Meritocracy*

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Abstract

We study how meritocracy, which we define as the extent to which worker-job matching patterns are output-maximizing, varies with economic development. Using harmonized microdata on multi-dimensional worker skills and job skill requirements in 28 countries, we document that there is more pronounced misallocation of talent in lower-income countries. To understand the sources and consequences of cross-country differences in talent allocation, we develop an equilibrium 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. The estimated model suggests that differences in skill endowments and technology account for most cross-country heterogeneity in aggregate output and wage inequality. However, improved worker-job sorting is crucial for realizing the gains from development. We show that there are large potential gains from eradicating gender differences, particularly in lower-income countries. We also find that regional labor market integration boosts global output through an improved allocation of talent across borders.

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1 Introduction

The concept of meritocracy has a long history in political philosophy and the social sciences, both as a form of governance—famously, the administration of large empires—and as an organizing principle for society. Meritocracy, which embodies the allocation of talent into positions based on the highest available returns, is widely recognized as a fundamental driver of economic productivity. As such, economic theories predict that greater meritocracy will lead to economic development across countries. The theoretical arguments are as persuasive as the empirical evidence is scant. Are labor markets in higher-income countries more or less meritocratic? How much of the cross-country differences in living standards are due to differences in talent allocation? And what are the implications of misallocation of talent for the distribution of wages within and between countries across the development spectrum?[1]

To address these questions, we use harmonized microdata from the OECD Survey of Adult Skills of the *Programme for the International Assessment of Adult Competencies (PIAAC)*, a representative sample of adults in 28 middle- and high-income countries. A unique feature of these data is their detailed account of both workers' skills and their job skill requirements. The most important skill dimensions we consider are numeracy and literacy, which are comparable both between and within countries. By making use of separate measures for the demand and the supply of different skill dimensions, we construct measures of talent misallocation that take into account both horizontal and vertical differentiation between individuals and jobs.

Our analysis proceeds in five steps. In the first step, we document a series of descriptive facts regarding the patterns of worker-job matching across countries. Our empirical analysis is centered around the observation that workers in higher-income countries are more likely to hold jobs that require a combination of skills that matches their own. That higher-income countries exhibit more positive assortative worker-job matching, or greater meritocracy, manifests itself both on the intensive margin—i.e., among the employed, worker skills and job skill requirements are more closely aligned—and on the extensive margin—i.e., the skill gap between employed and nonemployed workers is greater. To investigate the drivers of greater meritocracy in higher-income countries, we investigate cross-country patterns of worker skill and job skill distributions, frictional wage dispersion, and wage returns suggestive of technological differences. We find that higher-income countries' endowments of worker skills and job skill requirements are more closely aligned, that they have lower shares of frictional wage dispersion, and that they have higher returns to positive assortative matches and to worker skills compared to lower-income countries. Altogether, these facts are all pointing in the direction of higher-income countries having more meritocratic labor market outcomes.

In the second step, we develop an equilibrium matching model to interpret these facts. Each country's labor market is characterized by three fundamental factors: distributions of worker skills and job skill requirements, a production technology, and matching frictions. Workers differing in multidimensional skills and gender match with jobs differing in multidimensional skill requirements and firm size

[1] The welfare implications of meritocracy are ambiguous for two reasons. First, the losses due to deviations from meritocracy depend on their nature—e.g., a person may maximize their own happiness and not just their earnings. Second, meritocracy may be traded off with other objectives—e.g., a more meritocratic society may also be a more unequal one. For a discussion, see Arrow et al. (2000). For these reasons, this paper will not draw welfare implications.

(i.e., a proxy for productivity) to produce output. Workers may choose to remain nonemployed and jobs may choose to remain idle. In addition to monetary payoffs from matching in the form of wages for workers and profits for jobs, we allow for matching frictions in the form of stochastic labor market wedges entering workers' and jobs' payoffs, which lead to deviations from the output-maximizing worker-job allocation. The country-specific dispersion of these wedges leads to deviations from the output-maximizing worker-job allocation.

In the third step, we confront our model with the data in an attempt to quantify the relative contributions of the three fundamental factors toward cross-country differences in talent misallocation. To this end, we formally demonstrate that all model parameters are identified. Key to our undertaking, we show that the extent of matching frictions is identified based on frictional wage dispersion, defined as wage dispersion across identical worker types in identical job types. Intuitively, matching frictions affect both the allocation and wages but, through the lens of our model, dispersion in wages conditional on the allocation can be rationalized only through matching frictions.

In the fourth step, we separately estimate the model for each of the 28 countries in our data. We find that the model fits 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. Importantly, the estimated model reproduces our central fact that high-income countries are characterized by more assortative worker-job sorting, which our model interprets as a more productive allocation of talent. When computing a meritocracy index, defined as the ratio of actual output over potential output absent matching frictions, we find that this is considerably higher in more developed countries. For instance, Norway—the richest country 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. In other words, the output losses from talent misallocation are substantial, and more so in lower-income countries.

In the fifth and final step, we ask: Is the greater observed misallocation of talent in lower-income countries a cause or a consequence of economic underdevelopment? To answer this question, we use the estimated model to decompose cross-country differences in aggregate output and wage inequality in relation to patterns of talent misallocation. We find that differences in skill endowments and production technology account for most cross-country heterogeneity in outcomes, with matching frictions playing a relatively modest role. Specifically, giving poor countries access to frontier technology and a more skilled workforce along with more skill-intensive jobs almost eliminates most of the cross-country variation in income. However, a large share of the gains from adopting better skill endowments and technology are realized through improved worker-job sorting, which we estimate accounts for 27 percent of the gains in global output and 38 percent of the cross-country convergence in incomes. This reflects our finding that the returns to improving the allocation of talent are constrained by the available skill endowments and technology. Therefore, we view talent misallocation as a consequence of economic underdevelopment rather than a source.

We further use our model for two natural applications. First, we study the misallocation of women's talent on the extensive margin, which we show is decreasing in development. If we counterfactually set women's value of home production equal to that of men, we 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. In contrast, if we adjust the number of jobs to also adjust, we find large gains in (female) employment and 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 world 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.

