border labor mobility— relate to Andrew et al. (2021) and Ashraf et al. (2023) on the one hand; and to the large literature on the gains of migration and mobility (see Dustmann and Preston, 2019, for a survey) on the other, but differ by focusing on the role of skill misallocation.

accounts for at least two thirds of national income in many countries, understanding how meritocracy in the labor market affects labor productivity is of primary importance to understand performance differences across countries. This is where our paper comes in.

2 Data Description

2.1 The Data

Data Sources. 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 higher-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 tested 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. By using comparable skill measures across countries, we avoid mismeasurement due to discrepancies in the quality of education-based metrics like years of schooling within and across countries. The data span 38 countries, 28 of which have all the information (e.g., continuous wages) required for our study.[7]

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 since we do not have reliable wage information for them.

2.2 Variable Definitions

Skills. The PIAAC data reports test scores for both numeracy and literacy on a scale from 0 to 500. To give a sense of the range of skills measured by the test, the lowest score category (scores lower than 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

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

[6]A subset of PIAAC countries also report *Information and Communications Technology (ICT)* skills. Future waves of the PIAAC are planning to add more skill dimensions, including interpersonal skills, which have been shown to be of growing importance (Deming, 2017). Here we focus on numeracy and literacy skills as these are available for the largest number of countries.

[7]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.

modal category (226-275) is to "identify and act on mathematical information embedded in common contexts." While the top category (376-500) covers the 1% of the sample who can "understand complex representations and abstract and formal mathematical and statistical ideas, possibly embedded in complex text." To deal with the fact that skills and skill requirements are measured in different units and need to be made comparable for the analysis of 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.[8] 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 who are in the same country-specific quintile. This renders for each country a well-defined skill distribution of numeracy and literacy skills that take values between 0 and 1, while preserving differences of skill distributions across countries.

The main advantage of these 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 quantities difficult to compare. In line with this, in Figure 27 in Appendix A.4, we show that education explains only a small share of the variation in skills in the poorest countries.

Skill Requirements. To measure skill requirements for a given job defined by the four-digit ISCO occupation code, we look at all workers in a given country who report being employed in that occupation.[9] The survey asks them to report all tasks which they usually do in each area of skill. For instance, for numeracy, they are asked how many times they use a calculator, how many times they use algebra, and so on. We sum the number of tasks that each worker completes in each area—numeracy and literacy—and weigh them by the difficulty of the task based on the PIAAC documentation.[10] We then take the average of this measure across all workers who report doing the same job in a given country to arrive at a job-specific skill requirement of literacy and numeracy. To make the units of these skill requirements comparable to those of the constructed skills, we again transform them into percentiles. Specifically, we globally rank jobs across all countries by each skill requirement and give them a score that equals their position (i.e., percentile) in the global skill distribution. We discretize the resulting skill requirement distributions in the same way we discretize worker skills (see above).

Our country-specific measures of skill requirements are preferable to similar measures provided by the commonly used O*NET of the U.S. Department of Labor as they consider that different countries may use different technologies to produce the same goods. In other words, the skills required in a given job are not uniquely defined if technology is a choice variable. This means that

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[8]In contrast, the alternative of taking "local" percentiles within each country would render all countries' marginal skill distributions uniform.

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

[10]See Appendix A.1.1 for details.

worker-job matches may be misclassified if skill requirements from the U.S. O*NET are used universally for all countries. This is an issue that was found to be empirically relevant (Caunedo et al., 2023). Figure 28 in Appendix A.4 reports the R^2 of a regression of our PIAAC skill requirements on the corresponding O*NET measures for the same job. We find that O*NET explains only about 60–70 percent of the variation in literacy requirements in all countries and between 20–60 percent of the variation in numeracy requirements, with the fraction being higher in richer countries.

Meritocracy. The PIAAC data allows us to categorize skills in two ways: a standard "vertical" differentiation (which ranks skill levels) and a "horizontal" differentiation (which distinguishes between different types of skills). This requires a measure of meritocracy that captures the joint distribution of the two dimensions of skills and skill requirements, and the interplay between them. We propose two measures. Our first measure is a categorical variable that splits the worker-job pairs into those that are "well-matched" or "perfectly matched" (if a worker is matched to a job which requires their skills) and "not well-matched" (if a worker is matched to a job which requires skills that are dissimilar to their skill level). Our second measure is the distance between skills and skills' requirements in the worker-job matches that form.

To build the first measure, we assign each value of worker skill and each value of job skill requirement to the quintiles of their respective distribution within each country. Each worker is then characterized by a vector of numeracy and literacy skills, which takes values {1,...,5}. Likewise, each job is characterized by a vector of numeracy and literacy skill requirements which take values {1,...,5}. There are thus 25 possible combinations of worker types and 25 possible combinations of job types. We define a match to be "perfect" when skills and skill requirements match on both dimensions; that is, the worker's numeracy skills and their job's numeracy skill requirements are in the same quintile and, likewise, in the literacy dimension. In turn, we define a match to be "good" when the workers' skills and skill requirements are at most one quintile away from the perfect match.

The share of perfect matches is relatively low in all countries, ranging from 7% to 16%. This means that at most 16% of the worker-job pairs we observe are classified as perfectly matched. The more generous definition that counts contiguous quintiles as good matches increases that range to 35%-60%. Both measures indicate that differences between countries are large, there are about twice as many perfect and good matches in the most meritocratic countries of our sample compared to the least meritocratic ones. The advantage of the categorical measure is that it is simple to interpret. The price of simplicity is coarseness as this measure does not take into account how different skill and requirements are.

We therefore also build a continuous measure of meritocracy, which uses additional information. As mentioned above, to make the units of worker skills and job skill requirements comparable, we transform these measures using percentiles of the global distributions. We rank workers by each skill and give them a score that equals their position in the global skill distribution. We do the same for jobs' skill requirements. We then compute the Euclidean distance

$\sqrt{(x_n - y_n)^2 + (x_l - y_l)^2}$ for each worker and their job. The measure takes values between 0 (which we interpret as a perfect meritocracy) and $\sqrt{2}$ (which is the case when the difference between a worker's skills and their job's skill requirements is maximal—i.e. 1—in both the numeracy and literacy dimension).

2.3 Summary Statistics

Our sample consists of 120,448 observations, representing over 718.2 million individuals in 28 countries. Table 1 shows 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 PPP dollars to Norway at 62,399 PPP dollars—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. The distributions of the share of women 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-wage and highest-wage countries. Finally, the dataset contains between 2,854 and 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 large cross-country differences in years of schooling as well as numeracy and literacy skills. The average individual in our sample scores just above half of the available marks on each of the numeracy and literacy tests. In panels (a) and (b) of Figure 26 in Appendix A.4, we show the distribution of skills within each country, highlighting the two poorest (Ecuador and Mexico) and the two richest (Norway and USA). The average is higher in richer countries but the dispersion is similar. The skills measured by the PIAAC test are a product of individual innate talent and factors—like education—that shaped them from childhood to adulthood when they are assessed. These factors could plausibly amplify innate differences in talent, or iron them out. In the first case, countries with higher mean would have higher dispersion. In the second, the dispersion would be lower. The fact that the dispersion is similar in all countries indicates that factors like education shift the entire distribution to the right. Finally, employment shares vary widely across countries, especially among women.

Panel C shows labor demand characteristics. At this point, we just highlight the substantial dispersion in numerical and literacy skill requirement scores across jobs, the importance of which we will assess in our empirical analysis. In panels (c) and (d) of Figure 26 in Appendix A.4, we show the distribution of skill requirements within each country, highlighting the two poorest (Ecuador and Mexico) and the two richest (Norway and USA). Similar to skill scores, skill requirements are higher in richer countries. Another notable fact is the scarcity of large firms with more than 50 workers in some countries, with the lowest shares of large firms being found in Greece, Ecuador, and Spain, while the highest shares of large firms are found in the United Kingdom, Belgium, and the United States.

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[11]Appendix A.4 contains additional summary statistics by country.

Figure 1 plots the PIAAC data together with IPUMS data from the same countries and other countries across the development spectrum. The first goal of this exercise is to compare the PIAAC data to the census data to check the representativeness of our data. The second goal is to compare our sample countries to other countries in the world at different levels of development, as this will aid in placing our findings in the context of the literature.

We use data from the Jobs of the World project, which harmonizes census data from IPUMS and the Demographic Health Surveys (DHS). Most of our countries in the sample have data drawn from IPUMS.[12] Figure 1, top-left panel, plots the share of paid workers in the population against the log of GDP per capita in purchasing power parity. The grey dots are the data from the Jobs of the World database, and the red dots are from PIAAC. Reassuringly, they are very close. There is a positive relationship between the share of people in wage jobs and log GDP. This suggests that there are more jobs in rich countries. The right top panel of Figure 1 shows the average years of education, which vary between 4 and 14 worldwide. Our sample countries are at the top end of the spectrum. Even the poorest countries like Ecuador and Mexico have substantially more human capital than most of the countries in the world.

The bottom left panel of Figure 1, shows labor force participation of men and women. In all countries, women's labor force participation is lower than that of men. That is, all the points on the graph are below the 45-degree line. Our sample countries stand out for having relatively high labor force participation and, more strikingly, more gender-balanced labor force participation. That is, most of the points in the PIAAC data are close to the diagonal. Reassuringly, the PIAAC data points are close to those from the Census. The bottom right panel shows the ratio between the labor force participation of women to that of men across the development spectrum. We see the well-known U-shape, whereas the participation ratio is higher at very low, and then very high levels of development. Most of our countries are on the right-hand side of the U, at the top. That is, they are among the richest countries in the world that have the most equal participation ratio. Even the poorest countries in our sample, like Ecuador and Mexico, are past the 50% mark.

3   Meritocracy across Countries

In what follows we first investigate whether higher-income countries are more meritocratic by correlating our measures of meritocracy with GDP per capita. We then explore what underpins this correlation. We focus on three factors that have been highlighted by the literature on cross-country income differences: (1) differences in technology—broadly defined to not only include differences in machinery and equipment but also in the organization of labor—that determine match productivity; (2) differences in the endowments of worker skills and job skill requirements that determine match feasibility; and (3) differences in the extent to which idiosyncratic traits of workers and jobs

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[12]The Jobs of the World Database (JWD) is the core component of the Jobs of the World Project (JWP) available at http://jwp.iza.org that harmonizes data from National Censuses (IPUMS) and Demographic and Health Surveys (DHS). The project is part of the data-building activities of the G^2LMLIC program from the IZA Institute of Labor Economics.

Table 1: Summary Statistics across Countries

	Mean	Min	P25	P50	P75	Max
Panel A: Country Characteristics						
GDP per Capita (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.

Figure 1: Labor and Educational Outcomes across the Development Spectrum
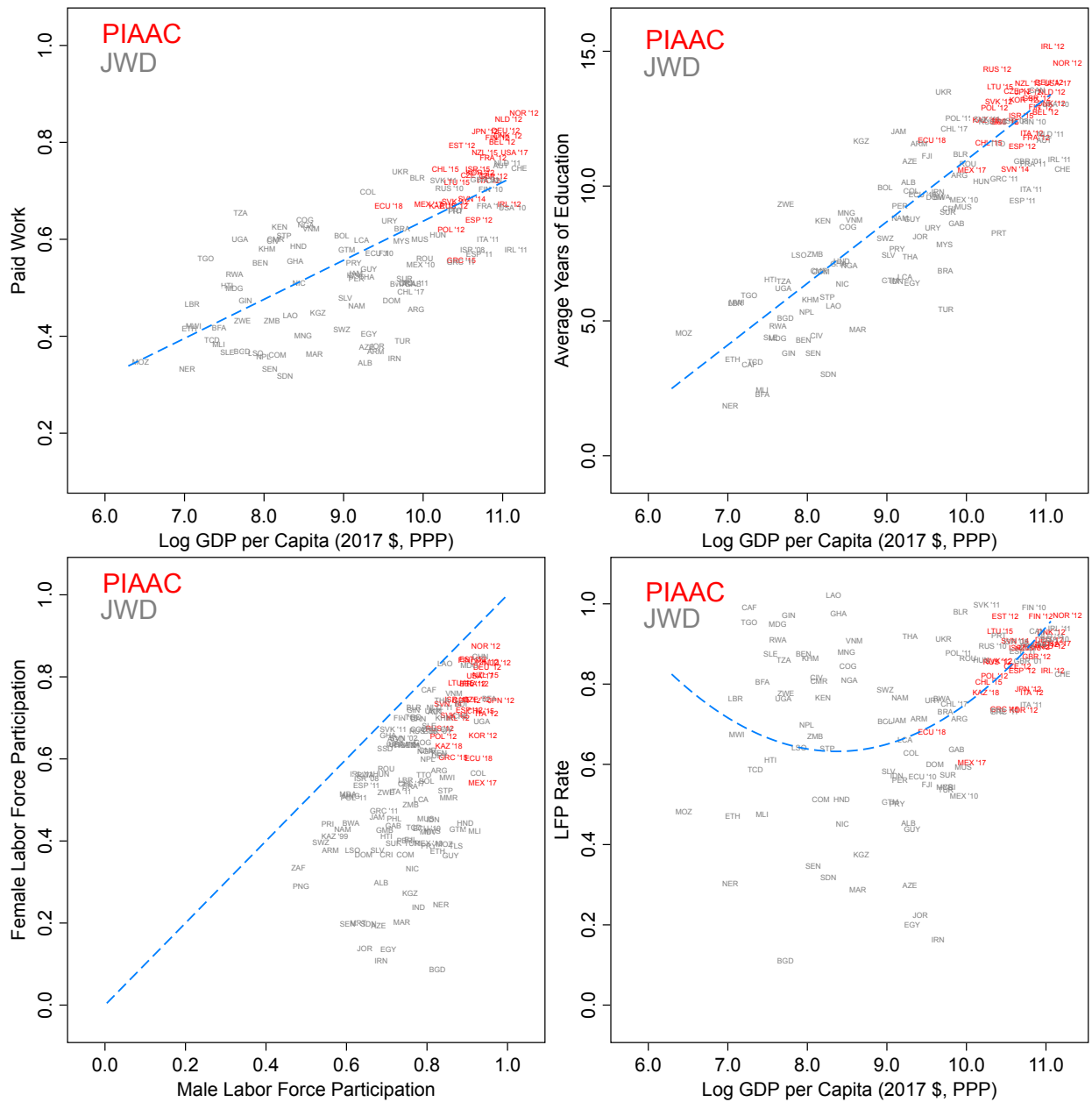
Notes: These graphs pool cross-country data from PIAAC and The Jobs of The World (JWD). The Jobs of the World Dataset harmonizes census data from National Censuses (IPUMS) and Demographic and Health Surveys (DHS) to retrieve labor market outcomes. Top-left panel plots the share of workers in paid employment as a share of total population against the log of GDP per capita in purchasing power parity. Top-right panel plots the average years of education of the population against the log of GDP per capita. The bottom left panel plots the relationship between male labor force participation (MLFP) and female labor force participation (FLFP). Labor force participation is calculated as the share of individuals working or seeking a job as a share of the total population. Lastly, the bottom right panel plots the relationship between the labor force participation rate (LFPR) and the log of GDP per capita, calculated as the share of females working or seeking jobs over the share of males working or seeking jobs. *Source:* PIAAC and Jobs of The World Dataset (JWD).

that are unrelated to productivity affect the matching process. The latter may reflect informal institutions, for instance social norms and the acceptance of corrupt behavior in hiring decisions, as well as formal institutions, such as the lacking enforcement of anti-discrimination laws or labor contracts—all factors that increase the importance of agents' non-productive attributes for their labor market outcomes.

3.1 Are Richer Countries More Meritocratic?

Meritocracy in Worker-Job Matches. Figure 2 shows that the shares of perfect and good matches, as defined in Section 2, are increasing in (log) GDP per capita, which suggests that higher-income countries have indeed more meritocratic labor markets. Figure 3, which relies on our continuous measure of meritocracy, underscores this finding through a strong negative relationship between the meritocracy gap—measured by the two-dimensional Euclidean distance between skills and skill requirements of formed matches—and GDP per capita: Workers' skills are a considerably better fit for their jobs' skill requirements in richer countries.

Figure 2: Stronger Sorting in Worker-Job Matching in Higher-Income Countries
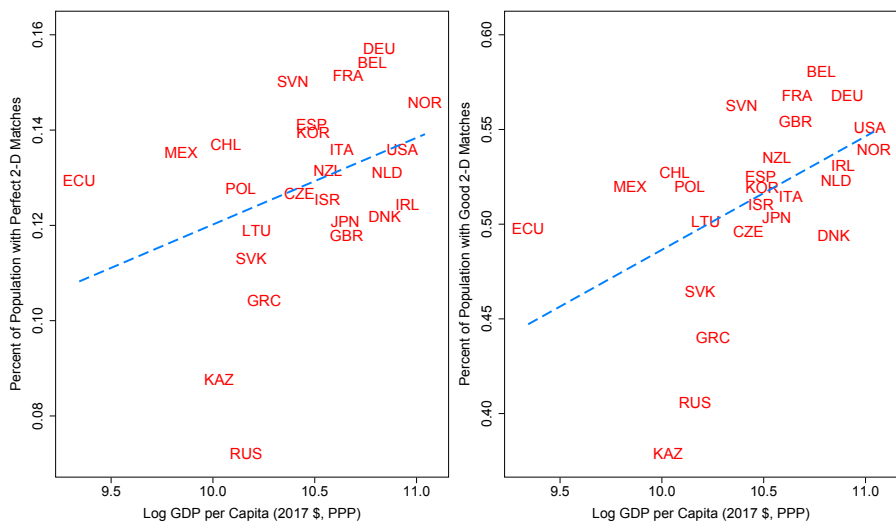
Notes: The left panel shows the share of workers whose skill quintiles in both dimensions—numeracy and literacy—are equal to the skill requirement quintiles of their job ("perfect match"). The right panel shows the share of workers whose skill quintiles in both dimensions are no more than one quintile away from the skill requirement quintiles of their job ("good match"). *Source:* PIAAC.

Two points are of note. First, we make no claims of causality. Instead, we document a rich set of empirical relationships, which are consistent with the hypothesis that meritocracy leads to economic development but equally consistent with economic development leading to meritocracy. Second, we take no stance on the implications of meritocracy on welfare. Counter to its productivity-enhancing incentive effects, meritocracy might reduce welfare by leading individuals to choose occupations, working hours, and careers that maximize their earnings but not their happiness. Moreover, by rewarding skill accumulation and skill fit, meritocracy creates inequality as it essentially rewards those lucky enough to have the right talent and the means to leverage it.

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Figure 3: Smaller Distance between Workers' Skills and their Jobs' Requirements in Higher-Income Countries
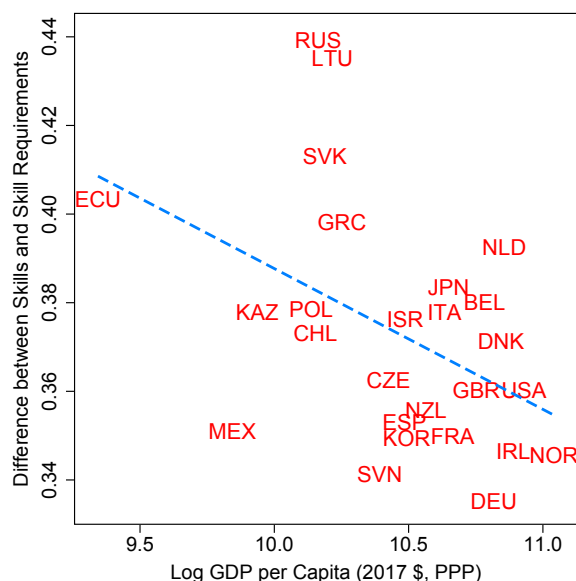

Notes: The figure plots the mean distance between workers' skills and the skill requirements of the job that they are employed in by country. Distances are computed as the L^2 norm between the 2×1 vector containing the global ranks of workers' numeracy and literacy skill quintiles and the 2×1 vector containing the global ranks of the workers' jobs' numeracy and literacy skill requirement quintiles. *Source:* PIAAC.

Meritocracy in Labor Force Participation. Table 1 shows that the rate of engagement in paid employment varies across countries and genders. To the extent that individuals who do not engage in paid employment are idle or perform tasks that require fewer skills, meritocratic selection requires the average person in the labor force to have higher skills than her counterfactual at home. Figure 4 shows the skill gap as a function of GDP. This gap is computed as the percentage difference in average skill levels between employed and unemployed individuals. Two observations emerge from this data. Firstly, the skill gap is positive in all sample countries, that is individuals are positively selected into paid employment. Secondly, there is a positive correlation between the skill gap and GDP, with the gap increasing from 1% in lower-income economies to as much as 50% in wealthier nations. Further insights are gained from splitting the data by gender. The correlation is positive for both genders but it is much stronger among men. This disparity could be attributed to the substantial barriers that women face in labor market participation in low-income countries. Such obstacles might mean that only the most highly qualified women engage in paid labor, thereby amplifying the observed skill gap in comparison to their male counterparts (Ashraf et al., 2023).

3.2 Potential Mechanisms

Mechanism 1: Endowments of Worker Skills and Job Skill Requirements. The feasibility of a given match (x, y) depends on the existence of a worker with skills x and a job with skill require-

Figure 4: More Positive Selection into the Workforce in Higher-Income Countries
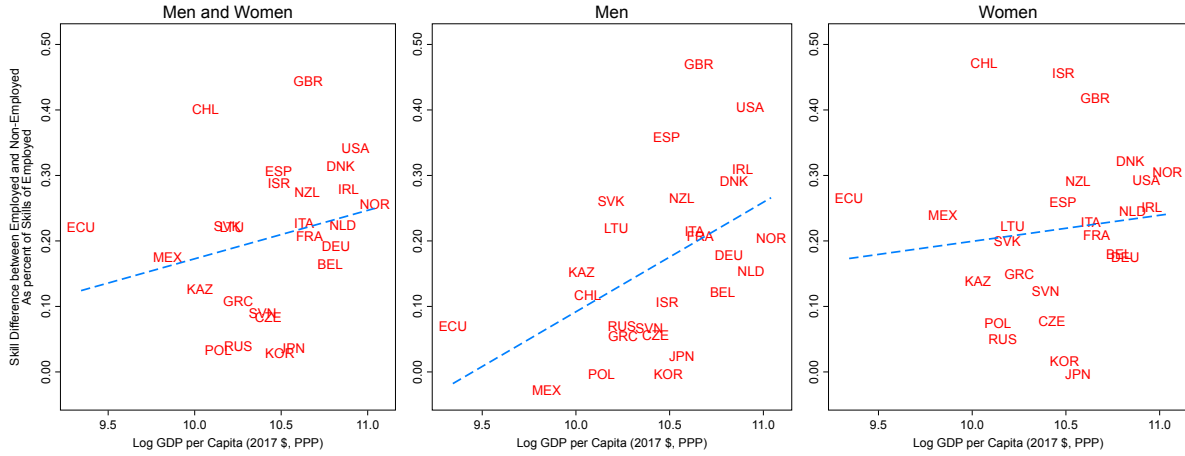
Notes: The figure plots the employed-nonemployed skill differential and GDP per capita across countries. For each individual, we average their literacy and numeracy skill scores and then compute the difference in average skill scores of the employed and the non-employed. A higher skill differential value indicates that workers with higher numeracy and literacy skills are more likely to select into employment, as opposed to remaining idle or engaging in home production. *Source:* PIAAC.

ments y. Generally speaking, the extent to which the economy's distribution of skills overlaps with that of skill requirements determines whether matches with a tight fit between worker and job traits are feasible. We note that the distribution of available skills today reflects past investments in human capital that are themselves a function of expected returns, and hence meritocracy today, but in the context of our paper we take it as given.