To sum up, this article presents the first comprehensive investigation into the link between talent misallocation and development, using a combination of harmonized microdata on workers' skills and jobs' skill requirements and an estimated equilibrium matching model. The combination of descriptive evidence and structural analysis allows us to establish the new fact that labor markets in poor countries are characterized by greater misallocation of talent. We use our model to investigate the sources and consequences of the meritocracy-income gradient across countries and find that misallocation of talent is a consequence, rather than a source, of development. We show that our analysis has important implications for the study of cross-country differences in female employment rates and labor market integration across countries—topics we only started to investigate in this paper.

Related Literature. Our work builds on four strands of the literature. First, we relate to the large literature on the sources of cross-country differences in income and skill premia. Prominent explanations to rationalize differences in these outcomes have centered around cross-country heterogeneity in 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 elevated matching frictions (Girsberger and Meango, 2022; Poschke, 2023; Donovan et al., 2023). In our model, all of these sources of cross-country heterogeneity—technology, worker skills and job skill requirements, and matching frictions—are jointly determine the allocation of workers to jobs. Our unified approach allows the data and our estimated equilibrium model to speak to the relative importance of these three factors in explaining cross-country differences in outcomes such as aggregate output and wage inequality.

Second, our work builds on the literature on factor misallocation. While misallocation of physical capital is widely thought of as one of the main causes behind low productivity in relatively poor countries, much less work has been done on the misallocation of labor, which after all makes up around two-thirds of value added. Most existing studies in this area have focused on misallocation of the quantity of homogeneous labor (e.g., Hsieh and Klenow, 2009; Buera et al., 2011; Midrigan and Xu, 2014; Bau and Matray, 2023). A recent exception is the important work of Jones et al. (2018) who study the misallocation of talent over time in the United States. We complement their work by studying misallocation of talent in cross-section of 28 countries spanning a significant part of the development spectrum.

Third, we contribute to the literature on matching and sorting. Of course, sorting between workers and jobs in the labor market is a well-studied phenomenon in matching theory (Becker, 1973; Shimer

and Smith, 2000; Lindenlaub, 2017; Lindenlaub and Postel-Vinay, 2023), with many applications to developed countries (e.g., Lise et al., 2016; Lise and Robin, 2017; Bagger and Lentz, 2018; Lise and Postel-Vinay, 2020; Martellini and Menzio, 2020, 2021). In comparison, we study the assortativeness of worker-job matching across a wide range of the development spectrum. To this end, we embed multidimensional heterogeneity (Lindenlaub, 2017) into an application of the seminal matching framework of Choo and Siow (2006) to a labor market context. This allows us to study the micro sources and macro consequences of cross-country differences in the (mis-)allocation of talent across multiple dimensions of worker and job heterogeneity.

Fourth, in terms of the applications of our framework to gender in development and the gains from labor market integration, we 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 summarized by Dustmann and Preston (2019) on the other. We distinguish our work by focusing on the role of talent misallocation, using uniquely detailed microdata on worker skills and job skill requirements together with an equilibrium matching model. One important advantage of our approach is the use of harmonized skill measures across countries spanning a significant part of the development spectrum, which circumvents the long-standing issue of the incomparable quality of education in research on economic development. To our knowledge, ours is the first paper to launch a large-scale (i.e., involving several countries) and structural (i.e., based on an equilibrium model) analysis of multidimensional (i.e., distinguishing between different dimensions of worker and job heterogeneity) misallocation of talent in relation to development.

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

2 Data Description

2.1 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 upper-income countries surveyed between 2012 and 2018.[2] A unique feature of these data is their detailed account of both workers' skills and their job skill requirements, including multidimensional skill measures in the areas of numeracy and literacy.[3] Importantly, skills are tested rather than self-reported or inferred. The survey as a whole, including the assessments, is designed to be comparable between

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

[3] 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.

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.[4]

2.2 Variable Definitions

Besides standard demographics (i.e., gender, age, educational attainment), our focus lies on measures of worker skills and job skill requirements. Workers' numeracy skill and literacy skill measures are measured on a scale from 0 to 500, corresponding to test scores. Each employed worker reports how often they perform a detailed list of tasks, categorized into numeracy, literacy, and others. To smooth out individual variation in task intensities, we compute mean shares of time spent on numeracy and literacy tasks at the most detailed available occupation (i.e., usually 3-digit ISCO) level in each country, which we then normalize following a procedure building on Caunedo et al. (2023). For most of our empirical analysis and in our structural analysis later on, we group worker skills and job skill requirements into either country-specific or global quintiles in each dimension.

2.3 Sample Selection

We restrict attention to all individuals in our data who are between the ages of 20 and 59, have non-missing numeracy and literacy skill scores, and report a continuous (as opposed to categorical) income measure when employed.

2.4 Summary Statistics

Our sample consists of 120,448 observations, representing over 718.2 million individuals. Table 1 shows summary statistics for our sample of 28 countries.[5]

Panel A shows general country characteristics. While the data cover middle and upper-income countries, the part of the development spectrum in our sample is substantial, with countries' GDP per capita ranging from Ecuador at 11,424 PPP dollars to Norway at 62,399 PPP dollars—a factor of around 5.5. In terms of population sizes, our sample ranges from Estonia at 0.7 million covered individuals to the United States at 285.4 million covered individuals. The distribution of the share of women and the age distribution 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 the set of potential ways of splitting the data in our analysis.

[4]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.

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

Panel B shows labor supply characteristics. It is well known that there are large cross-country differences in numeracy and literacy skills. These differences are also reflected in the worker skill measures in our sample. Relatedly, there is substantial heterogeneity in the years of schooling. Important for us, employment shares vary widely across countries, especially among women. The average individual in our sample scores just above half of the available marks on each of the numeracy and literacy tests. In Appendix B.1, 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. Under the assumption that innate skills are equally distributed among the world's population, this indicates that all the factors that interact with innate skills to produce the skills measured in adulthood have similar effects across the skills distribution. The main factor is education, which differs both in quantity and quality among countries. In the appendix, we show that education explains a negligible share of the variation in skills in the poorest countries. This is consistent with the concern, often expressed in the literature, that the quality of education varies substantially across countries so that the impact of one additional year of education is smaller.

Panel C shows labor demand characteristics. At this point, we just highlight substantial dispersion in numerical and literacy skill requirement scores across jobs, the magnitude of which we will assess in our empirical analysis. 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.

The PIAAC questionnaire asks respondents for detailed information about the nature of their jobs. Tasks are grouped into four areas: numeracy, literacy, ICT, and social interactions. Within each area, respondents are asked whether they perform several subtasks that can be ranked by skill level. For instance, tasks under numeracy include, among others, low-intensity tasks such as "using a calculator" and tasks that require advanced skills such as "algebra".

To compute job skill requirements we take the weighted mean of the tasks performed in each area by each respondent and then take the mean at the country and occupation level. Weights are proportional to the difficulty of the task, which we draw from PIAAC. By combining the data of workers who are doing the same job, as classified by ISCO 3-digit occupation codes, in a particular country, we can create a measure of the skill requirements for that job in that country. The local requirement measure is preferable to O*NET as it considers the fact that different countries may use different technologies to produce the same goods. In other words, the talents required in a given job are not uniquely defined if technology is a choice variable. This means that the same worker-job match may be misclassified if the skill requirement from O*NET is used, as it assumes that all countries use the same technology. In the appendix, we report the R^2 of a regression of skill requirements on the O*NET measure for the same job. We find that O*NET explains about half of the variation in literacy requirements in all countries and between one-fifth and one-half the variation in numeracy requirements, with the fraction being higher in richer countries.

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 at the country level. *Source:* PIAAC.

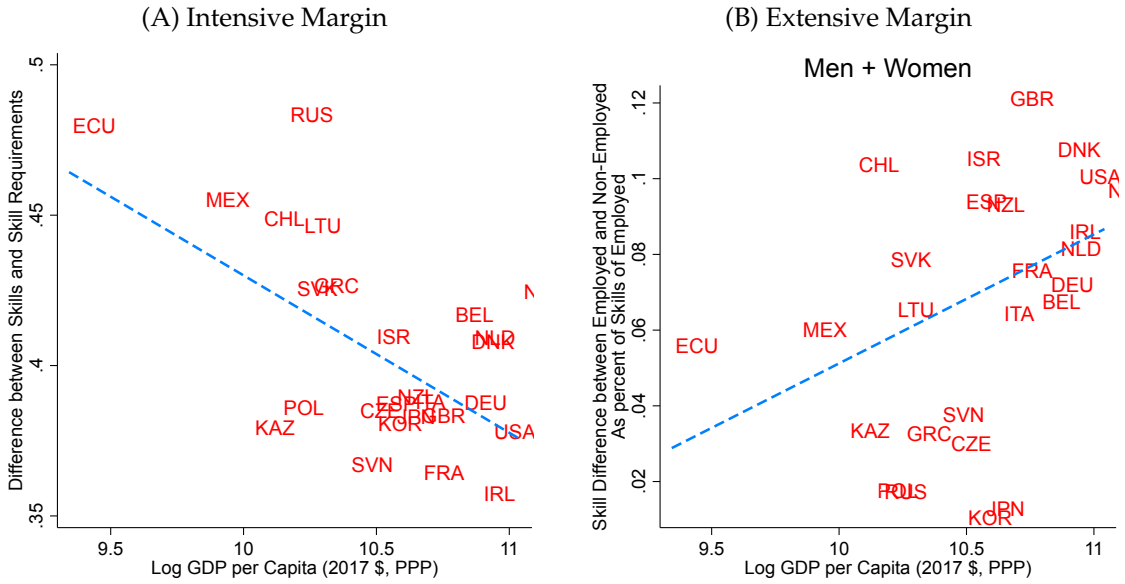
3 Facts about the Allocation of Talent and Development

In this section, we leverage the richness of the PIAAC data in order to document a sequence of descriptive facts related to worker skills, job skill requirements, and patterns of worker-job matching across countries. Our key insight is that

Fact 1. *There is more positive assortative worker-job matching in higher-income countries.*

We consider two dimensions of assortative matching, on the intensive margin (i.e., higher-skilled workers matching with higher-skill-requirement jobs) and on the extensive margin (i.e., more skilled workers selecting into employment). Figure 1 demonstrates that there is more positive assortative matching along both dimensions in higher-income countries. Panel A shows more positive assortative worker-job matching in the form of a pronounced negative relationship between a measure of worker-job mismatch and GDP per capita across countries. Worker-job mismatch is measured as the distance between a worker's multidimensional skill vector and that worker's job's multidimensional skill requirements vector. A lower mismatch value indicates that workers are employed in jobs with skill requirements that more closely match their own numeracy and literacy skills. Panel B shows that there is also more positive selection based on numeracy and literacy skills among workers in higher-income countries in the form of a positive relationship between the employed-nonemployed skill differential and GDP per capita across countries. 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.

Figure 1: More Positive Assortative Worker-Job Matching in Higher-Income Countries



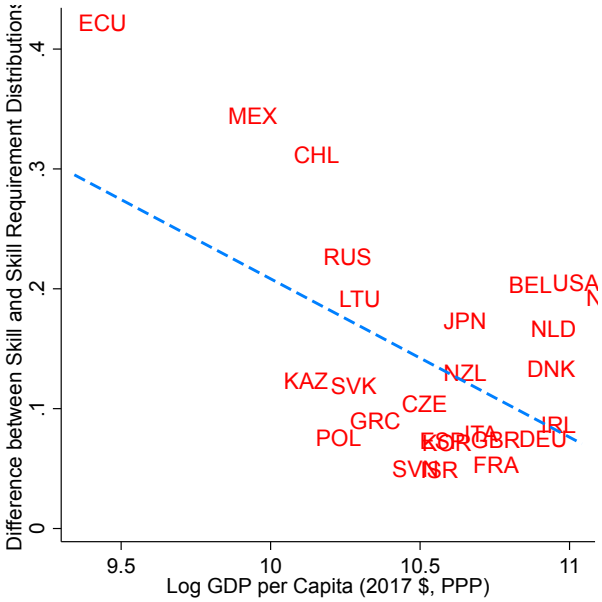
Notes: This figure shows patterns of intensive-margin sorting (Panel A) and extensive-margin sorting (Panel B) against GDP per capita across countries. Panel A plots the mean distance between workers' skills and the skill requirements of the job that they are employed in by country. Panel B plots the mean distance between the skills of employer versus nonemployed workers 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 within their country and the 2×1 vector containing the global ranks of the workers' jobs' numeracy and literacy skill requirement quintiles within their country. See the main text for details. *Source:* PIAAC.