To compare the distributions of skill supply and demand, we first take deciles of both numeracy and literacy skills of all workers (not just the matched ones) 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 5 illustrates this approach using U.S. data. 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. Two patterns are of note. First, there are several observations outside the diagonal, indicating 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 more easily seen in the third panel, where we take the difference between the first two panels. 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. In Figure 29 in Appendix B, we report the difference for every country and there we see that lower-income countries tend to have an excess supply of skills at the lower end of the distribution and an excess demand of skills at the higher end. The opposite is true for higher-income

countries. This indicates that a upskilling the work force 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.

Next, we summarize the information contained in these figures into a scalar that also takes into account the extent of the difference between skill endowments and skill requirements in each country. Figure 6 shows the distance between the distributions of worker skills and job skill requirements against GDP per capita across countries. Within each country, the distance between skill supply and demand is computed as the L^2 norm between the 2×1 vector containing the global ranks of all workers' (i.e., irrespective of employment status) numeracy and literacy skill quintiles and the 2×1 vector containing the global ranks of all jobs' (i.e., irrespective of the worker-job assignment) numeracy and literacy skill requirement quintiles. The figure illustrates that the distance is considerably smaller, and hence the overlap of skill supply and demand larger, in higher-income countries. This is one mechanism that can lead to more meritocratic labor markets in richer countries.
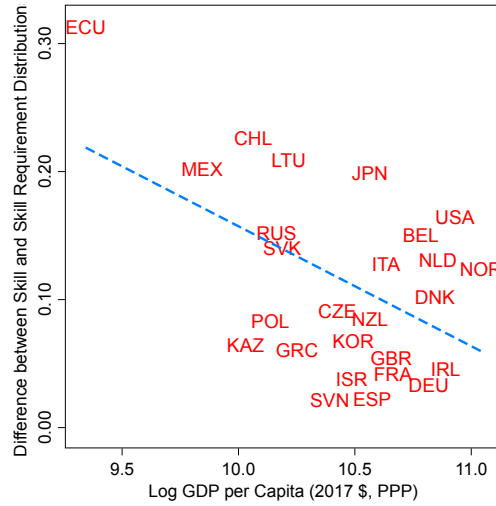
Figure 5: Worker Skills, and Job Skill Requirements in the U.S.
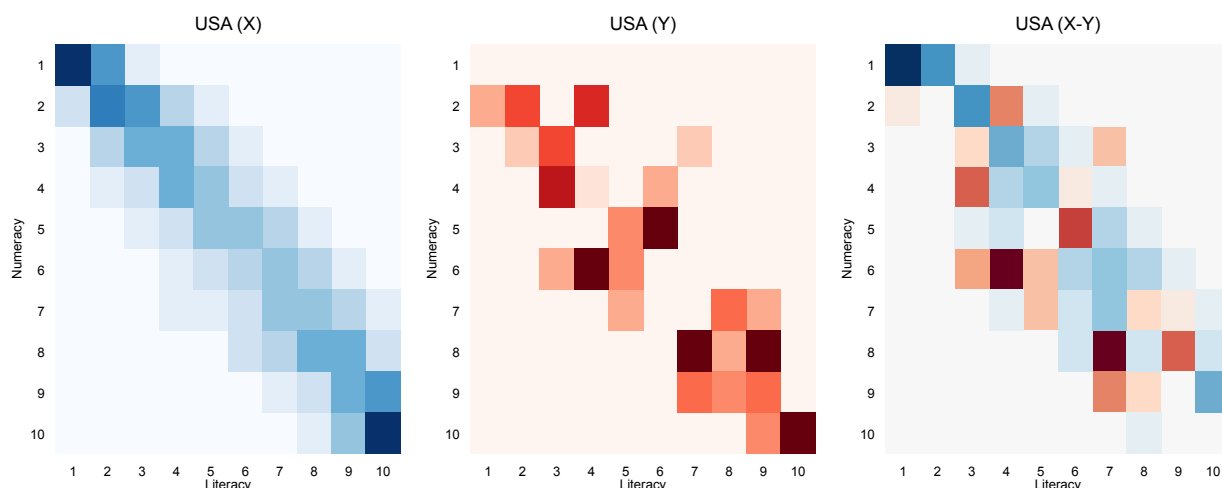
Notes: This figure shows 10×10 skill (first panel) and skill requirement (second panel) cells, based on deciles of the country's skill and skill requirement distribution. The first panel shows every combination of numeracy and literacy skills, where the color intensity is proportional to the size of 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.

Mechanism 2: Technology. The production technology determines the value of matching highly skilled workers with highly demanding jobs in the various skill dimensions. Differences in technology are a second source of cross-country heterogeneity in meritocracy and will generate a positive correlation between meritocracy and GDP if richer countries produce more complex products or production is organised in larger firms with deeper hierarchies so that the value of the right match is higher at higher rungs. While we do not observe technology or match output directly, we

Figure 6: More Aligned Worker Skills and Job Skill Requirements in Higher-Income Countries

Notes: This figure shows the distance between the distributions of person skills and job skill requirements against GDP per capita across countries. Unlike Figure 3 (and as in Figure 5), here we do not restrict the skill distribution to only employed individuals. In each country, the distance is computed as the L^2 norm between the 2×1 vector containing the global ranks of all workers' numeracy and literacy skill quintiles (i.e., irrespective of the workers' employment status) and the 2×1 vector containing the global ranks of all jobs' numeracy and literacy skill requirement quintiles. These differences are weighted by the mass of persons in each skill and skill requirement cell. *Source:* PIAAC.

can obtain suggestive evidence under the assumption that workers are paid wages in proportion to their marginal product. This way we can provide evidence on the relevance of this channel by examining the correlation between wages and our meritocracy measures.

Figure 7 examines the relationship between wages and the meritocracy gap across countries. For each country, we estimate a regression of log(wage) on the distance measure between skills and skill requirements in existing matches and plot the estimated coefficient against GDP per capita. Since a greater distance implies a larger meritocracy gap, the negative correlation between distance and wages in high-income countries is suggestive of a technology that puts a larger penalty on the misallocation of skills. Figure 7 supports the notion that the misallocation of worker skills to job skill requirements is more costly in richer countries. Stated differently, cross-country differences in technology indicate that meritocracy is more valuable in richer countries. This raises the possibility of a link running from development to meritocracy.

Mechanism 3: Matching Frictions. The third channel that can shape a country's degree of meritocracy and create a link between meritocracy and national income are frictions that occur in the matching process. In a perfect meritocracy, the only factors that determine worker-job sorting are worker skills and job skills requirements. In practice, however, idiosyncratic factors unrelated to productivity such as social connections or wealth likely affect the allocation of workers to jobs.

While there is no reason to believe *a priori* that the distribution of these traits in the population varies systematically with national income, the extent to which they affect the matching process might do. For example, the enforcement anti-discrimination laws might be weaker in poorer

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Figure 7: Higher Returns to Matching in Higher-Income Countries
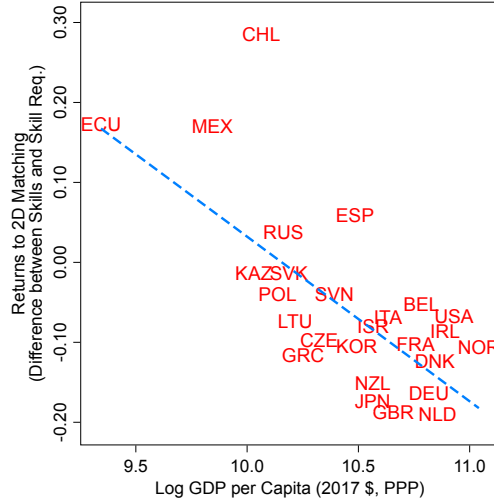
Notes: This figure shows that richer economies reward better quality of matches (i.e. those with lower differences between worker and corresponding job attributes) more. The *y*-axis plots coefficient β from the regression $\text{Log(wage)}_i = \alpha + \beta\text{Diff}_i + \gamma\text{MincerControls}_i + \varepsilon_i$, where Diff_i is computed as the L^2 norm between the 2×1 vector containing the global ranks of workers' numeracy and literacy skill quintiles and the 2×1 vector containing the global ranks of the workers' jobs' numeracy and literacy skill requirement quintiles. The lower is Diff_i, the higher the quality of the match. MincerControls_i include education, experience, and the square of experience. *Source:* PIAAC.

countries, or corruption more tolerated. To the extent that these factors are systematically more relevant in low-income countries, they could explain the relationship between meritocracy and national income that we observe in the data.

To assess this channel empirically, we exploit the insight that when matching is purely meritocratic, then it is solely determined by workers' and jobs' productive attributes and those traits should explain the entire variation in wages. That is, any two workers with the same skills are matched to jobs with the same skill requirements and earn the same wage—there is no conditional wage dispersion. To estimate this conditional wage dispersion, we allocate each worker into their respective global skill and skill requirement quintile and then form cells by interacting these traits. For each country, we estimate the share of log wages that is not explained by these cell dummies. This is a measure of meritocratic failure because the less the skill-skill requirement cells can explain, the larger the influence of other factors unrelated to productivity in determining pay. Figure 8 illustrates that our measure of meritocratic failure is negatively correlated with log GDP per capita. In lower-income countries, factors other than merit play a more significant role in determining wages and—as we infer—the worker-job matching. Thus, larger matching frictions are a potential third channel that renders low-income countries less meritocratic.

In summary, we find that labor markets are more meritocratic in richer countries, reflected by a smaller distance between workers' skills and their jobs' skill requirements, as well as by more positive selection into the labor force. We have provided evidence on three mechanisms that might underpin these correlations. First, the overlap between workers' skills and jobs' skill requirements is larger in richer countries, which implies that it is easier to form a good match, other things

Figure 8: Lower Residual Wage Dispersion in Higher-Income Countries
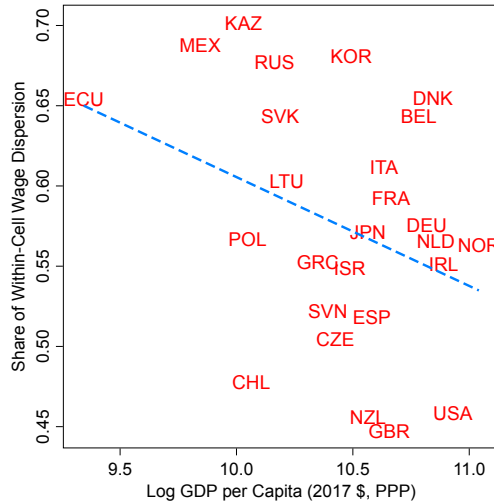
Notes: The figure plots the share of wage dispersion not explained by skills, skills requirements, and the match between the two. We first construct global quintiles for each dimension of skills and skill requirements. We then allocate each worker into cells formed by interacting these skill and skill requirement quintiles. The *y*-axis plots our measure of meritocratic failure, which is the share of within-cell wage dispersion, estimated as the ratio of the residual sum of squares over the total sum of squares from the following regression: Log Wage$_i = \alpha + \sum \beta_i \mathbb{1}\{\text{Cell}_i\} + \varepsilon_i$. *Source:* PIAAC.

equal. Second, the wage premium for a good match is higher in richer countries, which implies that there is a stronger incentive for individuals to look for jobs that closely match their skills. Third, worker skills and job skill requirements explain a larger share of wage dispersion in richer countries. This implies that idiosyncratic factors that are unrelated to productivity and reflect frictions play a smaller role in the matching process. These are equilibrium relationships and in the absence of an exogenous shock to any of these factors (endowments, technology, frictions) it is impossible to establish the existence and direction of causal links. In what follows we model how the three factors interact in shaping the allocation of workers to job. We then structurally estimate this model to quantify the relative importance of the different channels, and examine policy counterfactuals that aim to establish the sources of meritocracy and its consequence for economic development.

4   A Model of Meritocracy in the Labor Market

Motivated by these empirical facts, we now study the sources and consequences of meritocracy, or worker-job sorting in the labor market. To this end, we develop an equilibrium matching model in which the sorting of workers into jobs is determined by three factors, which we take as model primitives: endowments, technology, and idiosyncratic matching frictions.We are interested in the extent to which cross-country heterogeneity in these factors shapes worker-job sorting and thereby aggregate output, wage inequality, and the returns to skills. Figure 9 provides a schematic overview of the model.

Our model incorporates multidimensional heterogeneity (Lindenlaub, 2017) into the seminal

matching framework of Choo and Siow (2006) applied to a labor market context. Importantly, perfectly assortative matching is impeded by idiosyncratic *matching wedges*, whose distribution is guided by a country-specific scale parameter. Whereas the scale of the distribution of idiosyncratic heterogeneity in Choo and Siow (2006) is not identified and subject to an arbitrary normalization, the country-specific scale parameter in our model can be identified based on our labor market microdata. We also refer to these matching wedges as "idiosyncratic frictions" but 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.

Figure 9: Model Overview
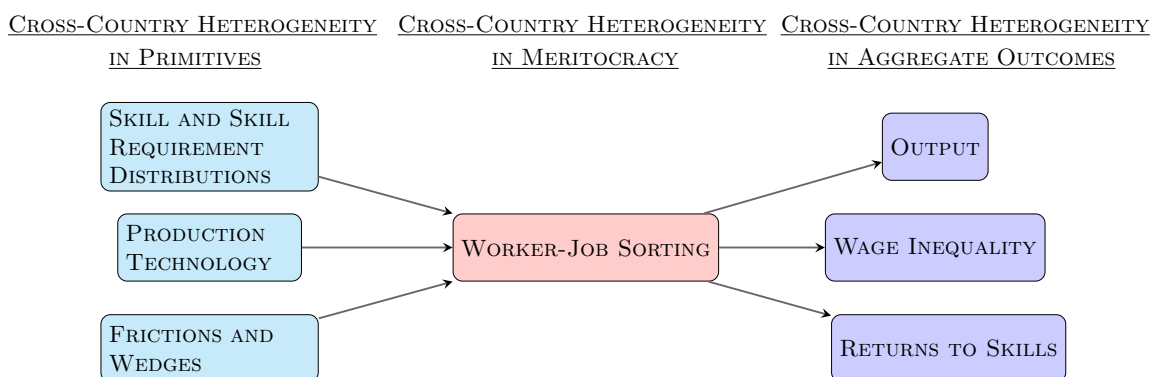
4.1 Environment

The world consists of a discrete number $N^C \in \mathbb{N}^+$ of countries, each with their own labor market. For simplicity, there is no interaction between different countries' labor markets in our baseline analysis—in an extension, we allow for regional or global labor markets. Each labor market is characterized by a country-specific skill distribution among workers, a country-specific skill requirement distribution among jobs, a country-specific relative mass 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 number of unemployed workers and idle jobs on the other.[13] Assuming transferable utility, worker-job matches maximize *total match surplus*, which consists of the sum of economic *match-type-specific surplus* and nonpecuniary *idiosyncratic surplus*. The former reflects systematic

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

gains from trade between a certain type of worker and a certain type of job. We interpret the latter as a reduced form for idiosyncratic matching frictions preventing the output-maximizing allocation of talent. Total match surplus is then split into a transfer to the worker in the form of a wage and a transfer to the job in the form of profits.

Endowments. On the labor supply side, there is a discrete number $N^W \in \mathbb{N}^+$ of workers, indexed by i, who are risk-neutral and characterized by their numeracy skill $x_n \in \mathbb{R}^+$, literacy skill $x_\ell \in \mathbb{R}^+$, and gender $x_g \in \{f, m\}$, which can be female (f) or male (m). Worker types $x = (x_n, x_\ell, x_g) \in \mathcal{X}$ follow a distribution $H(\cdot)$ with associated probability mass function $(h_x)_{x \in \mathcal{X}}$ and normalized total mass $m^W = 1$. On the labor demand side, there is a discrete number $N^J \in \mathbb{N}^+$ of jobs, indexed by k, which are risk-neutral and 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 distribution $G(\cdot)$ with associated probability mass function $(g_y)_{y \in \mathcal{Y}}$ and total mass $m^J > 0$.

Technology. In each worker-job match, output $f(x_n, x_\ell, y_n, y_\ell, y_s)$ depends on the productive attributes of the worker, (x_n, x_ℓ), and those of the job, (y_n, y_ℓ, y_s). In turn, the payoff of an unmatched worker of type x is given by $f_{x\varnothing}(x)$, where $y = \varnothing$ indicates the worker's choice to remain nonemployed. Similarly, the payoff of an unmatched job of type y is given by $f_{\varnothing y}(y)$, where $x = \varnothing$ indicates the job remaining idle. Note that workers' outside options are not only skill- but also gender-specific, which accommodates gender-specific comparative advantage in home production. In what follows, we assume $f_{\varnothing y}(y) = 0$.[14]

Idiosyncratic Matching Frictions. Idiosyncratic matching frictions give rise to heterogeneity in sorting along the extensive margin (i.e., employment versus nonemployment) as well as imperfect matching on the intensive margin between workers and jobs by preventing the output-maximizing allocation. Specifically, we assume that matching is guided not only by economic match-type-specific surplus but also by nonpecuniary considerations, which we model as idiosyncratic matching wedges in the form of random noise entering individual workers' and jobs' preferences. We denote by δ_{iy} the preference of worker i for job type $y \in \mathcal{Y} \cup \varnothing$; and similarly, by δ_{xk} the preference of job k for worker type $x \in \mathcal{X} \cup \varnothing$. We assume that these idiosyncratic matching wedges follow an Extreme Value (EV) Type I, or Gumbel maximum, distribution:

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

---

[14]That the value of an idle job equals zero is motivated by a free-entry argument, according to which job creation drives the value of a vacant job to zero. This yields a necessary normalization in our context since $f_{\varnothing y}(\cdot)$ is otherwise not identified.

Scale parameter $\sigma \in \mathbb{R}^+$ determines the extent of idiosyncratic matching frictions: $\sigma \to 0$ results in frictionless matching based on output maximization, as guided by the relative strength of productive worker-job complementarities, while $\sigma \to \infty$ results in random matching, independent of the production structure.

While we refer to the matching wedges, δ_{iy} and δ_{xk}, as "idiosyncratic frictions," we think of them as a reduced form for any factor preventing the output-maximizing allocation. Idiosyncratic matching frictions may reflect malignant reasons for mismatch such as information asymmetries (Stigler, 1961), coordination failures (Roth and Xing, 1997), nepotism (Akcigit et al., 2021), and corruption at the hiring stage (Weaver, 2021), but they may also reflect more benign reasons such as a desire to live close to one's parents (Chan and Ermisch, 2015).[15] Regardless of the specific interpretation, these matching wedges are separate from forces that affect the allocation and transfers based on match-type-specific output alone. We focus on 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 enables an accounting exercise within an equilibrium matching model, in the spirit of the literature on distortionary wedges in other contexts (Chari et al., 2007; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Hopenhayn, 2014; Jones et al., 2018).

4.2 Decisions

Matching is the outcome of a process by which jobs choose which worker to hire or to remain idle, and workers choose which job to work in or to remain nonemployed.

Jobs' Decisions. Given the idiosyncratic realizations of jobs' 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 in order to maximize its payoff:

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

where $\pi(x,y) := f(x_n, x_\ell, y) - w(x,y)$ are economic profits of a job of type y that matches with a worker of type x. Based on well-known results from discrete-choice models with extreme-value shocks (e.g., McFadden, 1973; Choo and Siow, 2006), the *conditional choice probabilities* associated with optimizing behavior of job type y are

$$\mu_{x|y} := \frac{\mu^J(x,y)}{g_y m^J} = \frac{\exp((f(x_n, x_\ell, y) - w(x,y))/\sigma)}{\exp(f_{\varnothing y}(y)/\sigma) + \sum_{\tilde{x} \in \mathcal{X}} \exp((f(\tilde{x}_n, \tilde{x}_\ell, y) - w(\tilde{x}, y))/\sigma)}, \tag{1}$$

$$\mu_{\varnothing|y} := \frac{\mu^J(\varnothing, y)}{g_y m^J} = \frac{\exp(f_{\varnothing y}(y)/\sigma)}{\exp(f_{\varnothing y}(y)/\sigma) + \sum_{\tilde{x} \in \mathcal{X}} \exp((f(\tilde{x}_n, \tilde{x}_\ell, y) - w(\tilde{x}, y))/\sigma)}, \tag{2}$$

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[15]In a similar spirit, Manski and Sheshinski (2023) interpret the idiosyncratic utility components in a discrete-choice model as deviations from the planner's welfare-maximizing allocation.

where $\mu^J(x,y)$ and $\mu^J(\emptyset,y)$ are the measures of type y jobs who choose worker type x and remain idle, respectively.