Fact 1 is our main result, which summarizes worker-job matching patterns across countries. In what follows, we investigate three determinants of matching: endowments, frictions, and technology. To this end, we present descriptive facts pertaining to each of the three determinants. Later, we will interpret these facts through the lens of our equilibrium matching model.

Fact 2. *The distributions of all available worker skills and job skill requirements are more aligned in higher-income countries.*

Figure 2 shows that the endowments of worker skills and skill requirements of available jobs in the economy are more closely aligned in higher-income countries.[6] To this end, we compute a distance measure between the distribution of multidimensional worker skills and the distribution of multidimensional job skill requirements. This distance metric represents the dissimilarity between available worker and job types in the economy, independent of the actual worker-job matching pattern. A lower value of the distance measure means that the available worker types are more closely aligned with workers' skill endowments in a given country. The fact that higher-income countries have greater alignment between worker and job types suggest that it may be easier to find a perfect match in higher-income countries compared to lower-income countries.

Figure 2: More Aligned Worker Skills and Job Skill Requirements in Higher-Income Countries



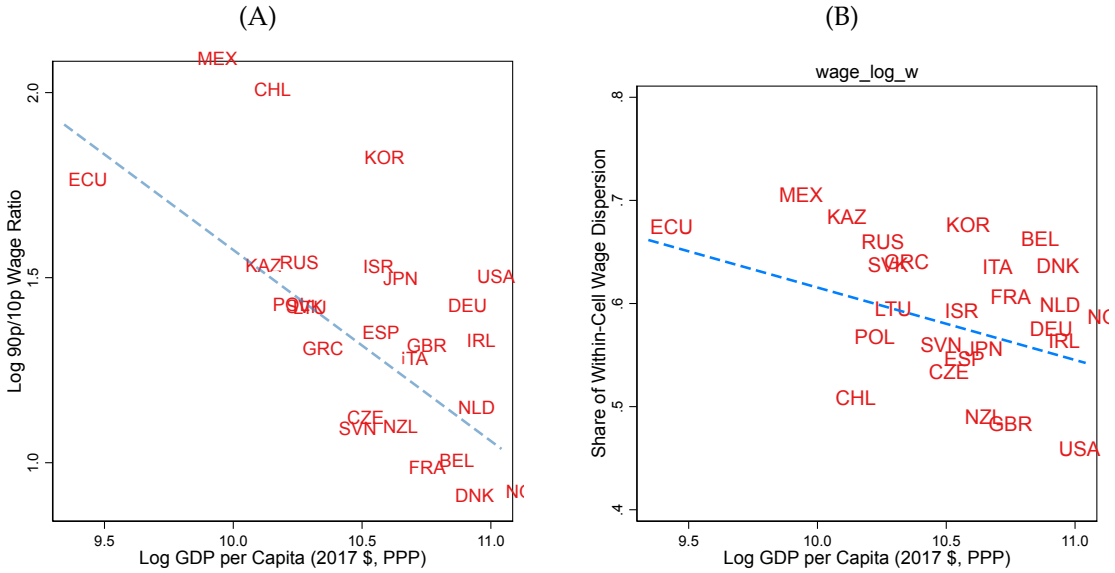
Notes: This figure shows the distance between the distributions of worker skills and job skill requirements against GDP per capita across countries. Distances are computed as the L^2 norm between the 2×1 vector containing the global ranks of workers' numeracy and literacy skill quintiles within their country 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 within their country. See the main text for details. *Source:* PIAAC.

Fact 3. *The share of residual wage variation conditional on worker and job attributes is lower in higher-income countries.*

[6] Figure 22 in Appendix B plots the country-specific distributions of worker skills and job skill requirements in each of the numeracy and literacy dimensions separately.

Figure 3 shows that worker skills, job skill requirements, and their interaction have greater predictive power for log wage dispersion in higher-income countries. Following a long tradition in labor economics, we interpret such residual wage variation conditional on worker and job attributes as frictional, in the sense of reflecting matching frictions that impede the optimal worker-job match. The intuition is that in a frictionless economy, there should be a unique assignment of a given worker type to a given job type, which results in the law of one price holding for wages—i.e., all workers of a given type in a job of a given type receive an identical wage.

Figure 3: Lower Residual Wage Variation in Higher-Income Countries

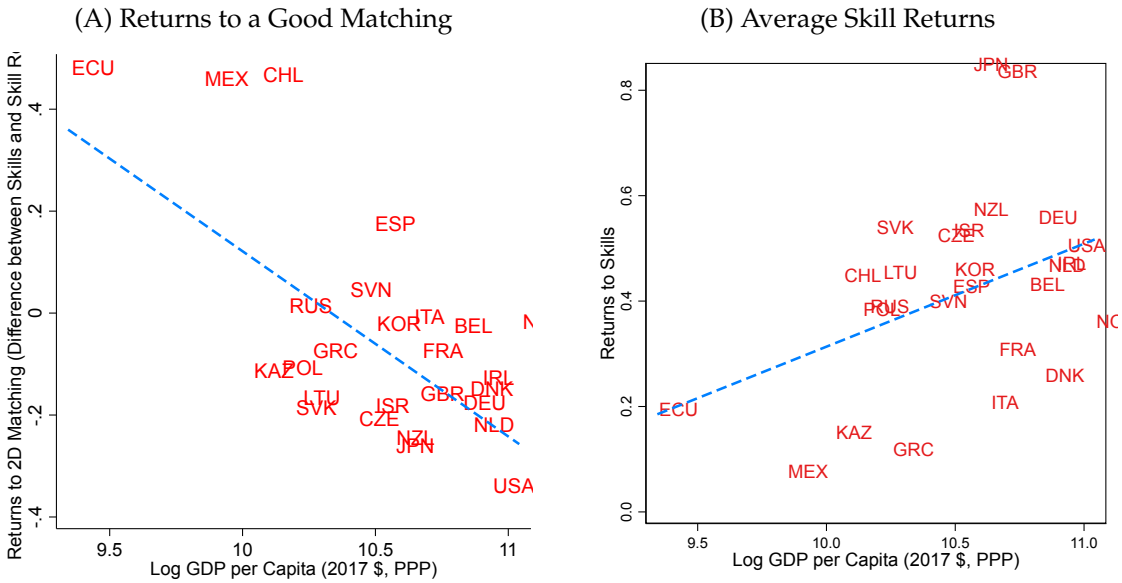


Notes: Panel A of this figure shows the $\log(P90/P10)$ wage percentile ratio by country. Panel B of this figure shows the share of residual wage variation (i.e., $1 - R^2$) based on a regression of log wages on interacted dummies for worker numeracy skill quintiles, literacy skill quintiles, and gender, and jobs' numeracy skill requirement quintiles, literacy skill requirement quintiles, and two firm size categories (i.e., ≤ 50 employees and > 50 employees). *Source:* PIAAC.

Fact 4. *The returns to matching worker skills and job skill requirements as well as the average returns to worker skills are greater in higher-income countries.*

Figure 4 shows that two distinct notions of wage returns are greater in higher-income countries. Panel A shows that the wage penalty associated with the distance between a worker's own multidimensional skill vector and the worker's job's multidimensional skill requirement vector is decreasing with GDP per capita across countries. The more negative is the penalty, the greater are the relative rewards for matching workers to jobs with adequate skill requirements. Similarly, Panel B shows that the average returns to numeracy and literacy skills are significantly greater in higher-income countries. Intuitively, the returns to matching a given worker into a given job depend on the production technology. Through this lens, this fact suggests that there are greater technological complementarities between worker skills and job skill requirements in higher-income countries.

Figure 4: Greater Wage Returns to Worker-Job Matching in Higher-Income Countries



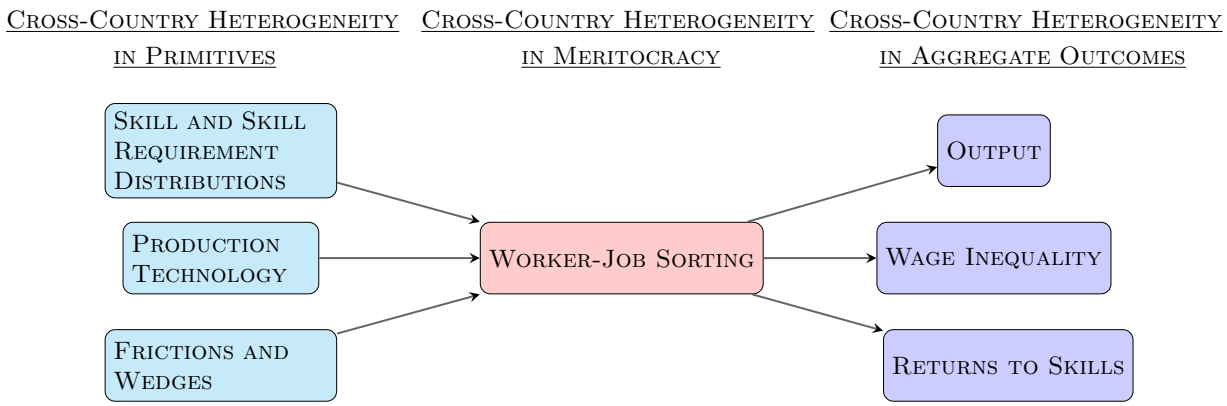
Notes: This figure shows wage returns against GDP per capita across countries. Panel A shows the estimated coefficients of a regression of log wages on the distance between worker skills and job skill requirements against GDP per capita across countries. Distances are computed as the L^2 norm between the 2×1 vector containing the global ranks of workers' numeracy and literacy skill quintiles within their country and the 2×1 vector containing the global ranks of the workers' jobs' numeracy and literacy skill requirement quintiles within their country. Panel B shows the average returns to worker skills from a Mincerian regression of log wages on workers' numeracy skill score, literacy skill score, gender, education, age, and age squared. The vertical axis plots the mean of the estimated coefficients on workers' numeracy and literacy skills by country. See the main text for details. *Source:* PIAAC.

4 An Equilibrium Model of Talent (Mis-)Allocation

Motivated by these empirical facts, we now study the sources and consequences of meritocracy, or talent (mis-)allocation 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: endowments, technology, and matching frictions. We are interested in the extent to which cross-country heterogeneity in these factors shapes worker-job sorting and thus aggregate output, wage inequality, and the returns to skills. Figure 5 provides a schematic overview of the model.

Our model incorporates multidimensional heterogeneity (Lindenlaub, 2017) into an application of the seminal matching framework of Choo and Siow (2006) to a labor market context. In our model, perfectly assortative matching is impeded by idiosyncratic *matching wedges*, the distribution of which 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 is determinate and identified based on our labor market microdata. We refer to these matching wedges as "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 talent*.

Figure 5: Model Overview



Notes: This figure provides a schematic overview of the equilibrium model presented in Section 4. On the left are primitives of the environment. In the center are the equilibrium matching patterns between workers and jobs. On the right are additional equilibrium outcomes, which are impacted by the equilibrium matching pattern.