Workers' Decisions. Similarly, given the idiosyncratic realizations of workers' 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 in order to maximize her payoff:

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

Workers' optimizing behavior yields the conditional choice probabilities for worker type x:

$$\mu_{y|x} := \frac{\mu^W(x,y)}{h_x m^W} = \frac{\exp(w(x,y)/\sigma)}{\exp(f_{x\emptyset}(x)/\sigma)+\sum_{\tilde{y}\in\mathcal{Y}}\exp(w(x,\tilde{y})/\sigma)} \tag{3}$$

$$\mu_{\emptyset|x} := \frac{\mu^W(x,\emptyset)}{h_x m^W} = \frac{\exp(f_{x\emptyset}(x)/\sigma)}{\exp(f_{x\emptyset}(x)/\sigma)+\sum_{\tilde{y}\in\mathcal{Y}}\exp(w(x,\tilde{y})/\sigma)}, \tag{4}$$

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

4.3 Equilibrium Definition and Characterization

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 mass of type (x,y) matches is

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

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

Definition 1 (Equilibrium). *An equilibrium consists of matching masses $(\mu(x,y),\mu(x,\emptyset),\mu(\emptyset,y))$ 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 (1)–(2) for jobs and (3)–(4) for workers; and*

- *labor market clearing (5) holds.*

Equilibrium total match surplus is the sum of the match-type-specific component due to economic output net of outside options and the nonpecuniary idiosyncratic component that reflects matching wedges:

$$s(x_i,y_k) := f(x_n,x_\ell,y) - f_{x\emptyset}(x) - f_{\emptyset y}(y) + \delta_{xk} + \delta_{iy}. \tag{6}$$

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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.

We now state a number of useful model properties, the detailed derivations of which are relegated to Appendix C.1. By well-known results, we can use 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, along with labor market clearing (5) to obtain the following expression for the *economic match-type-specific surplus* of match (x,y):

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

We call the surplus in (7) match-type-specific because it captures output net of agents' outside options, both of which depend on the types of matched worker and job types. Match-type-specific surplus does not include the two-sided idiosyncratic matching wedges, which differ across agents of the same type. Clearly, match-type-specific surplus is positively related to the frequency of (x,y)-type matches, $\mu(x,y)$.

To obtain equilibrium *match-type-specific wages*, $w(x,y)$, we use the worker's relative choice probability $\mu(x,y)/\mu(x,\varnothing)$, and market clearing along with the matching frequency, $\mu(x,y)$, from equation (7):

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

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 economic 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, jobs receive *match-type-specific profits* given by

$$\pi(x,y) := f(x_n, x_\ell, y) - w(x,y) = \frac{\sigma}{2} \log \left(\frac{\mu(x,\varnothing)}{\mu(\varnothing,y)} \right) + \frac{f(x_n, x_\ell, y) - f_{x\varnothing}(x) + f_{\varnothing y}(y)}{2} \tag{9}$$

In addition, we obtain equilibrium *idiosyncratic wages*, $w(x_i, y_k)$, which are based on total surplus $s(x_i, y_k)$—i.e., not just the economic match-type-specific part $\tilde{f}(x,y)$—and thus allow for wage variation within type (x,y) matches across workers indexed by i and across jobs indexed by k. We show in Appendix C.1 that, under our assumptions, worker i of type x receives the following *idiosyncratic wage* from job k of type y:

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

That is, worker i receives a payoff that consists of the match-type-specific 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 type y jobs. 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 worker i's wage up to the point of worker i enjoying the full value of the idiosyncratic surplus component δ_{iy}.

Equilibrium Existence and Uniqueness. The existence of an equilibrium follows from an extension 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. To start, note that the measure of matches $\mu(x, y)$ 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 dependence explicit, we denote the matching frequency for any (x, y)-match by $M_{xy}(\mu(x, \varnothing), \mu(\varnothing, y))$. Rewriting the matching frequency in (7) gives

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

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

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

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

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. This guarantees that an iterative procedure operating on (12)–(13) monotonically converges to a solution for $(\mu(x, \varnothing))_{x \in \mathcal{X}}$ and $(\mu(\varnothing, y))_{y \in \mathcal{Y}}$, based on standard results concerning the convergence of monotone and bounded sequences. This algorithm, called *Iterative Projective Fitting Procedure (IPFP)*, provides a computationally efficient solution to high-dimensional matching problems.[16] Plugging the solution for $(\mu(x, \varnothing))_{x \in \mathcal{X}}$ and $(\mu(\varnothing, y))_{y \in \mathcal{Y}}$ into $M_{xy}(\mu(x, \varnothing), \mu(\varnothing, y))$, we obtain the equilibrium matching frequencies $(\mu(x, y))_{x \in \mathcal{X}, y \in \mathcal{Y}}$. Similarly, we can use $(\mu(x, \varnothing))_{x \in \mathcal{X}}$ and $(\mu(\varnothing, y))_{y \in \mathcal{Y}}$ in combination with equations (8)–(10) to solve for the equilibrium values of match-type-specific wages $w(x, y)$ and idiosyncratic wages $\tilde{w}(x_i, y_k)$. This demonstrates that an equilibrium exists.

Moreover, uniqueness of equilibrium follows from Theorem 2 in Galichon et al. (2019), which builds on the arguments in Berry et al. (2013). Uniqueness crucially hinges on the assumption that the distributions of idiosyncratic components δ_x and δ_y are absolutely continuous and have full support—properties that are satisfied by the EV distribution we assume. While in matching

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

problems with discrete types, like ours, uniqueness is not generally obtained absent idiosyncratic matching frictions (i.e., $\sigma \to 0$), the presence of idiosyncratic frictions (i.e., $\sigma > 0$) generates preference heterogeneity that overcomes the problems stemming from the coarseness of worker and job types. Intuitively, in the presence of idiosyncratic frictions, 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 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.

Meritocracy. In our model, *meritocracy* referees to the degree to which workers with different skills sort into jobs with different skill requirements such that the economy's aggregate output is maximized. To formalize this notion, we denote the economy's parameter vector by $\theta :=$ $\left(H(\cdot), G(\cdot), m^J, \sigma, f_{x\varnothing}(\cdot), f(\cdot)\right)$, the set of actual worker-job matches by $\mathcal{A}(x,y)$ and the set of worker-job matches that results in the frictionless case of $\sigma \to 0$ by $\mathcal{A}^*(x,y)$. We then define an economy's *meritocracy index* as follows:

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

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

Meritocracy index $\mathcal{M}(\theta)$ is determined by the three groups of model primitives in θ, which all impact the extent of worker-job sorting: idiosyncratic matching frictions or labor wedges, technology and endowments.

A lower level of σ (i.e., less dispersion in labor wedges) is associated with more pronounced worker-job sorting along their productive attributes (x,y), which narrows the gap between actual and potential output and thus yields a higher meritocracy index. The meritocracy index equals one, $\mathcal{M}(\theta) = 1$, if the labor market is perfectly meritocratic, in the sense that no idiosyncratic factors beyond workers' and jobs' productive attributes impact sorting patterns (i.e., $\sigma \to 0$).[17] In contrast, $\mathcal{M}(\theta) < 1$ when idiosyncratic factors influence the worker-job allocation (i.e., $\sigma > 0$).

When frictions vanish, $\sigma \to 0$, actual and potential output coincide, $\mathcal{M}(\theta) = 1$, independently of a country's technology and endowments. However, in the presence of (positive and finite) frictions, $\sigma > 0$, technology and endowments also impact the gap between actual and potential output by influencing the incentives to sort on productive attributes: A technology f that features greater relative worker-job complementarities in the various dimensions yields larger returns to labor market sorting. This, in turn, improves the allocation of skills to skill requirements for a

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[17]Note that in the frictionless economy, $\sigma \to 0$, the equilibrium is unique in terms of the economic surplus generated, which is what matters here (but not in terms of wages).

given level of frictions σ and narrows the gap between actual and potential output. The meritocracy index increases as a consequence.

In turn, a better alignment of the economy's endowments of worker skills and job skill requirements is also associated with more sorting on (x, y): A good fit between the economy's skill supply and demand tends to increase the returns to sorting at any given level of frictions σ and thereby incentivizes workers to seek matches that better fit their skills—simply because more suitable jobs are available. This again tends to increase the meritocracy index.[18]

In sum, the lower a country's meritocracy index, the larger is its output loss due to either frictions or the lack of incentives to sort that stems from technology or endowments.

We say that an economy is more meritocratic if it has a higher meritocracy index, $\mathcal{M}(\theta)$. In a meritocratic economy, only the productive worker and job attributes impact the labor market allocation. Beyond this, the identity of workers and jobs does not matter.

5 Identification

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

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

where $H(\cdot)$ is the distribution of worker types, $G(\cdot)$ 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 value of nonemployment, and σ is the dispersion of labor wedges or, equivalently, the degree of matching frictions. Note that we normalize both the overall mass of workers, $m^W = 1$, and the production value of idle jobs, $f_{\varnothing y} = 0$, so neither of them appear in θ. The parameter space Θ is defined by placing natural bounds on all entries of θ. For the purpose of our identification result, we normalize the output of matches involving the lowest worker skill types $(\underline{x}_n, \underline{x}_\ell)$, where $\underline{x}_n := \min x_n$ and $\underline{x}_\ell := \min x_\ell$, to be $f(\underline{x}_n, \underline{x}_\ell, y_n, y_\ell, y_s) = 0$ for all $y = (y_n, y_\ell, y_s)$.[19]

Proposition 1. *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-match-type wage dispersion, and the aggregate profit share.*

Proof. See Appendix D.1. $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ □

Here, we discuss the identification of each group of model parameters—endowments, frictions and technology—focusing on the intuition behind the result in Proposition 1. We proceed in three steps.

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[18]Note that in the second and third cases if improved technology or more aligned endowments, optimal output in the denominator of the meritocracy index is also affected, but the effects on actual output in the numerator tend to dominate the effects on potential output in the denominator as we show in the simulated model below.

[19]Since we do not observe idle jobs, one normalization is necessary to identify the absolute level of match output—an issue that does not arise in marriage market applications of this model as the single rates of both men and women are observed.

First, regarding agents' endowments, since $H(\cdot)$ and $G(\cdot)$ are distributions over observable worker and job attributes, they are identified based on the empirical worker and job shares with different attributes.[20] In turn, the relative mass of jobs, m^J, is identified based on the aggregate profit share.[21]

Second, regarding the idiosyncratic matching frictions, the scale parameter of the distribution of labor wedges, σ, is identified based on wage dispersion within cells defined by (x, y)-type matches (building on the insights of Salanié, 2015). In a frictionless world (i.e., $\sigma \to 0$), any two workers of the same type x are matched to the same job type y and earn the same wage, so there is no wage dispersion within (x, y) cells. In the presence of matching frictions (i.e., $\sigma > 0$), there is misallocation of workers across jobs because idiosyncratic match surplus components matter for match formation. As a result, different workers of the same x type working in jobs of the same y type are characterized by different match surplus and thus wages. Thus, wage dispersion within (x, y) cells is monotonically increasing in the scale parameter of the distribution of labor wedges, σ. No other model parameter affects wage dispersion within (x, y) cells. Therefore, the degree of within-(x, y)-cell wage dispersion identifies σ.

Third, technology $(f, f_{x\varnothing})$ is identified based on observed matching patterns. Consider the outside option of workers. It is identified for each x based on the worker's probability of staying nonemployed relative to choosing a match with some job type y. This (relative) choice probability depends on the wage that can be obtained in that match (observed), the degree of labor market frictions (identified above), and the worker's outside option, thereby pinning down $f_{x\varnothing}$. In turn, for given distributions (G, H) and frictions σ, we can identify production function f from matching patterns of a given job type y with different types of workers. To do so we make use of our assumption that the least productive worker type $(\underline{x_n}, \underline{x_\ell})$ produces zero output with all job types y, $f(\underline{x_n}, \underline{x_\ell}, y) = 0$. Then the probability that a job of type y matches with a worker of type x relative to matching with the least productive worker depends on the output of that match, $f(x_n, x_\ell, y)$, its wage $w(x, y)$ (observed) and friction σ (identified above), thus pinning down $f(x_n, x_\ell, y)$ for each worker-job pair $(x, y) \in \mathcal{X} \times \mathcal{Y}$.

6 Estimation

We estimate our model separately on each of $N^C = 28$ countries, for which we have comprehensive microdata from the PIAAC survey. In doing so, we allow all model parameters—and thus endowments, technology, and 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 underlying Proposition 1.

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[20]Note that we identify $G(\cdot)$ of the distribution of *filled* jobs since we do not observe vacancies in our data. Our identifying assumption is that the distributions of filled and unfilled jobs are identical in a given country.

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

6.1 Functional-Form Assumptions

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

Endowments. We obtain the distributions of worker skills and job skill requirements directly from the data and here describe our discretization approach. 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 country-specific quantile of a given worker skill or job skill requirement a value corresponding to its global rank in that dimension. In addition, we classify workers into 2 gender groups, $x_g \in \{f, m\}$, 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.[22] For workers, since we observe both nonemployed and employed individuals in the PIAAC survey, this gives us 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 types. To this end, we assume that the unobserved population of all—i.e., idle and filled—job types is congruent to the distribution of filled jobs, which we observe in the PIAAC survey.[23] As a result, we obtain probability mass functions over 50 worker types, $(h_x)_{x \in \mathcal{X}}$, and 50 job types, $(g_y)_{y \in \mathcal{Y}}$.

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:

$$
\begin{aligned}
f(x, y) &= \alpha_{nn} x_n y_n + \alpha_{n\ell} x_n y_\ell + \alpha_{ns} x_n y_s + \alpha_{\ell n} x_\ell y_n + \alpha_{\ell\ell} x_\ell y_\ell + \alpha_{\ell s} x_\ell y_s \\
&= A \big(x_n y_n + \hat{\alpha}_{n\ell} x_n y_\ell + \hat{\alpha}_{ns} x_n y_s + \hat{\alpha}_{\ell n} x_\ell y_n + \hat{\alpha}_{\ell\ell} x_\ell y_\ell + \hat{\alpha}_{\ell s} x_\ell y_s \big)
\end{aligned}
\tag{15}
$$

This production function interacts worker skills (x_n, x_ℓ) with job attribute (y_n, y_ℓ, y_s). A worker's gender x_g does not directly affect output.[24] The 6 parameters $(\alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s})$ indicate the extent of complementarities or substitutabilities in production between the various worker and job attributes. Thus, they crucially shape the equilibrium matching patterns. Equation (15) defines *total factor productivity (TFP)* equal to the complementarity between worker numeracy skills and job numeracy skill requirements, $A := \alpha_{nn}$, while $(\hat{\alpha}_{n\ell}, \hat{\alpha}_{ns}, \hat{\alpha}_{\ell\ell}, \hat{\alpha}_{\ell n}, \hat{\alpha}_{\ell s})$ are all relative to the value of TFP A.

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[22]The number of grid points for both workers and jobs is chosen to balance two considerations: On the one hand, we want to capture the rich worker and job heterogeneity present in the data; on the other hand, we want the number of workers (jobs) of each skill (skill requirement) type to be sufficiently large to avoid problem in estimation, where we rely on wage dispersion conditional on match types (x, y).

[23]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 and alternatives to the exclusion restrictions commonly imposed in this literature.

[24]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 advantage in home production.

In terms of the outside options, we proceed as follows. On the worker side, we allow for a flexible value of home production, $f_{x\varnothing}(x_n, x_\ell, x_g)$, which we nonparametrically estimate across 6 groups of worker types consisting of 3 broad skill groups interacted with 2 gender groups.[25] 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, which circumvents the need to identify this object based on our data, can be motivated by a free-entry argument, whereby job creation drives the value of a vacant job to zero.[26]

Idiosyncratic Matching Frictions. Consistent with Section 4, matching frictions are modeled in the form of idiosyncratic matching wedges, δ, that impact the worker-job allocation and are assumed to follow an Extreme Value (EV) Type I distribution.

6.2 Estimation Procedure

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

$$\theta = \left((h_x)_{x \in \mathcal{X}}, (g_y)_{y \in \mathcal{Y}}, m^J, \alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s}, (f_{x\varnothing}(i, x_g))_{i \in \{1,...,3\}, x_g \in \{f,m\}}, \sigma \right).$$

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 country-specific worker and job distributions, $(h_x)_{x \in \mathcal{X}}$ and $(g_y)_{y \in \mathcal{Y}}$, outside of the model. In the second step, we use the model to estimate the remaining 14 parameters based on the *simulated methods of moments (SMM)*. For each country, this involves finding these 14 parameters which, for a given vector of data-based moments $\mathcal{M}^d$ and a vector of model-based moments $\mathcal{M}^m(\theta)$ as a function θ, minimizes some objective function $\Omega(\mathcal{M}^m(\theta), \mathcal{M}^d)$. Here, $\mathcal{M}^m(\theta)$ and $\mathcal{M}^d$ 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 to pin down our parameters are tightly linked to our identification argument in Proposition 1.

To estimate the scale parameter of labor wedges, σ, we make use of 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). Guided by our identification argument, we use the share of the within-worker-job-cell dispersion of log wages out of overall log-wage dispersion to pin down the degree of matching frictions relative to TFP σ/A. And we use an additional moment that is sensitive to levels rather than relative magnitudes, namely the mean log wage in PPP dollars, to inform the level of TFP, A, and thus the level

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[25]Categorizing workers into broad skill groups reduces the complexity 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 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.

[26]In theory, one could let the value of an idle job vary freely, analogously to our approach to estimating workers' value of nonemployment. In practice, however, the lack of vacancy data by job types in conventional labor market data prevents us from separately identifying this object.

of the scale parameter, σ.[27] We then choose 6 gender- and skill-specific nonemployment rates to pin down workers' outside options $f_{x\varnothing}(x)$; 6 moments reflecting the matching patterns between workers and jobs to pin down the parameters of production technology $f(\cdot)$; and 1 moment reflecting the share of profits in aggregate value added to inform the relative job mass m^J.[28]

In summary, our estimation procedure solves for the parameter vector $\theta^* \in \Theta$ such that

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

We set the objective function in equation (16) equal to the weighted sum of squared percentage differences between 15 pairs of moments from the parameterized model and the data

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

where we form percentage deviations between model and data moments by applying the *Hadamard division*, here denoted by the symbol $\oslash$.[29] Finally, $\mathbf{W}$ is a 15-by-15 weighting matrix, which we set equal to the identity matrix—i.e., we attach equal weight to each of the 15 moments. We solve (16) by using first a global optimization algorithm, followed by a local optimization algorithm that refines the global solution. For details of the numerical solution algorithm, see Appendix E.4.

6.3 Estimation Results

We now present how the parameter estimates vary across countries and the model fit. We then validate our model against untargeted data moments, including cross-country patterns in aggregate output, skill returns, wage inequality, and worker-job sorting.

Parameter Estimates. Figure 10 shows our estimates of the relative importance of matching frictions, measured as the scale parameter of the labor wedge distribution relative to TFP, σ/A, in each country. This ratio is the relevant proxy for an economy's matching frictions as it captures how much weight in the matching decisions of workers and jobs is put on idiosyncratic factors relative to productive attributes that enter output. We find that matching frictions are considerably higher in lower-income countries. For example, Ecuador, which is the lowest-income country in the PIAAC data, faces matching frictions that are around four times as high compared to the United States or Norway, which are the highest-income countries in the PIAAC data. These estimates directly reflect the empirical within-cell wage dispersion across countries that we documented in Figure 6 in Section 3. Through the lens of our model, this finding suggests that worker-job matching is closer to random in lower-income countries.

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[27] Proposition 2 in Appendix E.1 highlights an important homogeneity property of our model, which implies that a set of target moments comprised of workers' and jobs' choice probabilities (i.e., sorting patterns), log wage dispersion conditional on match (x, y), and the profit share pin down the degree of matching frictions relative to TFP, σ/A.

[28] See Appendix E.3 for details regarding the construction of data and model moments.

[29] The Hadamard division of a matrix A by another matrix B of the same dimension is $C = A \oslash B$, with each entry

Figure 10: Estimates of Matching Frictions across Countries
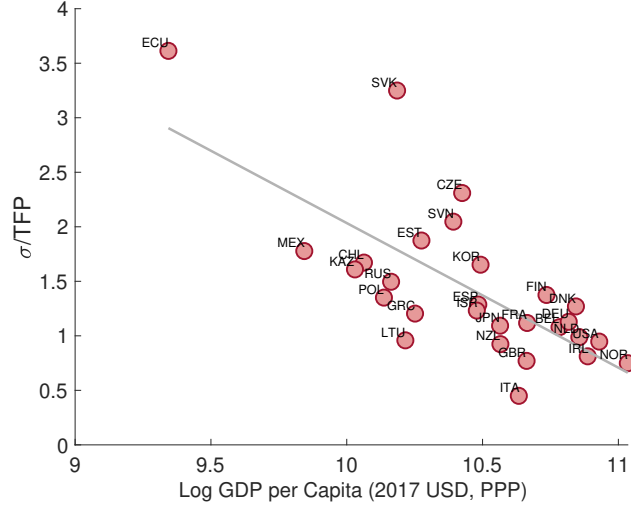
Notes: This figure plots estimates of the scale parameter of the labor wedge distribution relative to TFP σ/A against log GDP per capita across countries. Each red dot represents one country. The gray solid line represents the linear best fit. *Source:* Model simulations.

Figure 11 displays how the estimated production function parameters vary with log GDP per capita across countries and reveals a clear pattern: Complementarities between most worker skills and job skill requirements are more pronounced in high-income countries. This is particularly true for the coefficients on the numeracy-numeracy interaction, α_{nn}, and that on the literacy-literacy interaction, $\alpha_{\ell\ell}$. In turn, these estimates reflect stronger empirical sorting patterns between worker and job traits in higher-income countries—see Figure 2 in Section 3. In turn, while complementarities between numeracy skills and firm size are larger in higher-income countries, the opposite is the case for complementarities between literacy skills and firm size.

The left panel of Figure 12 highlights how the relative value of home production varies across the development spectrum. Consistent with our estimation strategy, we show results for six groups defined by the interaction between three broad skill categories and gender. For each group, we plot the value of home production relative to the mean value of market production across log GDP per capita. We find that the relative outside options tend to be higher for all skill groups in lower-income countries. This reflects the higher nonemployment rates we observe in lower-income countries. 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 nonparticipation rates among low-skilled women in relatively low-income countries (Ngai et al., 2022; Doss et al., 2023).

The right panel of Figure 12 shows that the relative mass of firms is lower in lower-income countries, suggesting that their labor markets are less competitive or subject to higher entry costs. These estimates are informed both by higher nonemployment rates in lower-income countries and by differences in the aggregate profit shares.

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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.