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 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 results in a number of worker-job matches on the one hand and some number of unemployed workers and idle jobs on the other hand.[7] 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 gains from trade between a certain type of worker and a certain type of job. We interpret the latter as a reduced form for 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.

Agents. 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 remaining 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 $f_{\varnothing y}(y) = 0$.[8]

Matching Wedges. Matching frictions give rise to heterogeneity in sorting along the extensive margin (i.e., employment versus nonemployment) and the intensive margin (i.e., worker-job matching) across workers and jobs by preventing the output-maximizing allocation of workers to jobs. Specifically, we assume that matching is guided not only by economic match-type-specific surplus but also by nonpecuniary idiosyncratic considerations, which we model as 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,

[7] 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.

[8] 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.

distribution:

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

The scale parameter $\sigma \in \mathbb{R}^+$ determines the extent of matching frictions: $\sigma \to 0$ results in frictionless matching based on the output-maximizing allocation guided by productive complementarities between workers and jobs, 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 "frictions," we think of them as a reduced form for any factor preventing the output-maximizing allocation. 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).[9] Regardless of the specific interpretation, these matching wedges are separate from forces affecting the allocation and transfers based on match-type-specific output alone. We focus on the dispersion of matching wedges, guided by the scale parameter σ, that rationalizes the observed matching pattern 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 $\{\delta_{xk}\}_{x\in\mathcal{X}\cup\emptyset}$, each job k of type y chooses a worker type x to match with or to remain idle in order to maximize its payoff:

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

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 given by

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

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

[9] 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 following 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 reflecting matching wedges:

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

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. This equilibrium outcome

coincides with the solution to the planner's problem of maximizing the economy-wide sum of total match surplus—i.e., the equilibrium allocation in our model economy is constrained efficient.[10]

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 $\mu^J(x,y)/\mu^J(\emptyset,y)$ for jobs of type y, and $\mu^W(x,y)/\mu^W(x,\emptyset)$ 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):

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

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

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

This equilibrium relationship sheds light on the model determinants of wages. The transfer from jobs of type y to workers of type x in any match (x,y) positively depends on their 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, $\mu(\emptyset,y)/\mu(x,\emptyset)$.

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

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

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 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 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 comprises the match-type-specific wage, $w(x,y)$, due to a match between a type x worker with type y job, but also comprises 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}.

[10] That is, the planner's solution subject to the same endowments, technology, and matching frictions coincides with equilibrium.

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 $M_{xy}(\mu(x,\emptyset),\mu(\emptyset,y))$. Rewriting the matching frequency in (7) gives

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

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

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

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

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 $(\mu(x,\emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset,y))_{y\in\mathcal{Y}}$, 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.[11] Plugging the solution for $(\mu(x,\emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset,y))_{y\in\mathcal{Y}}$ into $M_{xy}(\mu(x,\emptyset),\mu(\emptyset,y))$, we obtain the equilibrium matching frequencies $(\mu(x,y))_{x\in\mathcal{X},y\in\mathcal{Y}}$. Similarly, we can use $(\mu(x,\emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset,y))_{y\in\mathcal{Y}}$ 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 problems with discrete types, like ours, uniqueness is not generally obtained absent matching frictions (i.e., $\sigma\to 0$), the presence of 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 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.

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

5 Identification

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

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

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 the following 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 $y = (y_n, y_\ell, y_s)$. Next, we state our identification result.

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. □

Here, we discuss the identification of each group of model parameters, focusing on the intuition behind the result in Proposition 1. We proceed in five steps. First, since $H(\cdot)$ and $G(\cdot)$ are distributions over observable worker and job attributes, they are identified based on empirical worker and job shares.

Second, the scale parameter of the distribution of labor wedges, σ, is identified based on wage dispersion within cells defined by (x, y) matches. 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 due to the idiosyncratic match surplus components. 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, workers nonemployment value $f_{x\varnothing}(x)$ is nonparametrically identified based on workers' choice probabilities of staying nonemployed relative to choosing a match with some job type y. A given worker type's relative choice probability depends on the worker type's unknown outside option $f_{x\varnothing}(x)$, the match-specific wage (observed), and the degree of matching frictions (identified in the second step above), thus pinning down $f_{x\varnothing}(x)$ for each worker type $x \in \mathcal{X}$.

Fourth, the production technology $f(x_n, x_\ell, y)$ is identified based on observed worker-job matching patterns. Under the assumption that the least productive worker type produces zero output, $f(\underline{x_n}, \underline{x_\ell}, y) = 0$, the probability that a type y job matches with a type x worker relative to that of matching with the least productive worker $(\underline{x_n}, \underline{x_\ell}, x_g)$ depends on the unknown match output, $f(x_n, x_\ell, y)$, the match-specific

wage (observed), and the degree of matching frictions (identified in the second step above), thus pinning down $f(x_n, x_\ell, y)$ for each worker-job pair $(x, y) \in \mathcal{X} \times \mathcal{Y}$.

Fifth and finally, the relative job mass m^J is identified based on the aggregate profit share. Intuitively, for given matching frictions, outside options, and production technology, the aggregate profit share is monotonically decreasing in the relative mass of jobs competing for a given mass of workers.

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 from the previous section.

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.

Distribution of Worker Skills and Job Skill Requirements. 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. 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.[12] As a result, we obtain probability mass functions over 50 worker types, $(h_x)_{x \in \mathcal{X}}$, and 50 job types, $(g_y)_{y \in \mathcal{Y}}$.

Production Function. We assume a bilinear functional form for the output produced by a worker of type x matched with a job of type y:

$$f(x, y) = \alpha_{nn} x_n y_n + \alpha_{n\ell} x_n y_\ell + \alpha_{ns} x_n y_s + \alpha_{\ell n} x_\ell y_n + \alpha_{\ell\ell} x_\ell y_\ell + \alpha_{\ell s} x_\ell y_s \tag{14}$$

$$= A\big(x_n y_n + \hat{\alpha}_{n\ell} x_n y_\ell + \hat{\alpha}_{ns} x_n y_s + \hat{\alpha}_{\ell n} x_\ell y_n + \hat{\alpha}_{\ell\ell} x_\ell y_\ell + \hat{\alpha}_{\ell s} x_\ell y_s\big) \tag{15}$$

[12] 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.

This production function in (14) 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.[13] The 6 production function parameters $(\alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s})$ guide complementarities or substitutabilities in production between the various worker and job attributes. Thus, they crucially shape the equilibrium matching patterns. Equation (15) above 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.

Outside Options. 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.[14] 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.[15]

6.2 Estimation Procedure

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

$$\theta = \left((h_x)_{x\in\mathcal{X}}, (g_y)_{y\in\mathcal{Y}}, m^J, \alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s}, (f_{x\varnothing}(i, x_g))_{i\in\{1,\ldots,3\}, x_g\in\{f,m\}}, \sigma \right). \tag{16}$$

The vector θ contains 114 parameters, which we estimate separately for each country. Our estimation proceeds in two steps. In the first step, we estimate the 100 parameters corresponding to 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 the remaining parameters in $\theta \in \Theta$ 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 of the parameters 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. In addition, we exploit the following homogeneity property of our model.

Proposition 2. *The equilibrium wage functions $w(x, y)$ and $\tilde{w}(x_i, y)$, profit function $\pi(x, y)$, match-type surplus $\tilde{f}(x, y)$, and total match surplus $s(x_i, y_k)$ are all homogeneous of degree 1 in $(f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma)$.*

Proof. See Appendix D.2. □

[13] 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.

[14] Sorting workers into broad skill groups reduces the complexity of the estimation routine while retaining full flexibility across broad skill groups. 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.

[15] In theory, one could let the value of an idle job vary freely, analogously to our approach to esimating worker's 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. Our approach, motivated by the common assumption of free entry, circumvents this nonidentification problem.

The homogeneity property in Proposition 2 implies that a set of target moments comprised of workers' and jobs' relative choice probabilities, sorting patterns, and log wage dispersion would only pin down the degree of matching frictions relative to TFP, σ/A. Thus, in order to separately identify the scale parameter guiding labor wedges, σ, we need to target a moment that is sensitive to absolute levels rather than relative magnitudes. As such, we add the average log wage in PPP dollars to our list of target moments. Together with a moment measuring the share of log wage dispersion within (x, y) cells, this allows us to recover the scale parameter of the labor wedge distribution, σ without the type of normalization imposed on it by Choo and Siow (2006). 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; and 1 moment reflecting the share of profits in aggregate value added to inform the relative job mass m^J.[16]

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

$$\theta^* = \arg\min_{\theta \in \Theta} \Omega\left(\mathcal{M}^m(\theta), \mathcal{M}^d\right), \tag{17}$$

We set the objective function in equation (17) equal to the weighted sum of squared percentage differences between 15 pairs of moments from the parameterized model and the data

$$\Omega(\mathcal{M}^m(\theta), \mathcal{M}^d) = ((\mathcal{M}^m(\theta) - \mathcal{M}^d) \oslash \mathcal{M}^d)' \mathbf{W} ((\mathcal{M}^m(\theta) - \mathcal{M}^d) \oslash \mathcal{M}^d), \tag{18}$$

where we form percentage deviations between model and data moments by applying the *Hadamard division*, here denoted by the symbol $\oslash$.[17] 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 equation (17) 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.3.

6.3 Estimation Results

Having estimated the model as described above, we now present parameter estimates across countries. We demonstrate that the model fits the targeted data moments well in nearly all 28 PIAAC countries. We then validate our model against untargeted data moments, including cross-country patterns in aggregate output, skill returns, wage inequality, and worker-job sorting.

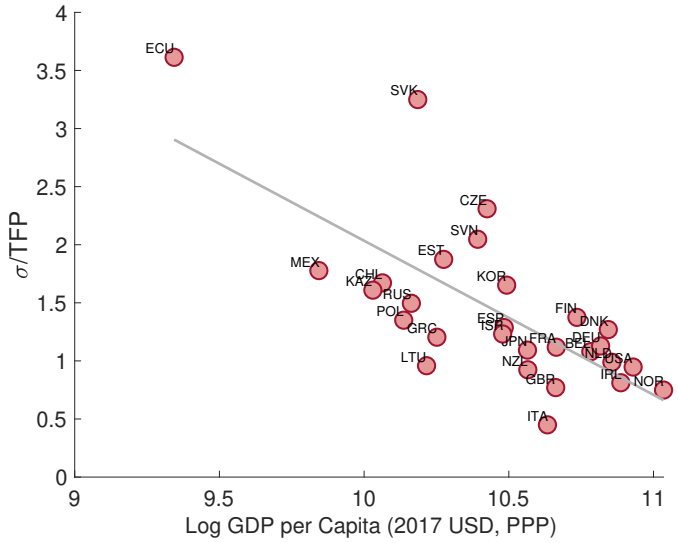
Parameter Estimates. Figure 6 shows our estimates of the relative importance of matching frictions, measured as the scale parameter of the labor wedge distribution relative to TFP, σ/A, in each country. We find that matching frictions are considerably higher in lower-income countries. For example, Ecuador, 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 empirical within-cell wage dispersion across countries—see

[16] See Appendix E.2 for details regarding the construction of data and model moments.

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

Figure 3 in Section 3. Through the lens of our model, this finding suggests that worker-job matching is closer to random in lower-income countries.