Figure 11: Estimates of Production Function Parameters across Countries
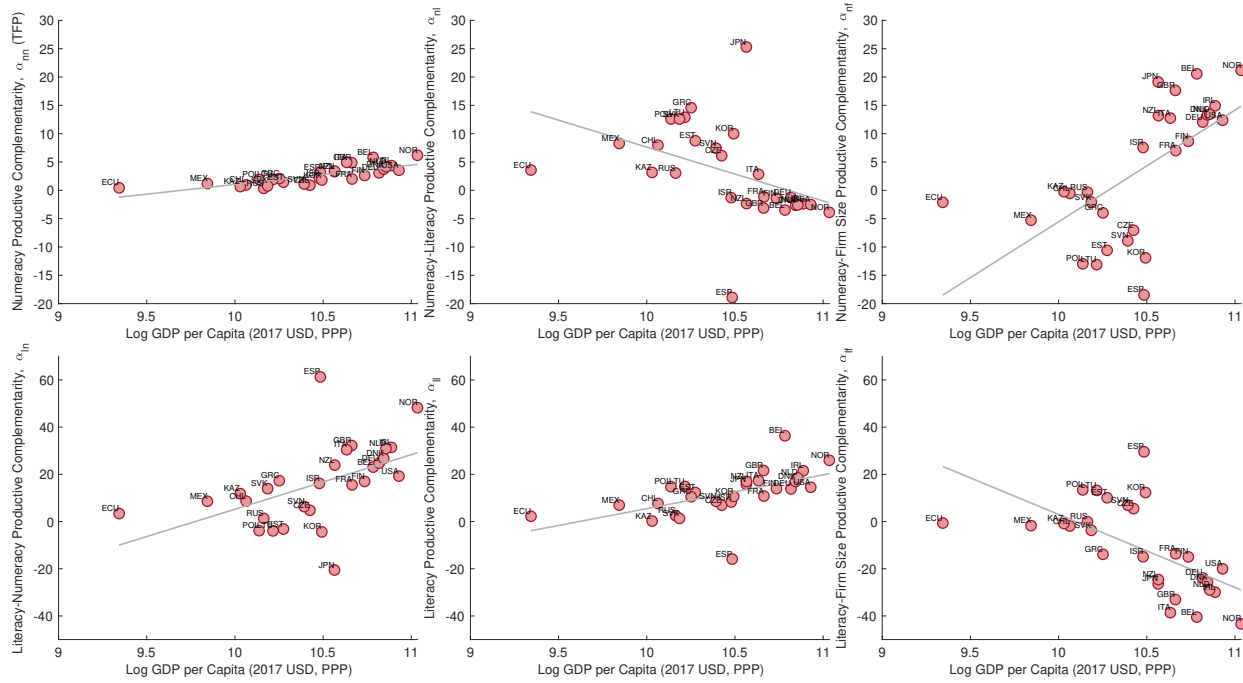
Notes: This figure plots estimates of the production function parameters $(\alpha_{nn}, \alpha_{nl}, \alpha_{ns}, \alpha_{ln}, \alpha_{ll}, \alpha_{ls})$ against log GDP per capita across countries. Each red dot represents one country. The gray solid lines indicate the linear best fit. *Source:* Model simulations.

Figure 12: Estimates of Outside Options and Relative Firm Masses across Countries
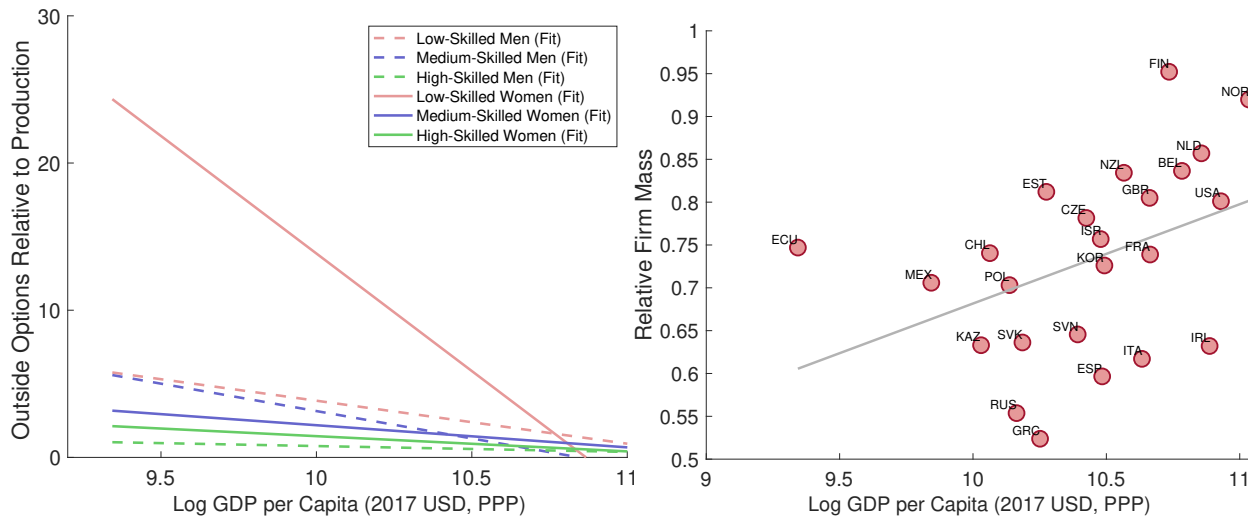
Notes: This figure plots estimates of the model parameters guiding broad worker groups' relative outside options $f_{x\varnothing}(x)$ (left panel) and the relative firm mass m^J against log GDP per capita across countries. Each line in the left panel represents the linear best fit for one broad worker group. See Appendix A.3 for the definition of broad worker groups. Each red dot in the right panel represents a structural estimate of m^J for one country. The gray solid line in the right panel indicates the linear best fit. *Source:* Model simulations.

Model Fit Based on Targeted Moments. We here select two low-income countries (i.e., Ecuador and Mexico), two medium-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 countries to showcase the model fit. Details for all 28 PIAAC countries are reported in Appendix E.5. Figure 13 displays the model fit for the six countries across this development spectrum. Each graph plots model-generated moments against targeted data moments, where the 15 moments are split into six categories, indicated by different colors. A perfect model fit would be implied by all points lying on the 45-degree line. Our parsimonious model fits well the data from all six countries, with nearly all moments lined up on the 45-degree line. This is not unexpected but confirms that our theoretical identification and estimation strategy indeed work well, and that the functional forms we impose (e.g., on the production function) are not overly restrictive.

Several features are worth highlighting. First, both in the data and in the model, the moments pertaining to sorting patterns (green markers) are lowest in low-income countries, moderate in medium-income countries and highest in high-income countries, consistent with our documented fact showing that there is greater assortative matching in higher-income countries. Second, both in the data and the model, nonemployment rates for both genders (blue markers) are decreasing in GDP per capita, especially for women. Third, both in the data and the model, the within-cell wage dispersion (pink markers) is decreasing in GDP per capita. This moment directly informs the dispersion of labor wedges, and thus the degree of matching frictions in our model, across countries. Finally, our model matches the observation that average wages (purple marker) are increasing in GDP per capita.

Model Validation Based on Untargeted Moments. We are interested in whether the estimated model—through the channel of varying mismatch across countries—can account for cross-country heterogeneity in key outcomes that were untargeted in our estimation, including aggregate output, wage inequality, and skill returns.

The top panels of Figure 14 demonstrate that the model reproduces the stark differences in hourly output per worker seen in the data. In our model, higher-income countries produce more output per worker due to superior technology, a more skilled workforce, more demanding jobs, as well as lower matching frictions. Whereas the first three factors have a direct positive effect on productivity, they also indirectly boost output by reducing worker-job mismatch: For instance, more skill-intensive jobs improve worker-job sorting in higher-income countries since their workers tend to have higher skill levels, i.e., there is a better fit between skill supply and demand. Similarly, the production function of higher-income countries features stronger worker-job complementarities in most dimensions that induce stronger positive worker-job sorting—see Figure 11.

The middle panels of Figure 14 illustrate that our model captures the fact that lower-income countries have greater wage inequality, measured either by the 90-10 log wage gap capturing overall wage inequality or by the 50-10 log wage gap capturing lower-tail wage inequality. This pattern arises in our model because poorer countries' workforces are tilted toward workers with

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Figure 13: Model Fit for Selected Low-, Medium-, and High-Income Countries
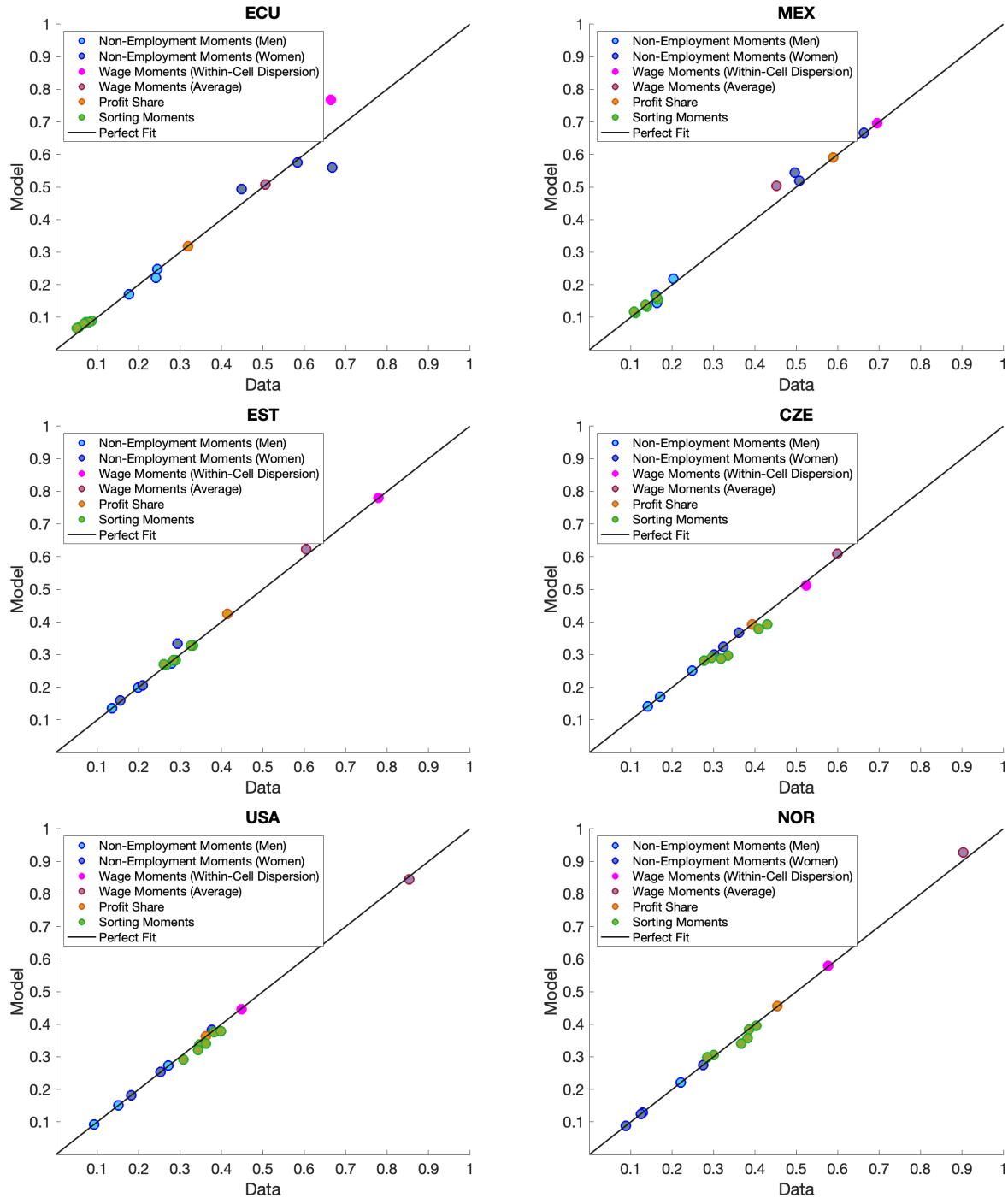
Notes: This figure illustrates the model fit by plotting model moments against data moments for selected low-income countries (Ecuador and Mexico, top panels), middle-income countries (Estonia and the Czech Republic, middle panels), and high-income countries (the United States and Norway, bottom panels). The 45-degree line indicates a perfect fit between the model and the data. See Appendix E.3 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 simulations.

lower skill levels, which leads bottom incomes to be relatively low; and because lower-income countries face greater matching frictions, which give rise to heterogeneous wages across workers of the same type, thus increasing overall wage inequality.

Finally, the bottom panels of Figure 14 show that our model reproduces the empirical pattern of increasing numeracy returns (conditional on literacy skills) across GDP per capita but flat or decreasing literacy returns (conditional on numeracy skills). While our model misses some of the levels of those skill returns in the data, it matches well the gradient across countries.

Cross-Country Differences in Meritocracy. Our estimated model predicts important differences in worker-job sorting patterns across the development spectrum in our data. Our goal is to understand the sources of these cross-country differences in the allocation of skills as well as their implications for outcomes across countries such as aggregate income and wage inequality.

To illustrate these cross-country differences in worker-job sorting patterns on the intensive margin, we first capture skill mismatch through the overlap of worker skill distributions across jobs with different skill requirements. Specifically, in each country, we group jobs into three categories—low, medium, and high—depending on their numeracy and literacy skill requirements. We then assess the overlap in the numeracy (literacy) skill distributions of workers in low- versus high-skilled jobs. As an example, we compare the lowest-income country (Ecuador) with the highest-income country (Norway) in our sample.. The left and middle panels of Figure 15 show that Ecuador displays considerably more overlap in worker skills across different job types. In other words, workers are less assortatively matched in Ecuador than in Norway. The right panels of Figure 15 highlight that this pattern is not special to these two countries but reflects a systematic relationship between skill mismatch and countries' prosperity. For each country and skill dimension, we compute the overlap of the worker skill distributions across low- and high-skilled jobs, which we then plot against GDP per capita. In line with the empirical evidence, higher-income countries in our model have less overlap in worker skill distributions across job types—i.e., higher-income countries feature more assortative matching and thus more meritocratic labor markets compared to lower-income countries.

We use the *meritocracy index* (Definition 2) as our main measure to summarize the model-implied patterns of worker-job sorting and skill mismatch for each country. Recall that it is defined as a country's actual (estimated) output relative to its potential output without matching frictions (i.e., $\sigma \to 0$), the case in which worker-job matching is only driven by productivity considerations. Figure 16 shows the model estimates of the meritocracy index across countries. The results reflect significantly greater meritocracy in higher-income countries, which are those whose actual output is relatively closer to potential. For instance, Norway—the highest-income country in the PIAAC survey—has a meritocracy index of around 0.6, roughly three times that in Ecuador—the lowest-income country in the PIAAC survey. That is, Ecuador loses about twice as much output, or 80 percent of its potential, due to its high degree of matching frictions and the lack of incentives to sort that stem from its backward technology and misaligned endowments. In turn, Norway's

Figure 14: Model Validation Based on Untargeted Moments across Countries
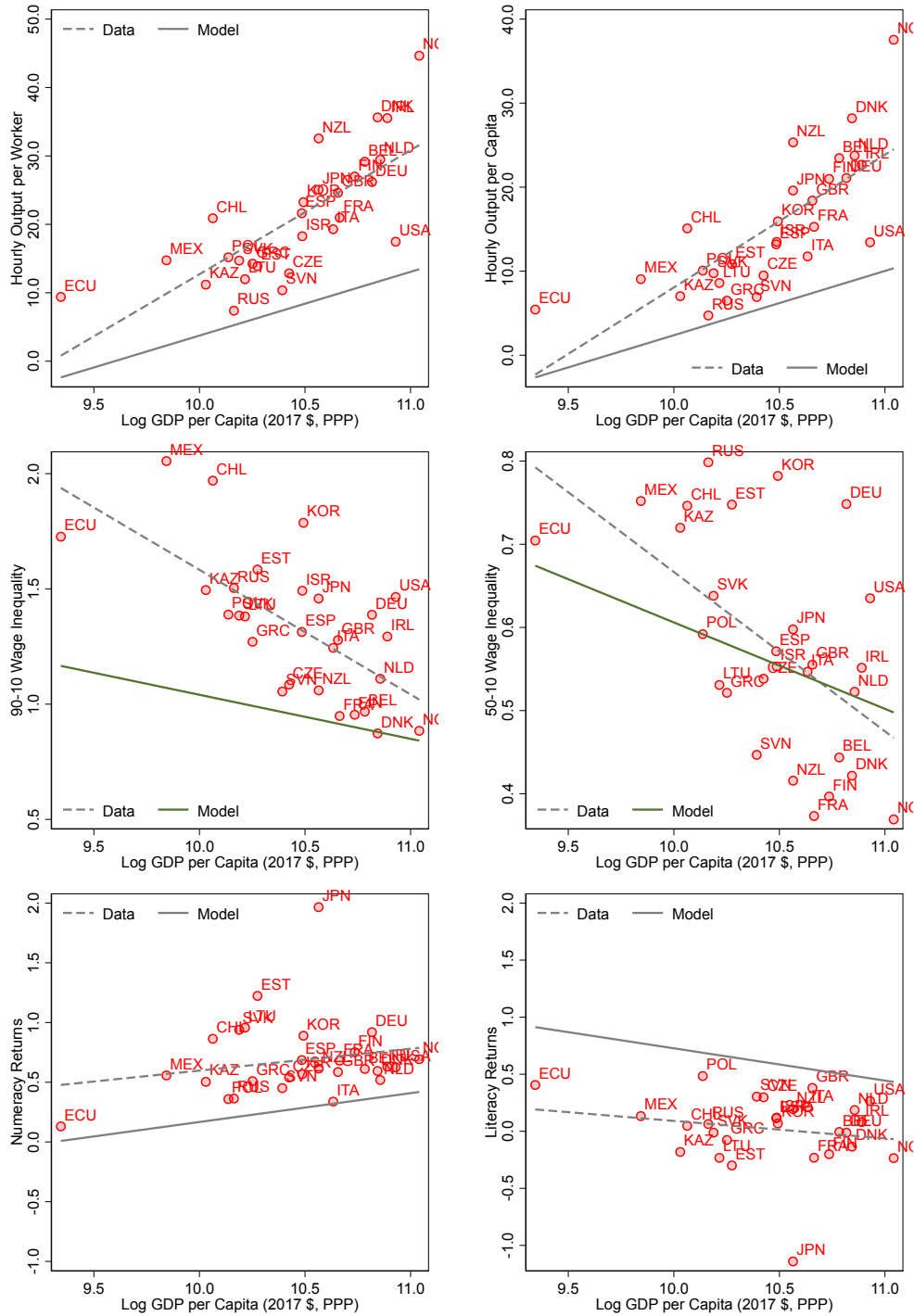
Notes: This figure shows the fit of the model vis-à-vis the data based on a set of untargeted moments against GDP per capita across countries. See Appendix A.3 for details on how the untargeted moments are constructed. Each red marker represents one country in the data. Dashed lines indicate the linear best fit to the data, while solid lines indicate the linear best fit to the model. *Source:* PIAAC, World Bank, and model simulations.

Figure 15: Skill Mismatch in a Low-Income Country, a High-Income Country, and across Countries
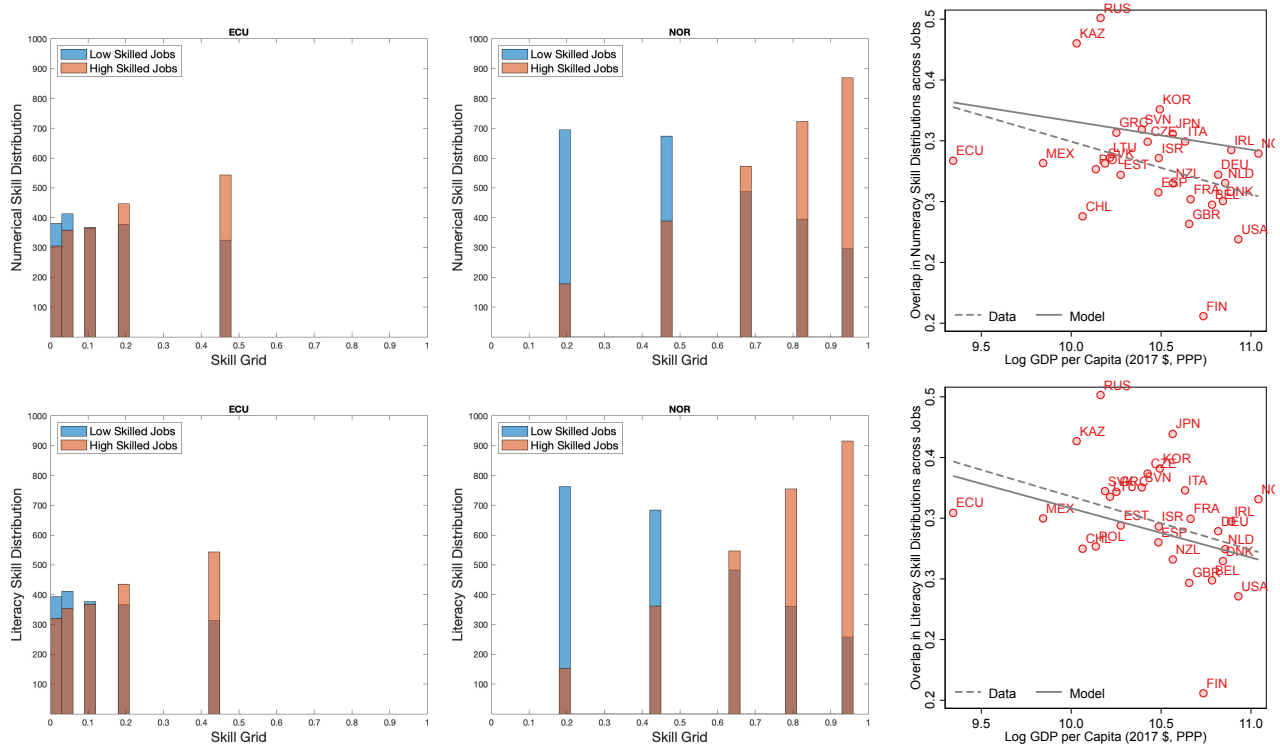
Notes: This figure illustrates the distribution of worker skill levels across low- and high-skill requirement jobs in Ecuador (left panels), in Norway (middle panels), and across all 28 in our data (right panels), separately for numeracy skills (top panels) and literacy skills (bottom panels). Blue bars represent low-skilled jobs, orange bars represent high-skilled jobs, and the brown bars represent the overlap between the two. See Appendix A.3 for the definition of job types. The right panels plot the share of overlapping observations between the two skill distributions across low- versus high-skilled jobs, red circles indicate countries in the data, the gray dashed line indicates the best linear fit to the data, and the gray solid line indicates the best linear fit to the model. *Source:* PIAAC and model simulations.

output would be around 40% higher in a perfectly meritocratic system.

Figure 16: Meritocracy across Countries
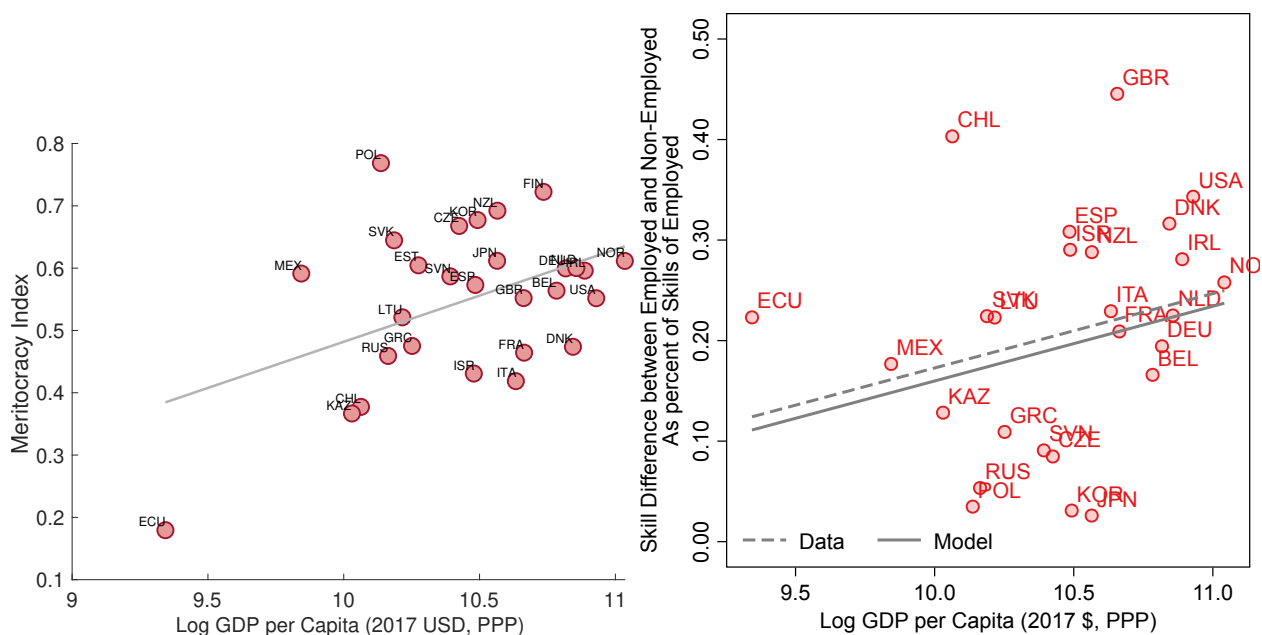
Notes: The left panel plots the meritocracy index, defined as a country's actual (i.e., estimated) output relative to its potential output without matching frictions (i.e., $\sigma \rightarrow 0$) against GDP per capita across countries in the estimated model. Each red dot represents one country in the 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 4 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: Model simulations.

Finally, our model also captures the observed cross-country differences in meritocracy on the extensive margin, i.e., labor force participation. When jobs are scarce, as indicated by an estimated relative job mass that is below one (see Figure 12, right panel), a meritocratic worker-job allocation requires that higher-skilled rather than lower-skilled workers participate in the labor market and hold jobs.[30] Further, if labor markets are meritocratic and the scarcity of jobs is more pronounced in poorer countries as indicated by a considerably lower mass of jobs relative to workers in Figure 12, this type of sorting should be especially prevalent there. The right panel of Figure 16 shows that this is not the case. To the contrary, both in the data and model, the gap between the average skill of employed workers relative to that of unemployed workers is around 10 percentage points higher in richer countries, which suggests that labor markets in lower-income countries are less meritocratic.

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[30]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 12.

7 Sources and Consequences of Meritocracy

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 and ask: How do some countries end up more meritocratic—i.e., with a meritocracy index closer to unity in Figure 16? We consider three determinants of meritocracy in a country's labor market: idiosyncratic frictions, technology and endowments. In the second step, we study the consequences of meritocracy for economic development by asking: How do low levels of meritocracy affect key outcomes across countries? To assess whether the lack of meritocracy is a quantitatively important hurdle for development, two observations are important. First, a reduction in idiosyncratic frictions of lower-income countries (i.e., $\sigma \to 0$)—while keeping their technology and endowments fixed—increases aggregate output toward their potential and thus their meritocracy index. Second, however, if potential output in these countries is low relative to higher-income countries, either due to their backward technology or misaligned endowments of workers and jobs, then the gains from more meritocracy are limited. In this case, reducing the frictions of low-income countries is not an effective tool for alleviating cross-country inequality. Instead, upgrades to their technology and distributions are needed, which increases the returns to worker-job sorting and thereby narrows the gap between their actual and—now higher—potential output.[31]

We consider a sequence of counterfactual simulations in the estimated model to gain a deeper understanding of both the sources and the consequences of skill misallocation across countries. In a series of applications, we then highlight the role of two factors for economic development: gender inequality in labor market sorting as well as regional labor market integration that improves the allocation of workers to jobs.

7.1 Cross-Country Differences in Meritocracy and Aggregate Outcomes

We decompose the observed disparities in economic outcomes across countries into the contributions of technology, matching frictions, and endowments of worker skills and job skill requirements. This decomposition allows us to quantify the underlying drivers of meritocracy and their impact on aggregate output and inequality across countries.

The Role of the Production Technology. We first assess the extent to which differences in production technology can account for the observation of higher GDP per worker and lower wage inequality in higher-income countries. To this end, we assign to all countries the production function of the highest-income country in our sample, namely Norway.[32] We then recompute each

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

[32]We have repeated the same exercise using the United States as the benchmark country—i.e., we assign the United States' technology to all other countries. The results of this alternative exercise are very similar to those presented below, which use Norway as the benchmark country.

country's equilibrium under the new technology and reassess cross-country differences in (i) meritocracy, (ii) aggregate output, and (iii) wage inequality.

Figure 17 shows outcomes (i)–(iii) in the baseline model and under this counterfactual. The left panel shows that universally imposing Norway's frontier technology leads to an increase in meritocracy across all countries. Intuitively, an increase in the returns to positive assortative matching induced by adopting a technology that features stronger worker-job complementarities in most dimensions leads to an equilibrium reduction in the misallocation of skills.

As a result, as shown by the middle panel, hourly output per worker increases by a roughly constant amount across countries, which implies that—when accounting for the universal boost in mean output through the coefficient of variation—cross-country inequality in output decreases by 41 percent (see Figure 22, right panel). Interestingly, the middle panel also shows that these changes are primarily driven by the direct effect of technological change, rather then the indirect effect that works through improvements in worker-job matching and thus meritocracy: The dashed line gives the counterfactual GDP per worker when universally implementing Norway's technology while keeping worker-job sorting—and thus meritocracy—at each country's baseline level. This shows that the additional effect on output from improved sorting (difference between blue solid and blue dashed line) is small and similar across countries.

At the same time, wage inequality within countries increases across the board, and more so in lower-income countries (Figure 17, right panel). This is because stronger worker-job complementarities of the frontier technology fuel the demand for skilled workers—a particularly scarce resource in low-income countries—who sit in the upper tail of the wage distribution and gain substantially from this technological shift.

From this exercise, we conclude that giving all countries access to the same frontier production technology would significantly boost output in all places, thereby reducing cross-country inequality, while, at the same time, increasing domestic wage inequality, especially in lower-income countries. Moreover, since improvements of meritocracy are uniform across countries, they are *not* central to reducing world-wide disparities in this scenario.

The Role of Matching Frictions.   Next, we assess the extent to which differences in matching frictions explain cross-country differences in GDP per worker and wage inequality. Figure 18 shows results from a counterfactual simulation that adopts in every country the comparatively low degree of matching frictions from the highest-income country in our sample, namely Norway. The left panel shows that such a reduction in frictions is associated with a significant increase in meritocracy in the lowest-income countries—e.g., our four lowest-income countries gain between 20 and 80 percent of output relative to potential. However, given the initially large cross-country heterogeneity in productivity, the middle panel shows that this effect of stronger worker-job sorting has a modest impact on cross-country differences in hourly output per worker: Actual output is increasingly approaching potential output in low-income countries, but their potential output

Figure 17: Counterfactual Imposing Norway's Production Function across Countries
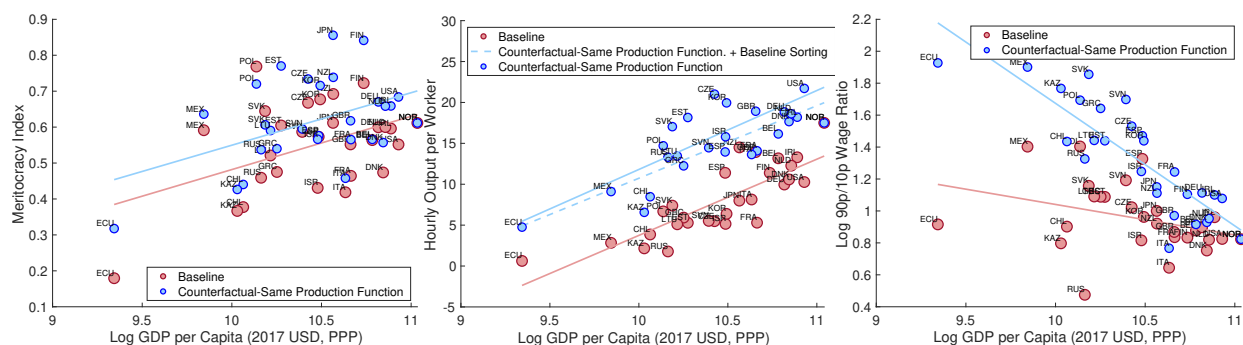
Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian production technology in all countries on the meritocracy index (left panel), hourly output per worker (middle panel), and wage inequality (right panel). Red circles represent the baseline model estimates for 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.

is comparably low.[33] Contrary to the previous counterfactual that equalized technology across countries, the right panel shows that equalizing frictions tends to reduce wage inequality overall and disproportionally so in lower-income countries. This is because lower frictions dampen within-cell wage dispersion—i.e., the variance of wages among similar workers who perform similar jobs—which leads to a reduction in overall wage dispersion. These effects are larger in lower-income countries, where frictions are more pronounced to begin with.

From this exercise, we conclude that equalizing matching frictions across countries would disproportionally benefit lower-income countries, which had the highest levels of frictions to start with. These places gain in terms of worker-job sorting relative to their high-income counterparts, captured by an increase in their meritocracy index. As a consequence, they experience a boost to output and reduction in wage inequality. Quantitatively, however, the effect on the cross-country variation in output is relatively small. The returns to improving the allocation of skills are limited because these countries are constrained by other factors, including their production technology as well as the endowments of worker skills and job skill requirements. Strengthening worker-jobs sorting helps low-income countries catch up only if the returns from sorting are sufficiently high, i.e., only if potential output is relatively high in comparison to the high-income countries.

The Role of Worker Skill and Job Skill Requirements. Finally, we assess the extent to which differences in endowments of worker skills and job skill requirements are related to heterogeneity in GDP per worker and wage inequality across countries. Figure 19 shows the simulated results of counterfactually assigning to each country the worker skill and job skill distributions of the highest-income country in our data, namely Norway. These counterfactual distributional shifts have two distinct implications on the countries they are imposed on: First, they tend to make

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[33]Indeed, the coefficient of variation of hourly output per worker across countries decreases by a modest eight percent—see the right panel of Figure 22.

Figure 18: Counterfactual Imposing Norway's Matching Frictions across Countries
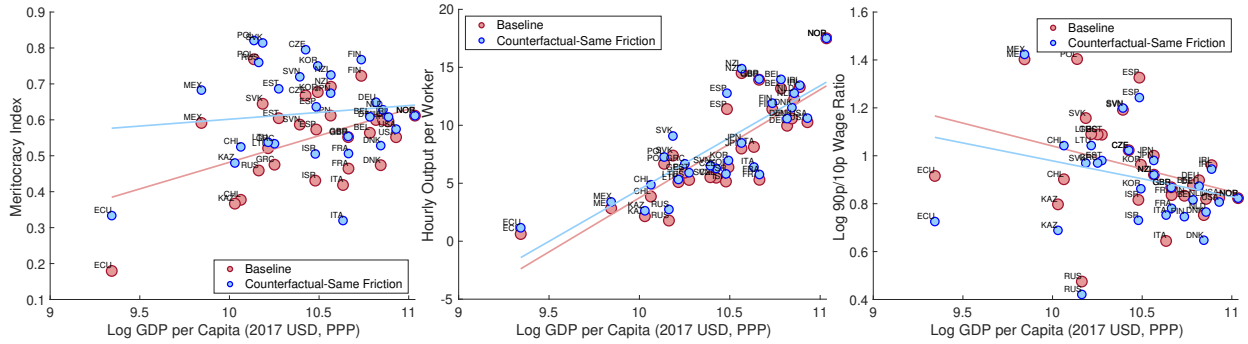
Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian matching frictions in all countries on the meritocracy index (left panel), hourly output per worker (middle panel), and wage inequality (right panel). Red circles represent the baseline model estimates for each 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. *Source:* Model simulations.

high-skilled workers and jobs more abundant. Second, they induce a better alignment of skills and skill requirements in most countries, thereby reducing an important source of worker-job mismatch and low meritocracy.

The left panel shows that this counterfactual leads to a pronounced increase in meritocracy in lower-income countries, reflecting the fact that a better alignment of skill supply and demand incentivizes more sorting. In fact, the effects of assigning the Norwegian endowments of skills and skill requirements to the rest of the world are so large that the cross-country slope of the meritocracy index flips to negative. The middle panel shows that these counterfactual skill and skill requirements also lead to sizable output gains, especially in lower-income countries, which reduces the cross-country variation of output per worker by 30%. Importantly, around two thirds of these output gains are due to the improved allocation of workers to jobs, as output gains are only around one third of the total effect when worker-job sorting patterns are fixed at baseline. The right panel makes the point that this counterfactual leads to a significant reduction of wage inequality within low-income countries, largely due to the associated increase in high-skilled workers in lower-income countries.

From this exercise, we conclude that the relative demand and supply of skills are an important factor shaping the allocation of workers to jobs and resulting aggregate outcomes across countries. Improving low-income countries' skill and job endowments in a way that better aligns them augments their potential output and—by increasing the returns to sorting—reduces worker-job mismatch. This pushes actual output closer to a new, improved potential output. As a result, low-income countries' output gains are substantial in this counterfactual, though large cross-country gaps in aggregate output remain.

The Role of Complementarities between Technology, Frictions and Endowments. Each of the previous three counterfactuals isolated the effects of one primitive at a time on cross-country differences in key outcomes. While each of the three primitives—the production function, matching

Figure 19: Counterfactual Imposing Norway's Worker Skills and Job Skill Requirements across Countries
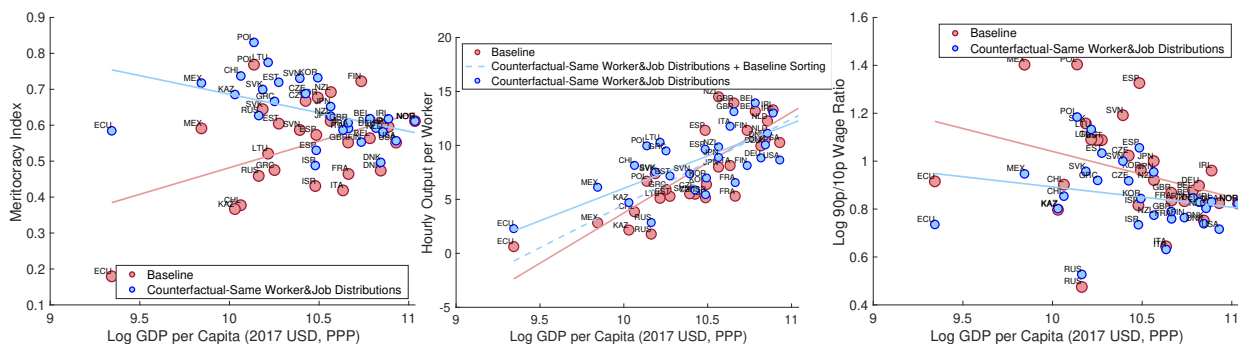
Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian distributions of worker skills and job skill requirements in all countries on the meritocracy index (left panel), hourly output per worker (middle panel), and wage inequality (right panel). Red circles represent 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.

frictions, and endowments of worker skills and job skill requirements—played an important role in shaping specific outcomes, the effects of changing one of them in isolation ignores important complementarities between them. In this section, we show that the returns to improving the allocation of workers to jobs through lower matching frictions depend on other country-specific factors. Thus, incremental reforms targeting one primitive at a time may miss a large share of the potential gains from removing cross-country heterogeneity in multiple primitives simultaneously.

We highlight two types of interactions. First, Figure 20 shows the results of simulating a dual counterfactual that adopts Norway's production function and matching frictions simultaneously. Relative to the baseline counterfactual of changing only the production function (green line in the left panel), the additional undoing of matching frictions in low-income countries leads to a large increase in meritocracy by moving those countries closer to their potential output (blue line in the left panel). As a consequence, output per worker in those countries increases by an additional 20 percent over and above the baseline counterfactual, which leads to a total reduction in the cross-country variation in output by 45 percent.[34] As such, the gains from simultaneously improving technology and matching frictions are greater than the sum of the parts. Intuitively, making a country more meritocratic due to lower frictions has greater returns (reflected in a higher potential output in the denominator of the meritocracy index) when there is appropriate technology that rewards stronger sorting between workers' and jobs' productive attributes.

Second, Figure 21 shows the results of simulating a dual counterfactual that adopts Norway's distributions of worker skills and job skill requirements in addition to its production function. The interaction effects between the technology and endowments are substantial. The meritocracy index (left panel) increases significantly among lower-income countries and becomes much

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[34]Figure 32 in Appendix F.1 shows that around one third of the gains in output per worker are due to an improvement in worker-job sorting induced by the adoption of the new technology and frictions.

Figure 20: Counterfactual Imposing Norway's Production Function and Frictions across Countries
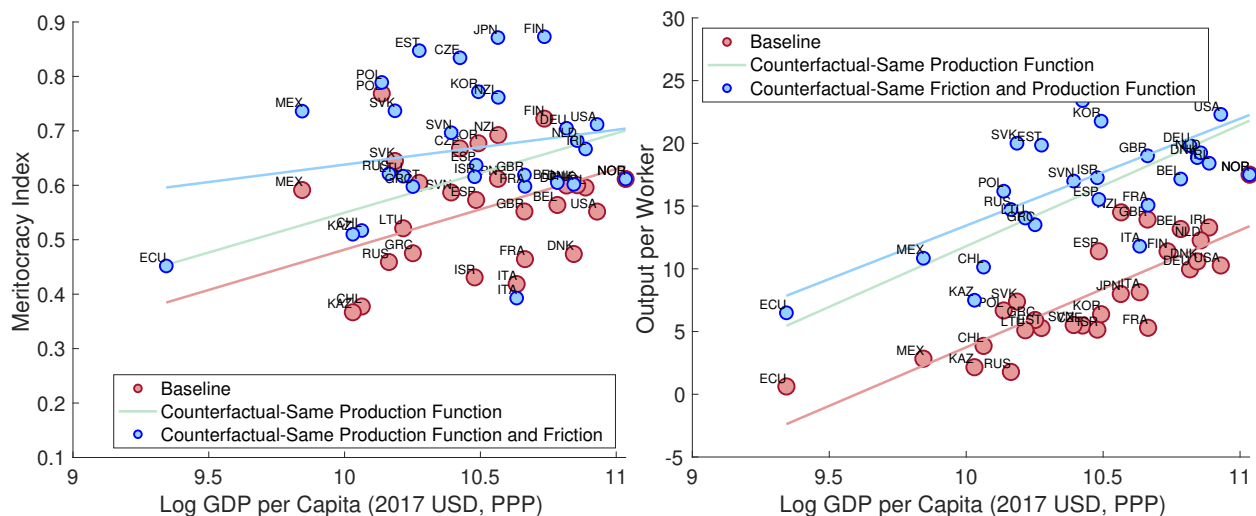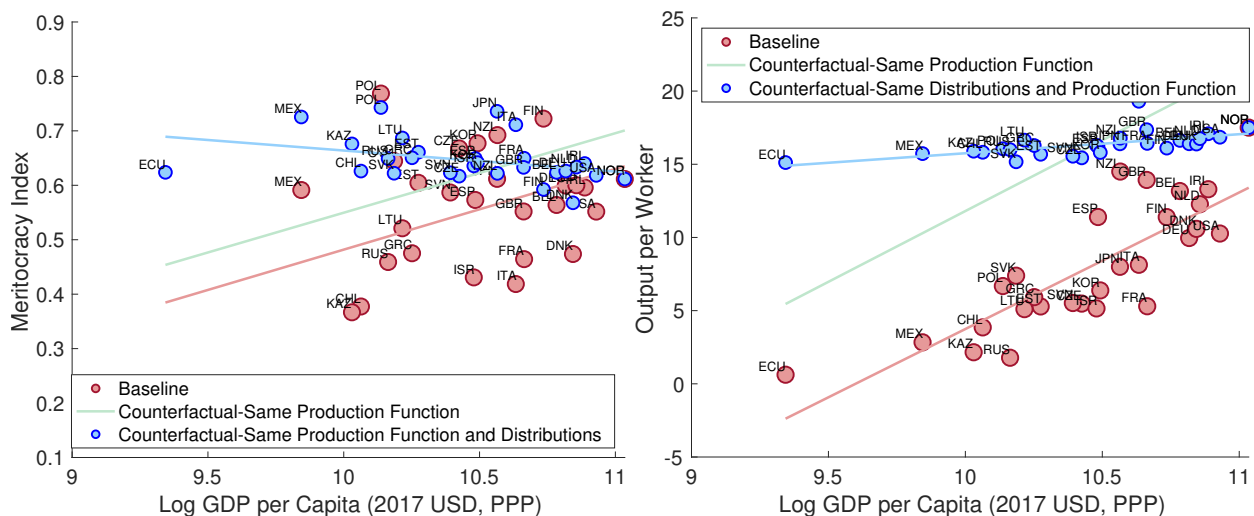

Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian production technology and matching frictions simultaneously in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates 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.

flatter across the development spectrum. As a consequence, output per worker (right panel) increases sharply among low-income countries, much more than the two individual counterfactuals would suggest. This is due to the fact that the combined change in technology and distributions disproportionally raises the benefits from sorting and associated output gains in lower-income countries. As a result, this dual counterfactual closes 91 percent of the cross-country gap in output per worker. Importantly, around half of this convergence is due to an improvement in worker-job sorting and thus an increase in meritocracy (see Figure 32 in Appendix F.1).

To conclude, the above exercises highlight important interaction effects between the primitives of an economy on labor market sorting and—through this channel—aggregate outcomes. From a policy perspective, this suggests that a multifaceted approach is needed in order to reduce income disparities across the development spectrum. Adopting frontier technology would be considerably more effective for lower-income countries if at the same time they could upskill their workforce and upgrade their jobs or lower their frictions. This way they can leverage the technical change to a full extent, not just through its direct impact but also indirectly by increasing the rewards to improved worker-job sorting and thus to enhanced meritocracy.

Effects on Mean Output and Inequality in Output across Countries. Figure 22 summarizes the main results of our counterfactual exercises pertaining to mean output (left panel) and inequality in output (right panel) across countries. We underscore the role changes in worker-job sorting—and thus meritocracy—play in each of them, by reporting not only the total effect of each

Figure 21: Counterfactual Imposing Norway's Production Function and Distributions across Countries

Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian production technology as well as distributions of worker skills and job skill requirements 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 the distributions of worker skills and job skill requirements unchanged. *Source:* Model simulations.

counterfactual (broad dark blue bars) but also the effect of a scenario that fixes the meritocracy index at each country's baseline level (narrow light blue bars).

Starting with mean output in the left panel, a few observations are worth highlighting. First, by far the largest global output gains (103 percent) are realized when adopting Norway's frontier technology, as opposed to by reducing frictions (7 percent) or by improving the endowments of worker skills and job skill requirements (10 percent). Second, the effects of removing frictions on mean output are twice as large (14 percent versus 7 percent) when better technology is in place. Third, a significant share of the total gains are due to improved worker-job sorting (comparing dark blue and light blue bars—e.g., 103 percent versus 85 percent due to technology, 7 percent versus 0 percent due to frictions, and 10 percent versus 2 percent due to distributions).

Moving on to cross-country differences in the right panel, we highlight the following results. First, the biggest impact on the relative economic development of lower-income economies, measured by the coefficient of variation for hourly output per worker across countries, is due to technology (−41 percent) and distributions (−30 percent), with a frictions having a more modest effect (−8 percent). Second, while the effect of technology on cross-country inequality is mostly direct, a relative improvement in worker-job sorting in lower-income countries more than doubles the effect due to distributions (−30 percent versus −13 percent) and drives essentially all of the effect due to frictions (−8 percent versus 0 percent). Third, there are strong complementarities between simultaneously improving countries' technologies and endowments. The combination of the frontier technology and more aligned distributions closes 91 percent of the cross-country income gap,

which is more than the sum of the two individual components (−41 percent and −30 percent). Importantly, almost half of it is driven by improved worker-job sorting (−91 percent versus −56 percent).

To summarize, our equilibrium model shows that improved worker-job matching is key to harvesting the gains from improved technology, frictions, as well as distributions of worker skills and job skill requirements. Conversely, the gains from removing matching frictions are limited in economies without appropriate technology or a decent fit between skill supply and demand since potential output is low. In this case, narrowing the gap between actual and potential output brings about little benefits in the cross-country comparison. We conclude that the lack of meritocracy in low-income countries is mostly a consequence of economic underdevelopment—i.e., of the limited access to advanced technology and productive worker/job endowments—rather than a source.

Figure 22: Summary of Counterfactuals: Global Mean and Coefficient of Variation of Output per Worker
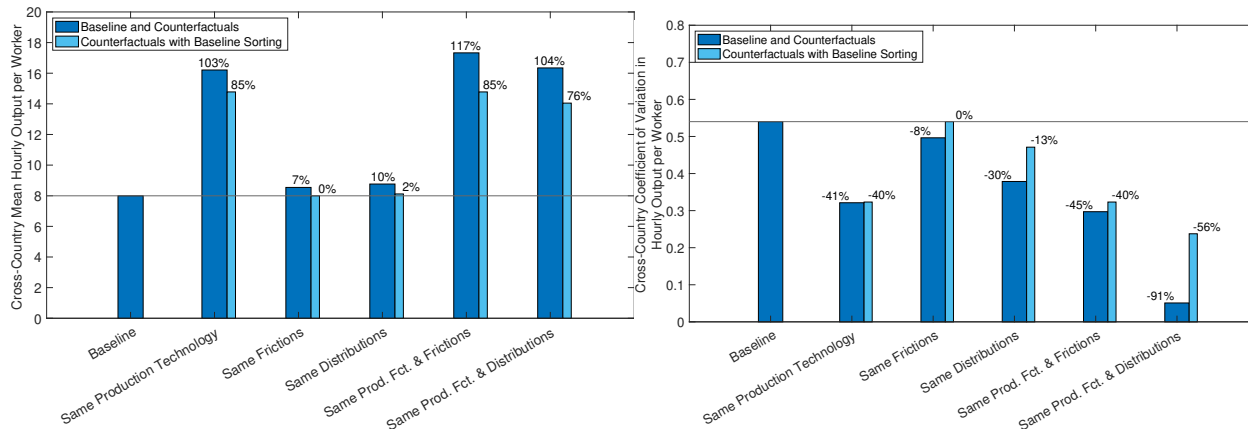
Notes: This figure summarizes the results from all counterfactual simulations in terms of their effects on global mean output per worker (left panel) and coefficient of variation of output per worker across countries (right panel). The dark blue broad bars indicate outcomes based on the baseline scenario 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 baseline. *Source:* Model simulations.

7.2   Gender Gaps in Employment and Pay across Countries

Our framework naturally lends itself to studying misallocation of skills along the extensive margin (i.e., employment versus nonemployment) in addition to the intensive margin (i.e., worker-job matching) highlighted thus far. In this section, we study a particularly salient dimension of misallocation, namely the employment differences by gender and how they relate to economic development. Despite the universal increase in female labor force participation over the past decades, there is still significant under-utilization and misallocation of women's skills. The sources can stem from both supply-side factors—e.g., fertility, marriage, and child-rearing or social norms that limit women's labor force attachment—and demand-side considerations, such as discrimination or underschooling of women which lowers their productivity relative to men. In our estimated

model, we directly account for differences in the skill distribution between men and women and show in Figure 33 (Appendix F.2) that skills are similar across gender in most countries. Thus, the underqualification of women is most likely not the main driver of gender differences in labor market outcomes. In turn, we capture the mix of possible supply-side barriers by differences in women's outside option. The estimated home production technology reported in Figure 11 (left panel) shows that there are sizeable differences across gender, which suggests that they are an important source behind observed gender gaps in labor market outcomes.

We start by documenting the link between gender inequality and economic development. First, there is skill misallocation on the extensive margin, in the sense that—despite women being similarly skilled as men—female non-employment rates are much higher. Figure 23 shows that in the lowest-income countries of our sample female nonemployment is more than 30 percentage points higher than male nonemployment. In turn, for rich countries the gap is much smaller with around 5 percentage points. Second, there is also skill misallocation related to gender on the intensive margin (conditional on working), which varies across countries. Figure 34 in Appendix F.2 shows that in low-income countries, the share of women among high-skilled workers in the economy tends to be higher than their share in occupying high-skilled positions, while for higher income countries the opposite is the case. In turn, for low-skilled women these patterns are reversed: In low-income countries, women's share in the economy is lower than their share in low-skilled positions. Compared to the gender differences on the extensive margin of labor force participation, however, these differences on the intensive margin are relatively small.

To understand the impact of these gender differences on countries' aggregate outcomes, we consider two counterfactuals. First, we eradicate the gender differences in outside options by assigning women the same outside option $f_{x\varnothing}(x)$ as men. On the extensive margin, Figure 23 shows that this counterfactual pushes a large number of women from nonemployment into employment, particularly so in lower-income countries, where gender differences in outside options were higher to begin with. For example, the nonparticipation rate of women in Ecuador drops by 12 percentage points, from 54 to 42 percent. More generally, associated with this counterfactual is a significant flattening of female nonemployment rates across the development spectrum. However, for a fixed supply of jobs and degree of matching frictions, this counterfactual also leads to an almost one-for-one crowding out of male employment. The effect of this gender composition change on output will then depend on whether the average skills of the workforce increase, that is if the women who enter are more skilled than the men they replace as in Ashraf et al. (2023) and Jones et al. (2018).

On the intensive margin, the right panel of Figure 23 shows that more women in the workforce—by creating more competition for jobs—also induce a (modest) reduction in skill misallocation that leads to a more meritocratic worker-job allocation. This is especially in lower-income countries, which were characterized by more mismatch to start with. As a result, the gradient of meritocracy across countries flattens.

Figure 24 shows the effects of closing the gender gap in outside options on the aggregate

Figure 23: Misallocation of Women and Men on the Extensive and Intensive Margin
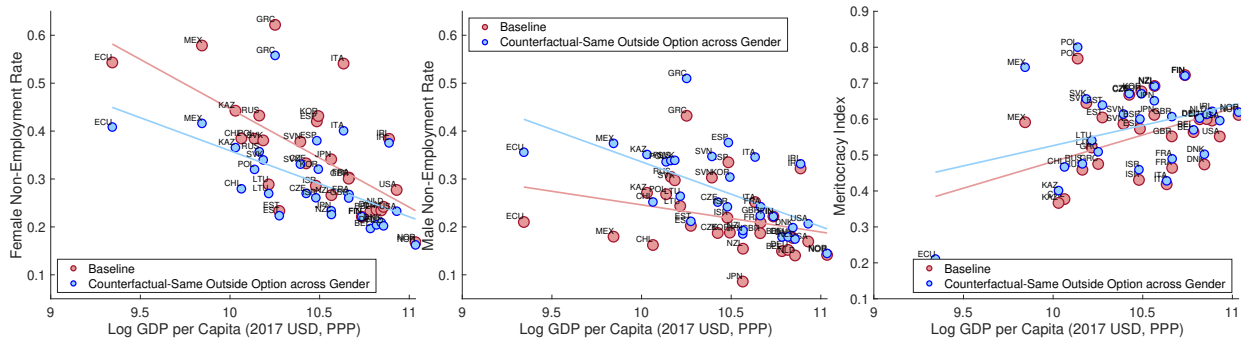
Notes: This figure shows the model-based counterfactual effects of giving women in each country the same outside options as that of men on women's nonemployment rates (left panel), men's nonemployment rates (middle panel), and the worker-job sorting measured by the meritocracy index (right panel). The red circles and red solid line show the baseline simulation results against GDP per capita across countries and their best linear fit. The blue circles and blue solid line show the counterfactual results plotted against GDP per capita across countries and their best linear fit. *Source:* Model simulations.
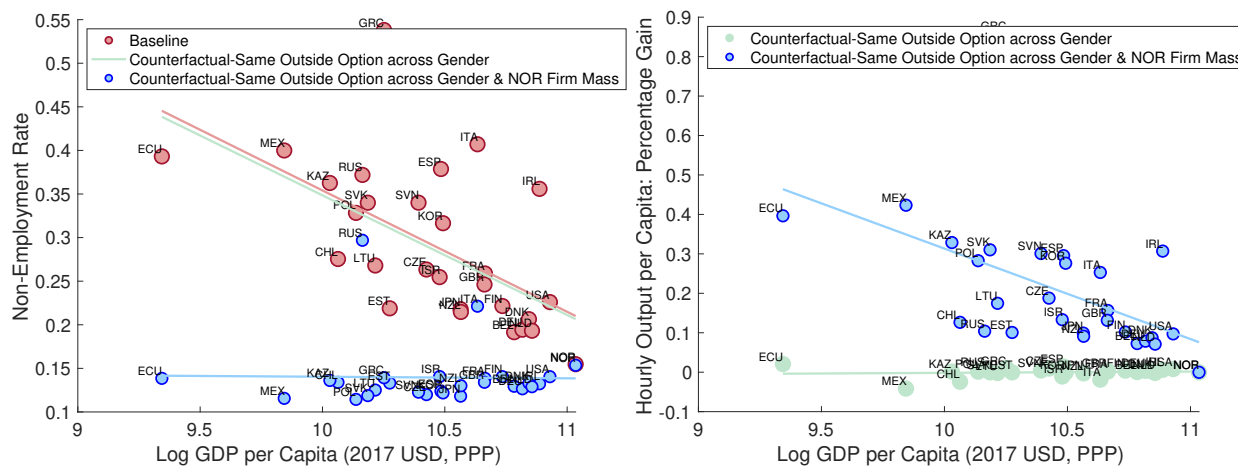
nonemployment rate (left panel) and on aggregate output gains relative to the baseline (right panel). By itself, this counterfactual has little impact on these outcomes, indicating that—if the number of jobs in the economy is fixed—replacing men with women has little impact on output. This suggests that in this sample women who enter the workforce are not more skilled than the men they replace. This can be reconciled with the findings of Ashraf et al. (2023) and Jones et al. (2018) by noting that the labor force participation ratio in our sample countries is always higher than in the countries for which Ashraf et al. (2023) find that women are more positively selected and that, therefore, replacing men with women has a positive effect on productivity.

In the medium- to long-run, however, the amount of jobs in an economy is not fixed, there is no "lump of labor". To investigate the interaction between gender barriers and the scarcity of jobs, in a second counterfactual, we additionally increase the mass of jobs to the level of Norway, which effectively augments the available employment opportunities for workers in lower-income countries. This dual counterfactual leads to a sharp drop in nonemployment rates in lower-income countries (blue circles and blue solid line in the left panel), yielding an almost constant nonemployment rate of around 14 percent across countries. Associated with this are substantial gains in hourly output per worker (blue circles and blue solid line in the right panel), especially for the lowest-income countries. From this, we learn that the scarcity of jobs may be an obstacle to increasing female employment rates and, as a result, economic development, at least in the short run.

7.3 Integrating Labor Markets across Countries

In this section, we are interested in the effects of integrated labor markets on global economic output by reducing barriers to the output-maximizing allocation of workers to jobs. In our baseline analysis, we took as given the boundaries of each country when considering the allocation of skills. While in most countries, workers remain attached to their country of birth, migration

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Figure 24: The Role of Female Labor Force Participation in Development with 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 red 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 blue 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.

is often associated with large output and welfare gains for migrants (Borjas, 1999; Hendricks and Schoellman, 2018; Lagakos et al., 2018a; Martellini et al., 2023; Schoellman, 2010). To this end, we allow for free worker flows across country borders in a sequence of counterfactuals that explores the effects of widening the boundaries of local labor markets. First, we consider regional labor market integration, splitting labor markets: Continental Europe plus Great Britain, Scandinavia, Southern Europe, Ex-USSR, Asia plus New Zealand, North America and South America. Second, we consider continental labor market integration: Europe, America, and Asia. Finally, we consider global labor market integration. In each of these scenarios, we assume that the sets of worker skills and job skill requirements in an integrated labor market consist of the unions of the respective sets in the member countries. Moreover, we assume that workers in an integrated labor market have access to the technology and frictions from the highest-income country in the region.

Figure 25 illustrates our results from simulating increasingly integrated labor markets. Compared to the baseline scenario, in which labor markets are segmented by country, output per capita is more than 50 percent higher under regional integration. Under continental integration, we find output almost doubles. The largest gains are attained when moving to a single integrated world market with free labor and technology flows, in which case output per capita almost triples compared to the baseline. Our simulations neglect many important aspects of international migration, including moving costs and other nonmonetary aspects of location decisions. Nevertheless, this exercise highlights that there are large potential output gains from increased mobility of workers, jobs, and technology across borders.

Figure 25: Global Output per Capita for Different Levels of Labor Market Integration
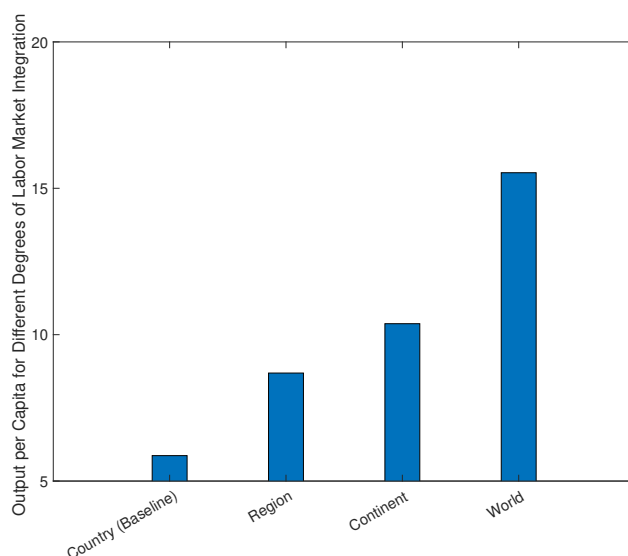
Notes: This figure shows output per capita in the model for four scenarios representing different levels of labor market integration: (i) our baseline of 28 countries, (ii) seven regions consisting of Asia and New Zealand, Ex-USSR, North America, Northern Europe excluding Scandinavia, Scandinavia, Southern Europe, and South America, (iii) three continents consisting of the Americas, Asia and Europe, and (iv) the world consisting of a single integrated labor market. In each scenario, workers in an integrated labor market have access to the technology and frictions associated with the highest-income country in the region. *Source:* Model simulations.

8   Conclusion

Are labor markets in richer countries more meritocratic, in the sense that workers are matched to the jobs that render them most productive? If so, why is this the case and what are the aggregate implications? To address these questions, we use harmonized microdata on workers' skills and jobs' skill requirements in 28 countries. We first show that labor markets in higher-income countries are characterized by greater meritocracy—i.e., stronger sorting between multidimensional worker skills and job skill requirements.

To understand the sources of cross-country differences in skill allocation and their implications, we develop an equilibrium matching model, in which the allocation of workers across jobs depends on three factors: endowments of worker skills and job skill requirements, the production technology, and matching frictions. We show that the model is identified—allowing us to disentangle matching frictions from the production technology—and separately estimate it for each of the 28 countries in our data. Using the estimated model, we first quantify the contribution of each of the three factors toward observed worker-job matching patterns, aggregate output, and wage inequality.

We find that differences in skill endowments and production technology account for most cross-country heterogeneity in outcomes, with matching frictions that directly reduce the extent of a country's meritocracy playing a relatively modest role. However, a large share of the gains from adopting better and more aligned worker-job endowments and advanced technology are realized through improved worker-job sorting. Therefore, the returns to improving the allocation of

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workers to jobs are constrained by the available skill and skill requirement endowments and technology. We conclude that the lack of meritocracy in poor countries' labor markets is a consequence of economic underdevelopment rather than a source. As a result, policies aimed at reducing idiosyncratic frictions to improve match quality only will not be effective unless they are combined with interventions that enhance match productivity.

We 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 but that the gains from unleashing the power of the female workforce are complementary with the availability of jobs. Second, we show that regional labor market integration significantly boosts global output through an improved allocation of workers to jobs across borders.

References

Akcigit, Ufuk, Harun Alp, and Michael Peters, "Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries," *American Economic Review*, 2021, *111* (1), 231–275.

Andrew, Alison, Oriana Bandiera, Monica Costa-Dias, and Camille Landais, "Women and Men at Work," *IFS Deaton Review of Inequalities*, 2021.

Arrow, Kenneth, Samuel Bowles, and Steven Durlauf, *Meritocracy and Economic Inequality*, Princeton University Press, 2000.

Ashraf, Nava, Oriana Bandiera, Virginia Minni, and Víctor Quintas-Martínez, "Gender and the Misallocation of Labor Across Countries," *Working Paper*, 2023.

Bagger, Jesper and Rasmus Lentz, "An Empirical Model of Wage Dispersion with Sorting," *Review of Economic Studies*, 2018, *86* (1), 153–190.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul, "Social Connections and Incentives in the Workplace: Evidence From Personnel Data," *Econometrica*, 2009, *77* (4), 1047–1094.

Bassi, Vittorio, Raffaela Muoio, Tommaso Porzio, Ritwika Sen, and Esau Tugume, "Achieving Scale Collectively," *Econometrica*, 2022, *90* (6), 2937–2978.

Bau, Natalie and Adrien Matray, "Misallocation and Capital Market Integration: Evidence From India," *Econometrica*, 2023, *91* (1), 67–106.

Beaman, Lori and Jeremy Magruder, "Who Gets the Job Referral? Evidence from a Social Networks Experiment," *American Economic Review*, December 2012, *102* (7), 3574–93.

Becker, Gary S., "A Theory of Marriage: Part I," *Journal of Political Economy*, 1973, *81* (4), 813–846.

Berry, Steven, Amit Gandhi, and Philip Haile, "Connected Substitutes and Invertibility of Demand," *Econometrica*, 2013, *81* (5), 2087–2111.

Borjas, George J, "The Economic Analysis of Immigration," *Handbook of labor economics*, 1999, *3*, 1697–1760.

Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin, "Finance and Development: A Tale of Two Sectors," *American Economic Review*, 2011, *101* (5), 1964–2002.

Caselli, Francesco, *Technology Differences over Space and Time*, Princeton, NJ: Princeton University Press, 2017.

_ **and Antonio Ciccone**, "The Human Capital Stock: A Generalized Approach: Comment," *American Economic Review*, 2019, *109* (3), 1155–1174.

_ **and Wilbur John Coleman II**, "The World Technology Frontier," *American Economic Review*, 2006, *96* (3), 499–522.

Caunedo, Julieta, Elisa Keller, and Yongseok Shin, "Technology and the Task Content of Jobs across the Development Spectrum," *World Bank Economic Review*, 2023, pp. 1–22.

Chan, Tak Wing and John Ermisch, "Proximity of Couples to Parents: Influences of Gender, Labor Market, and Family," *Demography*, 2015, *52* (2), 379–399.

Chari, V. V., Patrick J. Kehoe, and Ellen R. McGrattan, "Business Cycle Accounting," *Econometrica*, 2007, *75* (3), 781–836.

Chen, Liang, Eugene Choo, Alfred Galichon, and Simon Weber, "Matching Function Equilibria with Partial Assignment: Existence, Uniqueness and Estimation," *Working Paper*, 2021.

Choo, Eugene and Aloysius Siow, "Who Marries Whom and Why," *Journal of Political Economy*, 2006, *114* (1), 175–201.

Comin, Diego and Martí Mestieri, "If Technology Has Arrived Everywhere, Why Has Income Diverged?," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 137–178.

Deming, David J., "The Growing Importance of Social Skills in the Labor Market," *Quarterly Journal of Economics*, 2017, *132* (4), 1593–1640.

Donovan, Kevin, Will Jianyu Lu, and Todd Schoellman, "Labor Market Dynamics and Development," *Working Paper*, 2023.

Doss, Cheryl, Douglas Gollin, Charles Gottlieb, and Markus Poschke, "Understanding the Gender Division of Work across Countries," *Working Paper*, 2023.

Dustmann, Christian and Ian P. Preston, "Free Movement, Open Borders, and the Global Gains from Labor Mobility," *Annual Review of Economics*, 2019, *11* (1), 783–808.

Galichon, Alfred and Bernard Salanié, "Cupid's Invisible Hand: Social Surplus and Identification in Matching Models," *Review of Economic Studies*, 2021, *89* (5), 2600–2629.

_ , **Scott Duke Kominers, and Simon Weber**, "Costly Concessions: An Empirical Framework for Matching with Imperfectly Transferable Utility," *Journal of Political Economy*, 2019, *127* (6), 2875–2925.

Girsberger, Esther Mirjam and Romuald Meango, "The Puzzle of Educated Unemployment in West Africa," *Working Paper*, 2022.

Goldberg, David E., *Genetic Algorithms in Search, Optimization & Machine Learning*, Addison-Wesley, 1989.

Heckman, James J., "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for such Models," in "Annals of economic and social measurement, volume 5, number 4," NBER, 1976, pp. 475–492.

_ , "Sample Selection Bias as a Specification Error," *Econometrica*, 1979, *47* (1), 153–161.

Hendricks, Lutz and Todd Schoellman, "Human Capital and Development Accounting: New Evidence from Wage Gains at Migration," *Quarterly Journal of Economics*, 2018, *133* (2), 665–700.

_ **and** _ , "Skilled Labor Productivity and Cross-Country Income Differences," *American Economic Journal: Macroeconomics*, 2023, *15* (1), 240–268.

Hjort, Jonas, "Ethnic divisions and production in firms," *The Quarterly Journal of Economics*, 2014, *129* (4), 1899–1946.

Honoré, Bo E. and Luojia Hu, "Selection Without Exclusion," *Econometrica*, 2020, *88* (3), 1007–1029.

Hopenhayn, Hugo A., "Firms, Misallocation, and Aggregate Productivity: A Review," *Annual Review of Economics*, 2014, *6* (1), 735–770.

Hsieh, Chang-Tai and Peter J. Klenow, "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

Jones, Benjamin F., "The Human Capital Stock: A Generalized Approach," *American Economic Review*, 2014, *104* (11), 3752–3777.

_ , "The Human Capital Stock: A Generalized Approach: Reply," *American Economic Review*, 2019, *109* (3), 1175–1195.

Jones, Charles I., Peter J. Klenow, Robert J. Hsieh, and Erik Hurst, "Misallocation of Talent," *Journal of Political Economy*, 2018, *126* (3), 633–700.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman, "Life-Cycle Human Capital Accumulation Across Countries: Lessons from U.S. Immigrants," *Journal of Human Capital*, 2018, *12* (2), 305–342.

_ , _ , _ , _ , and _ , "Life Cycle Wage Growth across Countries," *Journal of Political Economy*, 2018, *126* (2), 797–849.

Lagarias, Jeffrey C., James A. Reeds, Margaret H. Wright, and Paul E. Wright, "Convergence Properties of the Nelder-Mead Simplex Method in Low Dimensions," *SIAM Journal on Optimization*, 1998, *9* (1), 112–147. Copyright: Copyright 2017 Elsevier B.V., All rights reserved.

Lewandowski, Piotr, Albert Park, Wojciech Hardy, Yang Du, and Saier Wu, "Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data," *World Bank Economic Review*, 2022, *36* (3), 687–708.

Lindenlaub, Ilse, "Sorting Multidimensional Types: Theory and Application," *Review of Economic Studies*, 2017, *84* (2), 718–789.

_ **and Fabien Postel-Vinay**, "Multi-Dimensional Sorting under Random Search," *Journal of Political Economy*, 2023, *(forthcoming)*.

Lise, Jeremy and Fabien Postel-Vinay, "Multidimensional Skills, Sorting, and Human Capital Accumulation," *American Economic Review*, 2020, *110* (8), 2328–2376.

Malmberg, Hannes, "Skill Bias and Development: Evidence from Trade and Industry Data," *Working Paper*, 2022.

Manski, Charles F. and Eytan Sheshinski, "Optimal Paternalism in a Population with Bounded Rationality," *NBER Working Paper No. 31349*, 2023.

Martellini, Paolo, Todd Schoellman, and Jason Sockin, "The Global Distribution of College Graduate Quality," *Journal of Political Economy*, 2023, *1* (1), 1–31.

McFadden, Daniel, "Conditional Logit Analysis of Qualitative Choice Behaviour," in P. Zarembka, ed., *Frontiers in Econometrics*, New York, NY: Academic Press New York, 1973, pp. 105–142.

Midrigan, Virgiliu and Daniel Yi Xu, "Finance and Misallocation: Evidence from Plant-Level Data," *American Economic Review*, 2014, *104* (2), 422–458.

Ngai, Rachel, Claudia Olivetti, and Barbara Petrongolo, "Structural Transformation over 150 Years of Women's and Men's Work," *Working Paper*, 2022.

OECD, "Technical Report of the Survey of Adult Skills (PIAAC)," Technical Report 2019.

Porzio, Tommaso, "Cross-Country Differences in the Optimal Allocation of Talent and Technology," *Working Paper*, 2023.

Poschke, Markus, "Wage Employment, Unemployment and Self-Employment across Countries," *Working Paper*, 2023.

Restuccia, Diego and Richard Rogerson, "Policy distortions and aggregate productivity with heterogeneous establishments," *Review of Economic Dynamics*, 2008, *11* (4), 707–720.

Rossi, Federico, "The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation," *American Economic Review*, 2022, *112* (1), 235–266.

Roth, Alvin E and Xiaolin Xing, "Turnaround Time and Bottlenecks in Market Clearing: Decentralized Matching in the Market for Clinical Psychologists," *Journal of political Economy*, 1997, *105* (2), 284–329.

Salanié, Bernard, "Identification in Separable Matching with Observed Transfers," *Review of Economic Studies*, 2015, *82* (1), 113–152.

Schoellman, Todd, "The Occupations and Human Capital of US Immigrants," *Journal of Human Capital*, 2010, *4* (1), 1–34.

Sen, Amartya, "Merit and Justice," in Kenneth Arrow, Samuel Bowles, and Steven Durlauf, eds., *Meritocracy and Economic Inequality*, Princeton, NJ: Princeton University Press, 2000, chapter 1, pp. 5–16.

Sobol', Ilya M., "Distribution of Points in a Cube and Approximate Evaluation of Integrals," *Zhurnal Vychislitel'noi Matematiki i Matematicheskoi Fiziki (in Russian)*, 1967, *7* (4), 784–802.

Stigler, George J, "The Economics of Information," *Journal of political economy*, 1961, *69* (3), 213–225.

Weaver, Jeffrey, "Jobs for Sale: Corruption and Misallocation in Hiring," *American Economic Review*, 2021, *111* (10), 3093–3122.

Appendix for
"Meritocracy across Countries"

Oriana Bandiera   Ananya Kotia   Ilse Lindenlaub

Christian Moser   Andrea Prat

February 14, 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 OECD 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 who were surveyed in 33 countries OECD (2019). The raw microdata are publicly available for download at `https://www.oecd.org/skills/piaac/`.

A.1.1 Key variables

Data on skills and skill requirements. PIAAC formally assesses three domains of cognitive skill: literacy, numeracy, and problem-solving in technology-rich environments (ICT). For our analysis, we use only numerical and literacy skills, as ICT is missing for several key countries in our sample. The PIAAC data report test scores for both 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 and how often they perform certain tasks in each skill group. For instance, for numeracy, they are asked how many times they use a calculator, how many times they use algebra, and so on. We sum the number of tasks that each worker completes in each area—numeracy and literacy—and weigh them by the difficulty of the task. PIAAC categorizes numeracy and literacy tasks into five proficiency levels based on task difficulty. We use these proficiency levels (level 1 is the lowest skill proficiency and level 5 is the highest) to weigh each task for its difficulty level. To do this, we match each task in the PIAAC questionnaire to the closest skill proficiency level based on the descriptions of these proficiency levels in OECD (2019). For e.g. 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 the analysis of 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 dis-

tributions to ensure a similar treatment in data and model. To do so, we average the global skill scores among all workers who are in the same country-specific quintile. This renders for each country a well-defined skill distribution of numeracy and literacy skills that take values between 0 and 1, while preserving differences of 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 a worker as working in a 'small' firm if their firm has up to 50 employees and 'large' if their firm employs 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 since we do not have reliable wage information for them.

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).

A.3 Construction of Data Moments

In this section, we describe how each of the targeted moments used in estimation is constructed in 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 those cells that have at least 5 observations.

- 6 moments reflecting the unemployment rates by broad skill group and gender: we compute the non-employment rates for individuals in six cells formed by interacting three broad worker skill groups (low, medium, and high) with gender (male and female).

- 2 moments reflecting the total mean wage as well as the within-worker-job-cell share of log-wage dispersion out of overall log-wage dispersion:
    - mean of log wages; and
    - the unexplained variance share, $1 - R^2 = RSS/TSS$, where RSS is the residual sum of squares and TSS is the total sum of squares in a regression of log wages on dummies for cells defined as the intersection of 25 worker skill types and 50 job types as described above.

- 1 moment reflecting the distribution of output between workers and jobs:
    - the share of profits in aggregate value added, or the composite of the labor share.

- 6 moments reflecting the matching pattern between workers and jobs, using the *basis function* approach proposed by Galichon and Salanié (2021). We construct six basis functions $\sum_{x,y} \mu_{xy} \phi_{xy}$, where μ_{xy} is the frequency of each cell formed by 25 worker skill types and 50 job types as described above. ϕ_{xy} is the product of skill and skill requirement scores of worker and job pairs in each cell.

A.4 Summary Statistics

Figure 26: Distributions of Worker Skills and Job Skill Requirements across Countries
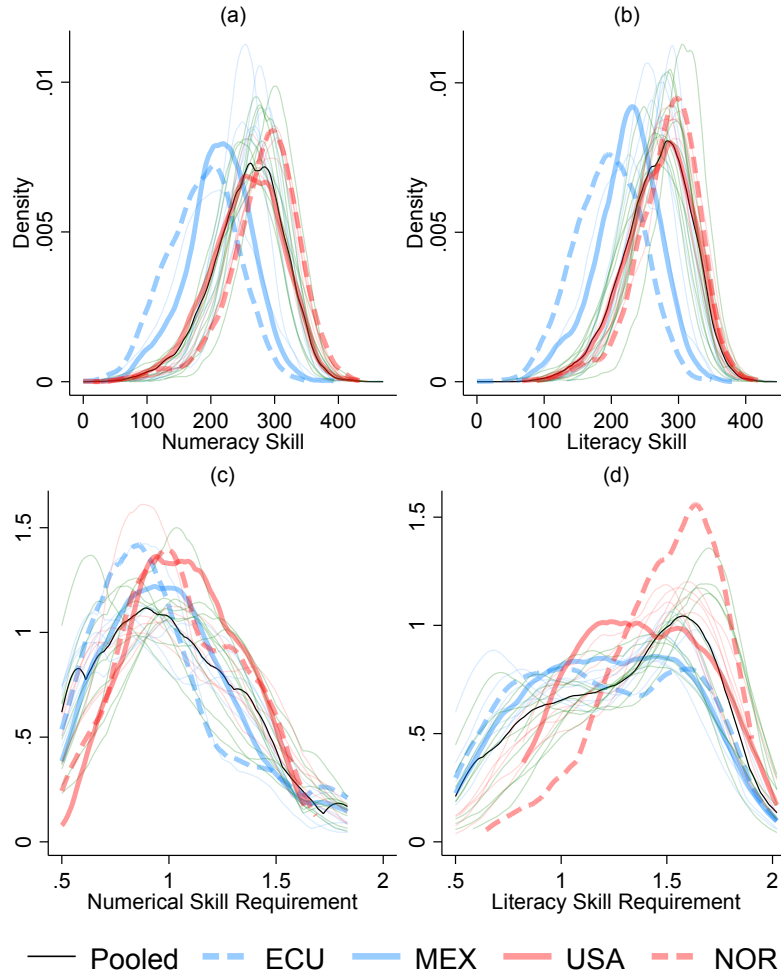

Notes: This figure shows the empirical distributions of worker skills (top panels) and job skill requirements (bottom panels) for numeracy (left panels) and literacy (right panels). The black solid line indicates the global distribution obtained by pooling all countries. Each thin solid line represents 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 27: Correlation between Skills and Education
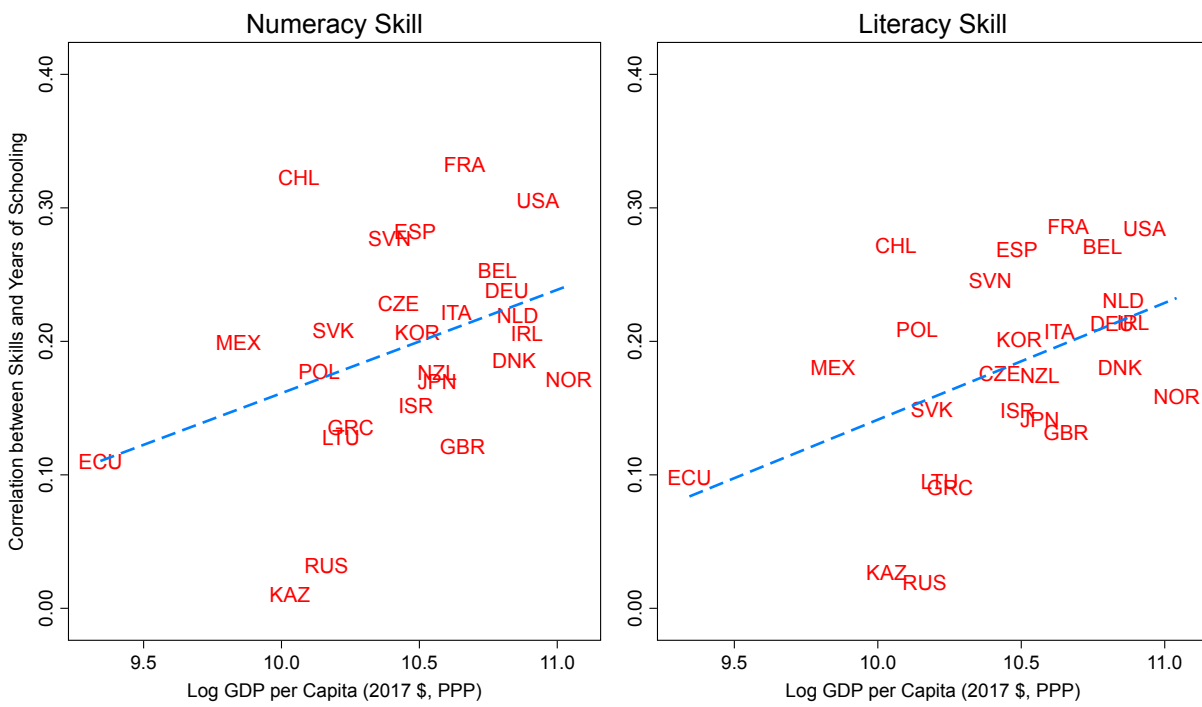
Notes: Both panels report the the R^2 of a regression of PIAAC skill scores on the years of education, the left panel for numeracy skills and the right panel for literacy skills. *Source:* PIAAC.

Figure 28: Correlation between PIAAC and O*NET Measures of Skill Requirements
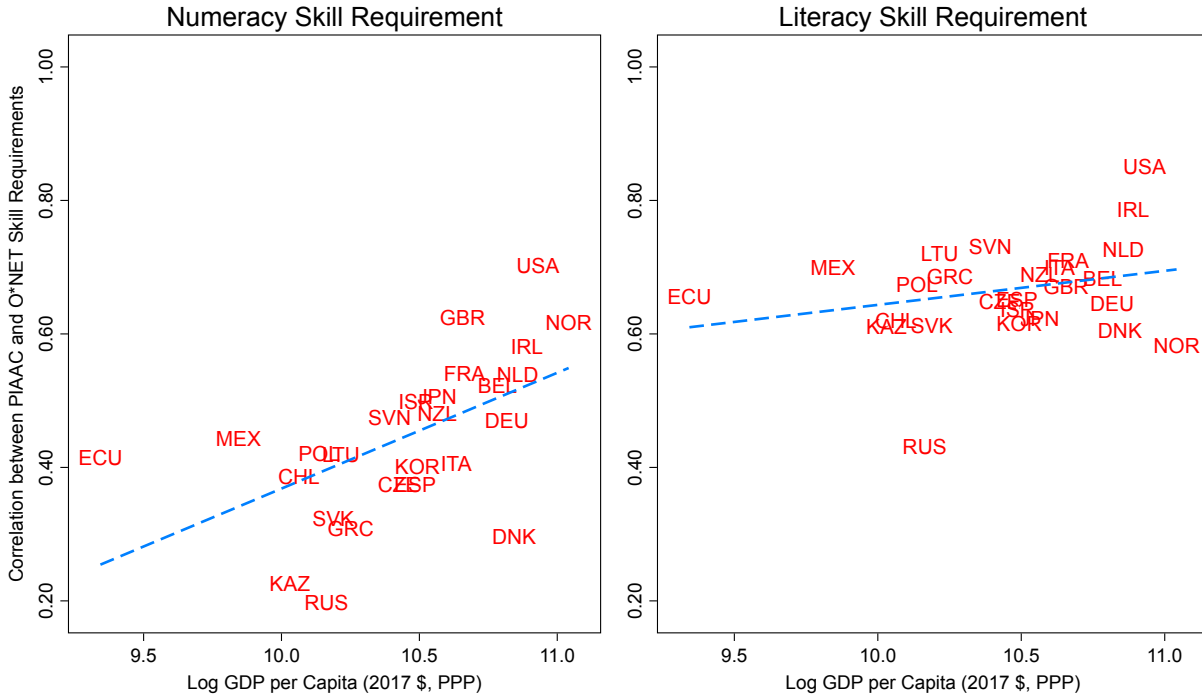
Notes: Both panels report the R^2 of a regression of the PIAAC skill requirement measures on the O*NET measures, the left panel for numeracy skill requirements and the right panel for literacy skill requirements. Skill requirement scores from O*NET data are computed as follows. We use three modules of the O*NET that provide numerical and literacy task contents in form of 128 skill requirements (these are characterized under the broad heads (1) work activities, (2) skills, and (3) abilities to each of O*NET's 873 occupations, where O*NET's occupation nomenclature is called O*NET SOC). 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 numerical, 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 numerical 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]. *Source:* PIAAC.

B Facts Appendix

Figure 29: The Difference between Worker Skills and Job Skill Requirements across Countries
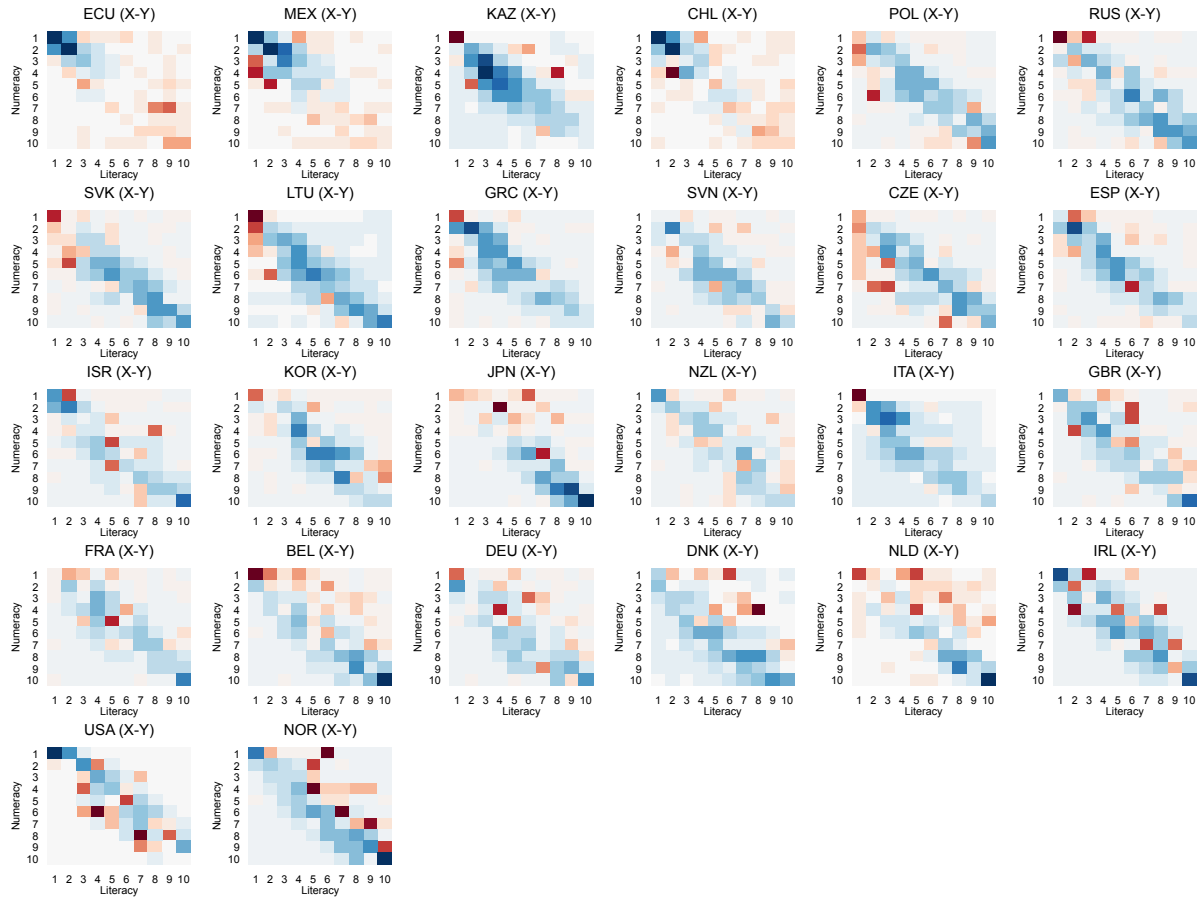
Notes: This figure replicates the third panel of Figure 5 for all 26 countries in our sample. The figure shows 10 ×10 cells that plot the difference between the number of workers in each skill cell and the number of jobs in the corresponding skill requirement cell. Each skill and skill requirement cell 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 5 for more details. Source: PIAAC *Source:* PIAAC.

C   Model Appendix

C.1   Derivations

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

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

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

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

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

We solve (19) for $\tilde{f}(x,y) := f(x_n, x_\ell, y) - f_{x\varnothing}(x) - f_{\varnothing y}(y)$ to obtain the expression for match-type-specific surplus $\tilde{f}(x, y)$ in (7).

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

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

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

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

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

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:

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

Following Salanié (2015), we now impose the following restrictions on the pre-transfer split of the idiosyncratic surplus components:

$$\delta_{x,k\to i} = 0 \quad \implies \quad \delta_{xk} = \delta_{x,k\to k} \tag{23}$$
$$\delta_{i\to i,y} = 0 \quad \implies \quad \delta_{iy} = \delta_{i\to k,y}. \tag{24}$$

That is, workers do not appropriate any share of the idiosyncratic surplus components before transfers. This has the intuitive implication 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, $\theta := \left(H(\cdot), G(\cdot), \sigma, f_{x\varnothing}(\cdot), f(\cdot), m^J \right)$. As stated in the text, (i) 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 $f(\underline{x}_n, \underline{x}_\ell, y_n, y_\ell, y_s) = 0$ for all $y = (y_n, y_\ell, y_s)$; (ii) we assume that the distribution of filled jobs is representative of the population distribution $G(\cdot)$. The proof proceeds in five steps.

Step 1: Identifying the worker type distribution $H(\cdot)$ and the job type distribution $G(\cdot)$.

Since $H(\cdot)$ and $G(\cdot)$ 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 of the distribution of idiosyncratic matching frictions, σ.

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 $f_{x\varnothing}(\cdot)$. Computing the log relative choice probabilities of worker type x staying nonemployed compared to that of matching with job type y based on (3)–(4), we have

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

On the left-hand side (LHS) of (26), both the share of nonemployed workers $\mu(x, \varnothing)$ and the share $\mu(x, y)$ of type (x, y) matches are observed. On the right-hand side (RHS), σ is known from Step 2 above and $w(x, y)$ is observed. Thus, we can solve (26) for the outside option $f_{x\varnothing}$ 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 $\underline{x} := (\underline{x}_n, \underline{x}_\ell, \underline{x}_g)$ based on (3)–(4):

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

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 LHS of (27), both the share of type (x,y) matches and the share of type $(\underline{x},y)$ matches are observed. On the RHS, 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

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

Into these expressions, we plug in

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

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

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 $\mu(\varnothing,y)$:

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

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

Note that $\widehat{\mu}(x,\varnothing)$ in (28) is directly observed in our data, since it refers to the share of all workers of type x who are nonemployed. Furthermore, all terms in the expression for $\widehat{\mu}(\varnothing,y)$ on the RHS of (29) are already identified. Then, we can express the profit share in match (x,y) as

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

Taking expectations over worker types x and firm types y, separately in the numerator and the denominator on each side of the equation, the LHS of (30) is the observed profit share in a country, while the RHS 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.

Thus, under our assumptions, all model parameters $\theta = (H(\cdot), G(\cdot), \sigma, f_{x\varnothing}(\cdot), f(\cdot), m^J)$ are identified. $\square$

E Estimation Appendix

E.1 Homogeneity Properties

Proposition 2. *Match-type-specific wages $w(x, y)$, idiosyncratic wages $\tilde{w}(x_i, y_k)$, profits $\pi(x, y)$, match-type-specific surplus $\tilde{f}(x, y)$, and total match surplus $s(x_i, y_k)$ are all homogeneous of degree 1 in*

$$\mathcal{P} := (f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma).$$

As a result, the choice probabilities $(\mu(x, y), \mu(\varnothing, y), \mu(x, \varnothing))$, 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 $(\mu(x, y), \mu(\varnothing, y), \mu(x, \varnothing))$ 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)

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

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

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

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

where the second equality follows from the previous result, so the profit function, π, 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 $F(\delta; \sigma)$ satisfies

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

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 also homogeneous of degree 1 in $\mathcal{P}$.

Next, for all (x, y), we can write match-type-specific surplus $\tilde{f}(x, y; \mathcal{P})$ as

$$\tilde{f}(x, y; \lambda \mathcal{P}) = \lambda f(x_n, x_\ell, y) - \lambda f_{x \varnothing}(x) - \lambda f_{\varnothing y}(y)$$
$$= \lambda \tilde{f}(x, y; \mathcal{P}),$$

so match-type-specific surplus function $\tilde{f}$ is homogeneous of degree 1 in $\mathcal{P}$.

Finally, total match surplus $s(x_i, y_k; \mathcal{P})$ for a given worker i of type x and a given job k of type y can be written as

$$s(x_i, y_k; \lambda \mathcal{P}) = \lambda f(x_n, x_\ell, y) - \lambda f_{x \varnothing}(x) - \lambda f_{\varnothing y}(y) + \lambda \delta_{xk} + \lambda \delta_{iy}$$
$$= \lambda s(x_i, y_k; \mathcal{P}),$$

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

To summarize, we have shown that match-type-specific wages $w(x, y)$, idiosyncratic wages $\tilde{w}(x_i, y_k)$, profits $\pi(x, y)$, match-type-specific surplus $\tilde{f}(x, y)$, and total match surplus $s(x_i, y_k)$ are all homogeneous of degree 1 in $\mathcal{P}$.

Given the results above, it follows from equations (1)–(4) that the conditional choice probabilities of 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,

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

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 $\mathcal{P}$. $\qquad\square$

E.2 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 server equipped with 112 cores, namely Intel Xeon Gold 6150 64-bit x86 multi-socket high performance microprocessors with 2.70GHz clockspeed.

E.3 Targeted Moments

In this section, we describe how each of the targeted moments used in estimation is constructed in the model and the data. The vector of moments based on the parameterized model, $\vec{\mathcal{M}}^m(\vec{\theta})$, and the vector of moments based on the data, $\vec{\mathcal{M}}^d$, each contain 15 elements consisting of:

- 6 moments reflecting the unemployment rates by broad skill group (see Appendix A.3 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, or the composite of 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 where these moments are coming from, 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:

$$f^\lambda(x, y) = \sum_{k=1}^{K} \lambda_k \phi_k(x, y)$$

where $\lambda \in \mathbb{R}^K$ is the parameter vector to be estimated and $\tilde{\phi} := (\phi_1, \ldots, \phi_K)$ are K known linearly independent basis surplus vectors. In our case, $\lambda = \{\alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell n}, \alpha_{\ell\ell}, \alpha_{\ell s}\}$ and $K = 6$ 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 μ as the average values of the basis output vectors:

$$C_k(\mu) = \sum_{\substack{x \in \mathcal{X} \\ y \in \mathcal{Y}}} \mu(x, y) \phi_k(x, y)$$

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

$$C_k(\hat{\mu}) = C_k\left(\mu^\lambda\right) \quad \forall k.$$

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.
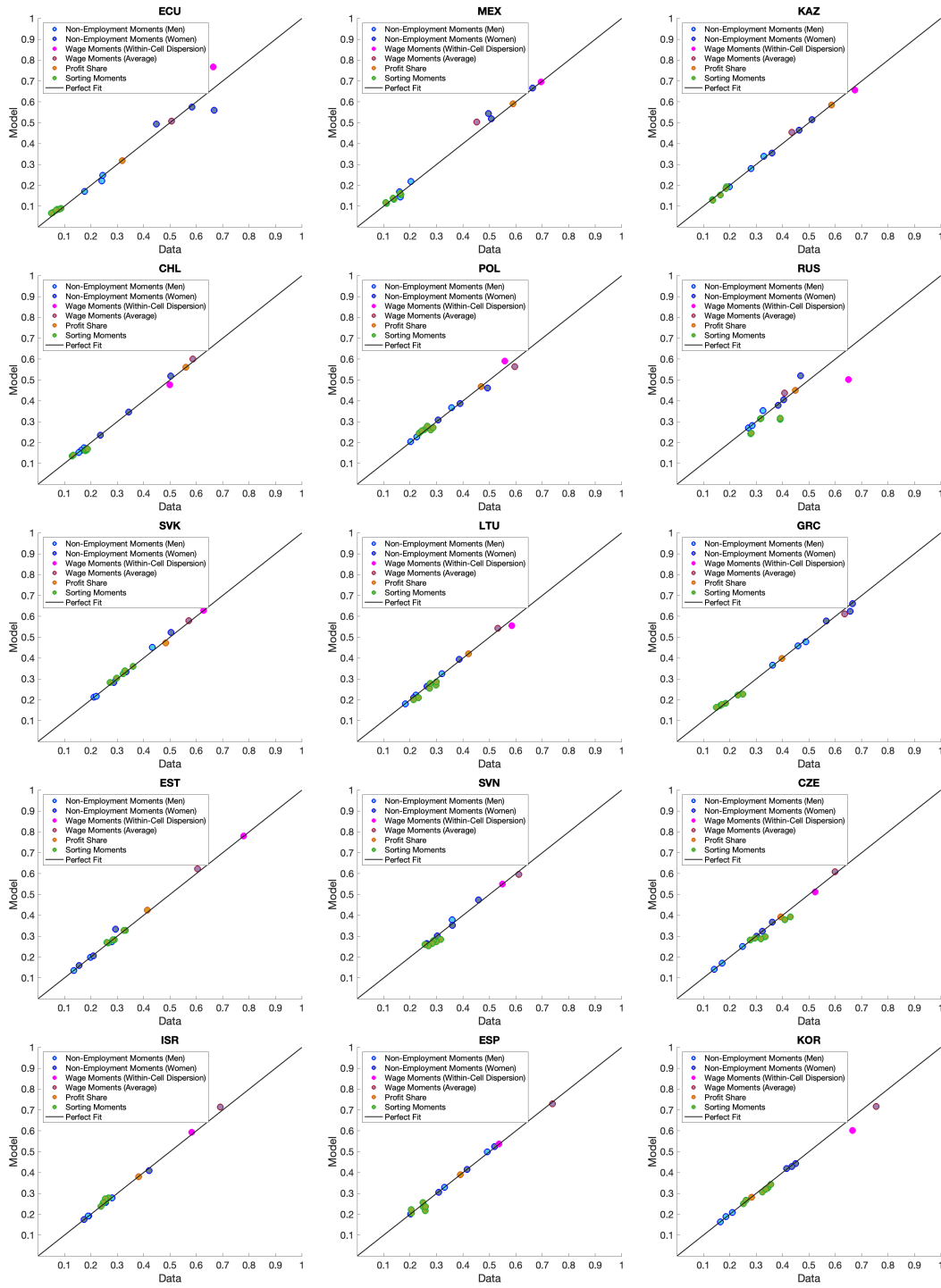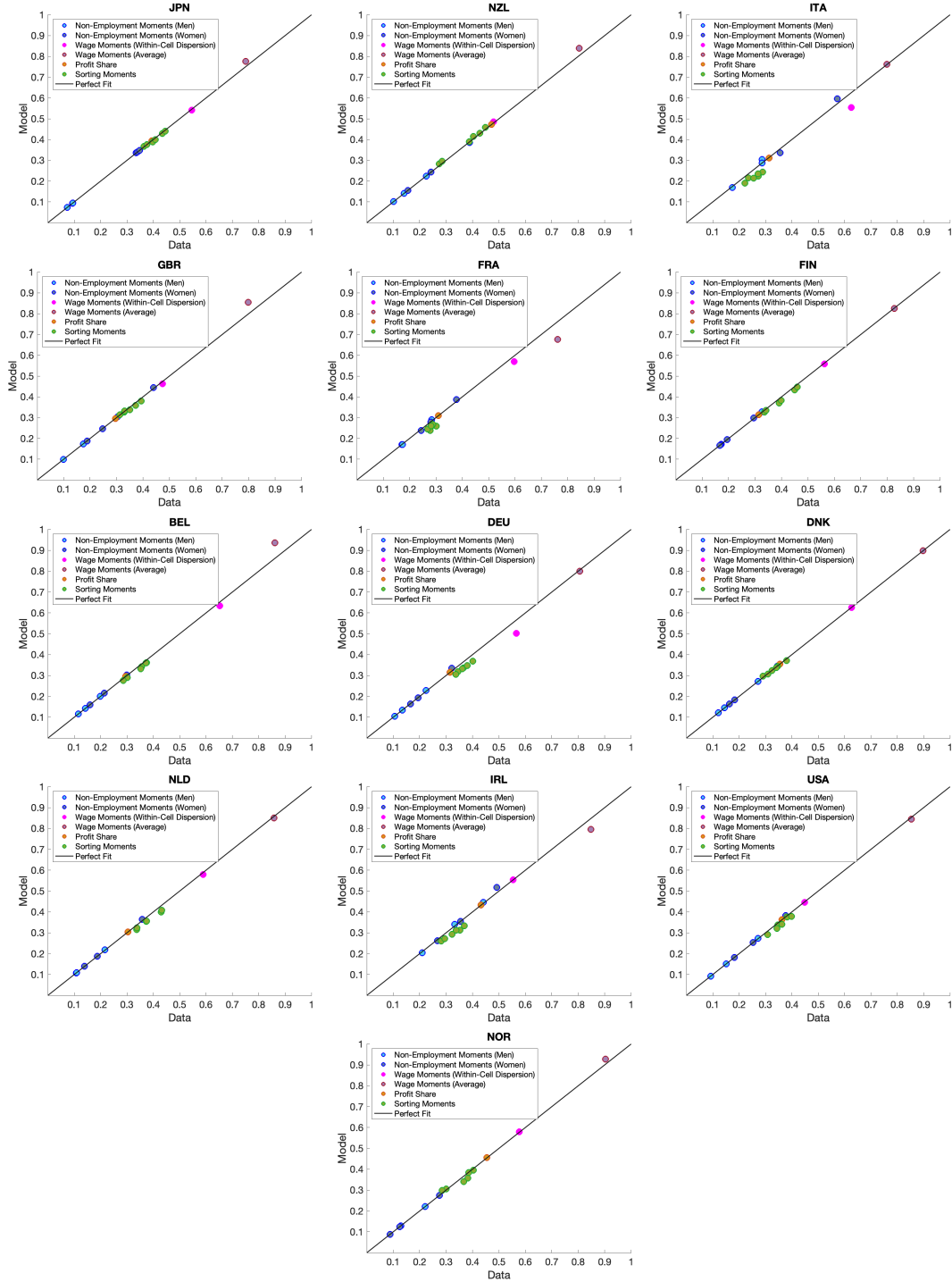
E.5 Details of Model Fit
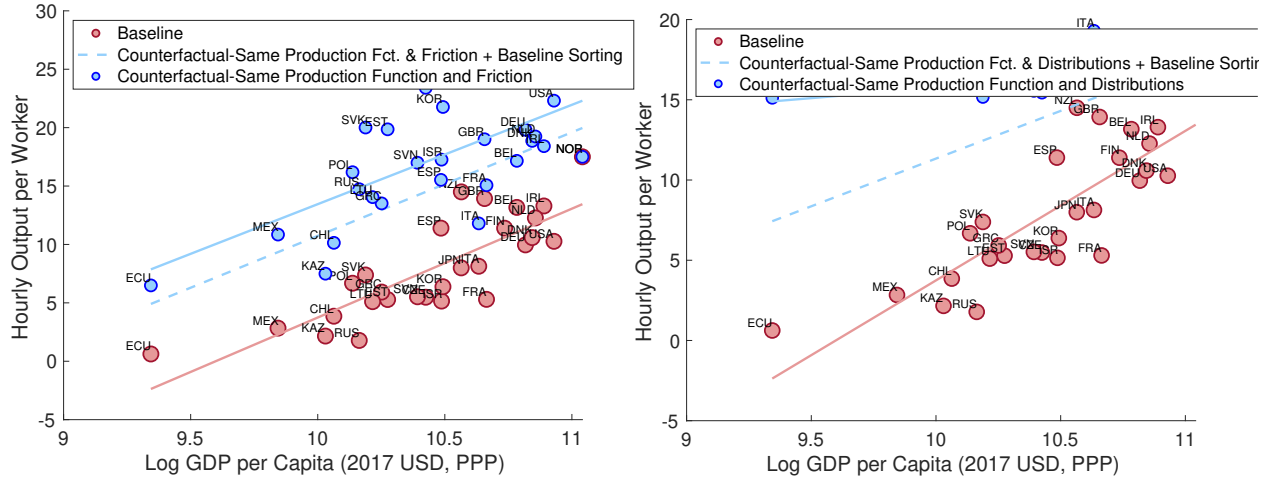
Figure 30: Model Fit: Middle-Income Countries

Figure 31: Model Fit: High-Income Countries

F Counterfactuals Appendix

F.1 Additional Counterfactual Simulations

Figure 32: 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) and the effects of implementing the Norwegian production technology as well as distributions of worker skills and job skill requirements (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.

F.2   Skill Misallocation by Gender in the Data

Figure 33: Gender Differences in Skills across Countries
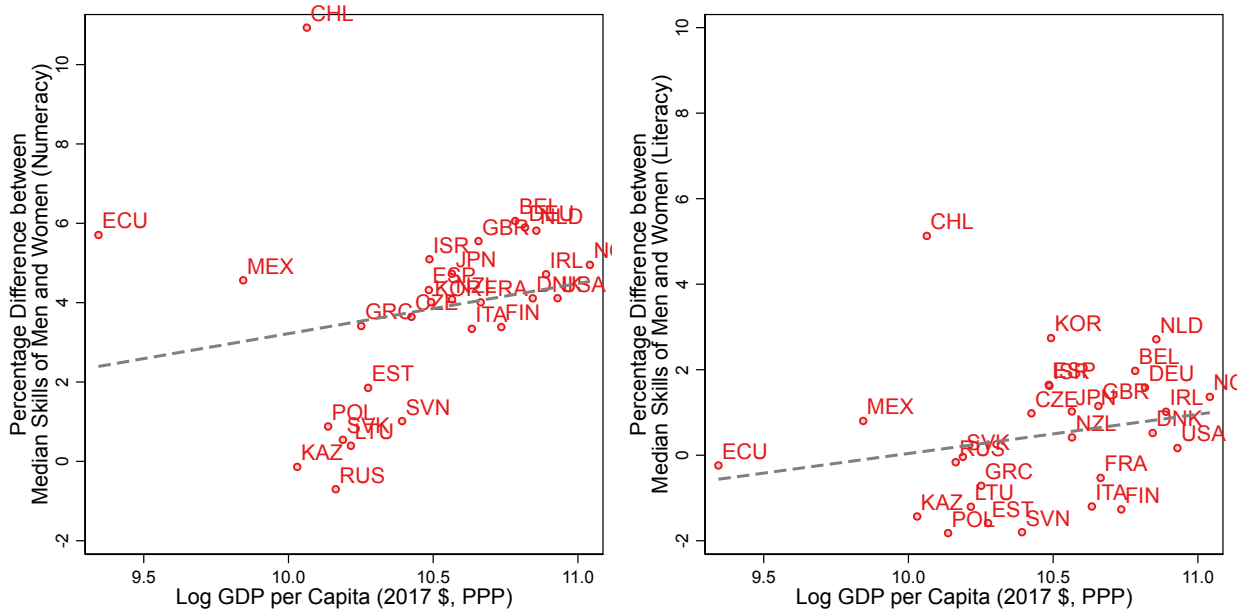
Notes: We report the percentage difference between the median skill of men and that of women in each country, as a function of their log GDP per capita. The dashed line indicates the linear best fit. The left panel shows on numeracy skills, while the right panel shows literacy skills. *Source:* PIAAC.

Figure 34: Share of Low/High-Skilled Women in the Economy and in Low/High-Skilled Jobs
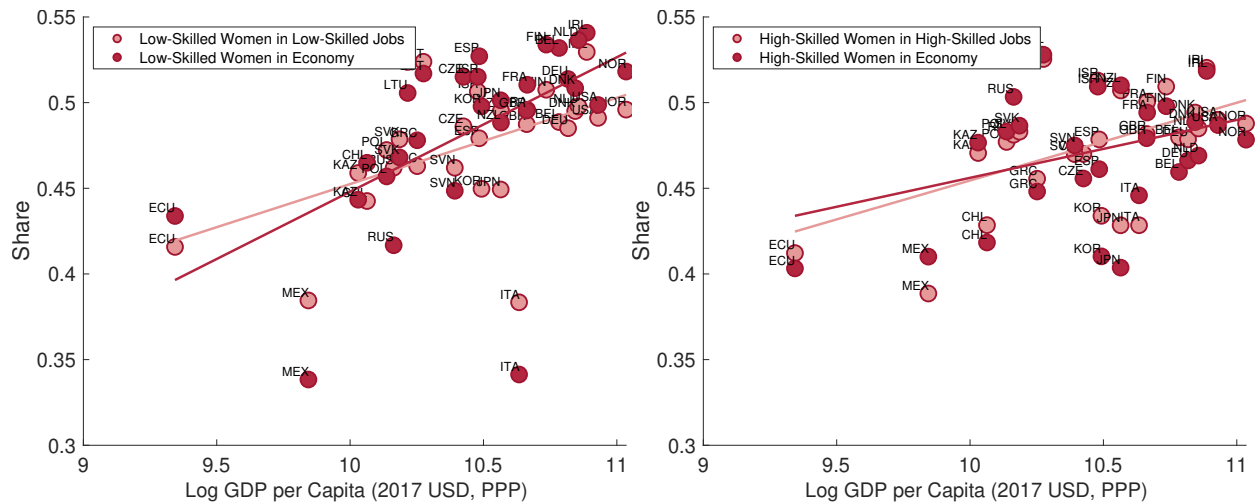
Notes: In the left panel, we plot the model share of low-skilled women in each country (red) and the share of low-skilled women in low-skilled jobs in each country (pink), where lines indicate the linear fit of the statistic under consideration with countries' log GDP per capita. The right panel has the same structure but focuses on high-skilled women. See Appendix A.3 for the definition of these broad skill groups. *Source:* Model simulations.