Figure 6: Estimates of Matching Frictions across Countries



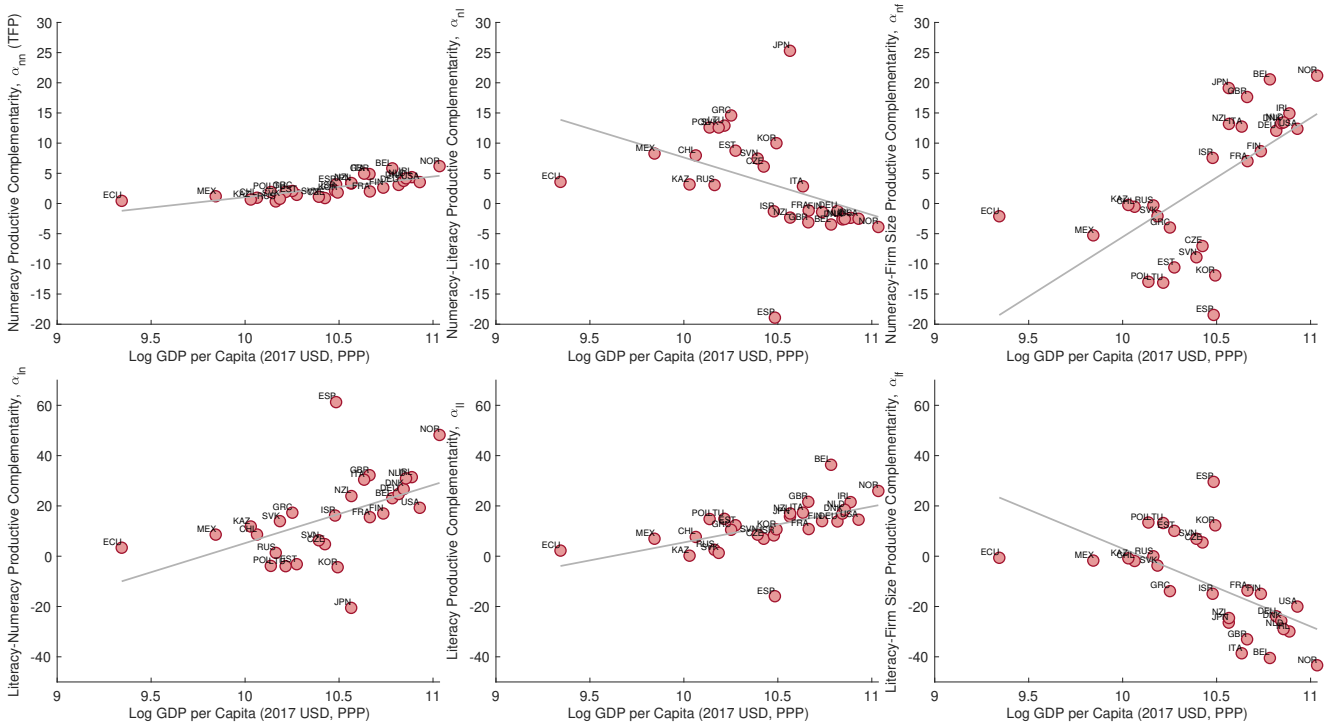
Notes: This figure plots estimates of the scale parameter of the labor wedge distribution relative to TFP σ/A against log GDP per capita across countries. Each red dot represents a structural estimate of σ/A for one country. The gray solid line represents the linear best fit. *Source:* Model simulations.

Figure 7 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 higher 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 1 in Section 3. 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 8 highlights how the relative value of home production varies with the part of the development spectrum captured by our data. 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. Naturally, 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).

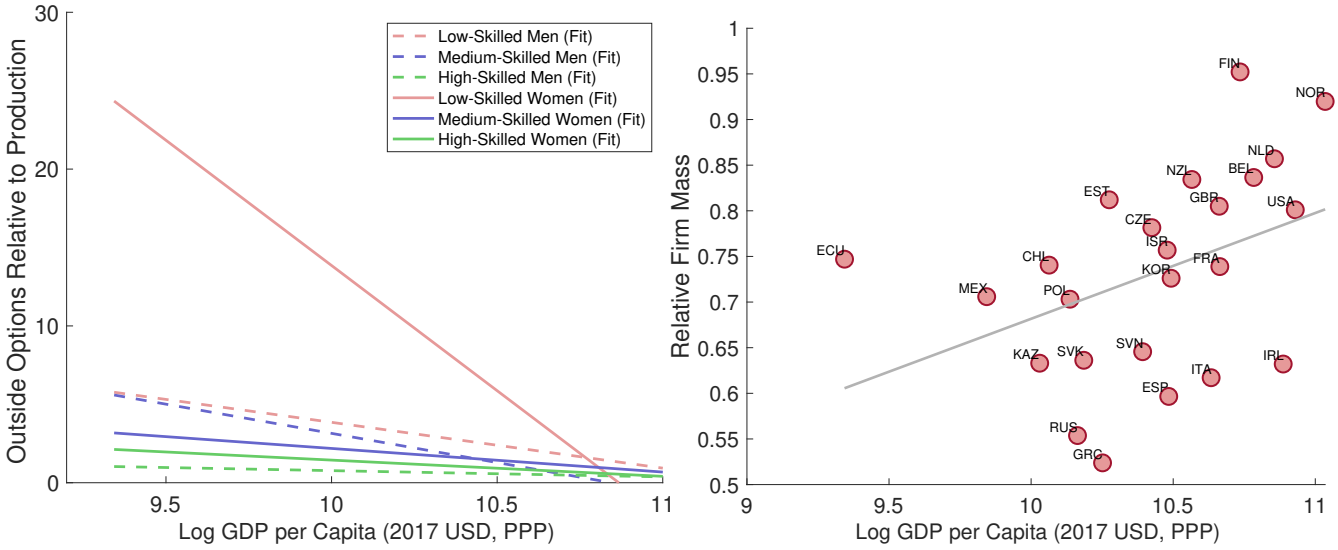
The right panel of Figure 8 shows that the relative mass of firms is lower in lower-income countries, suggesting that labor markets in lower-income countries are less competitive or subject to higher entry costs. These estimates are informed both by higher nonemployment rates in lower-income countries and by differences in the aggregate profit shares.

Figure 7: 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 8: 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 $f_{x\emptyset}(x)$ (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.2 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.4. Figure 9 displays the model fit for the six countries across the part of the development spectrum covered by the PIAAC survey. Each graph plots model-generated moments against targeted data moments, where the 15 moments are split into six categories. A perfect model fit would be indicated 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 or near 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 in the model, nonemployment rates for both genders (blue markers) are decreasing in GDP per capita, especially for women. Third, both in the data and in 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.

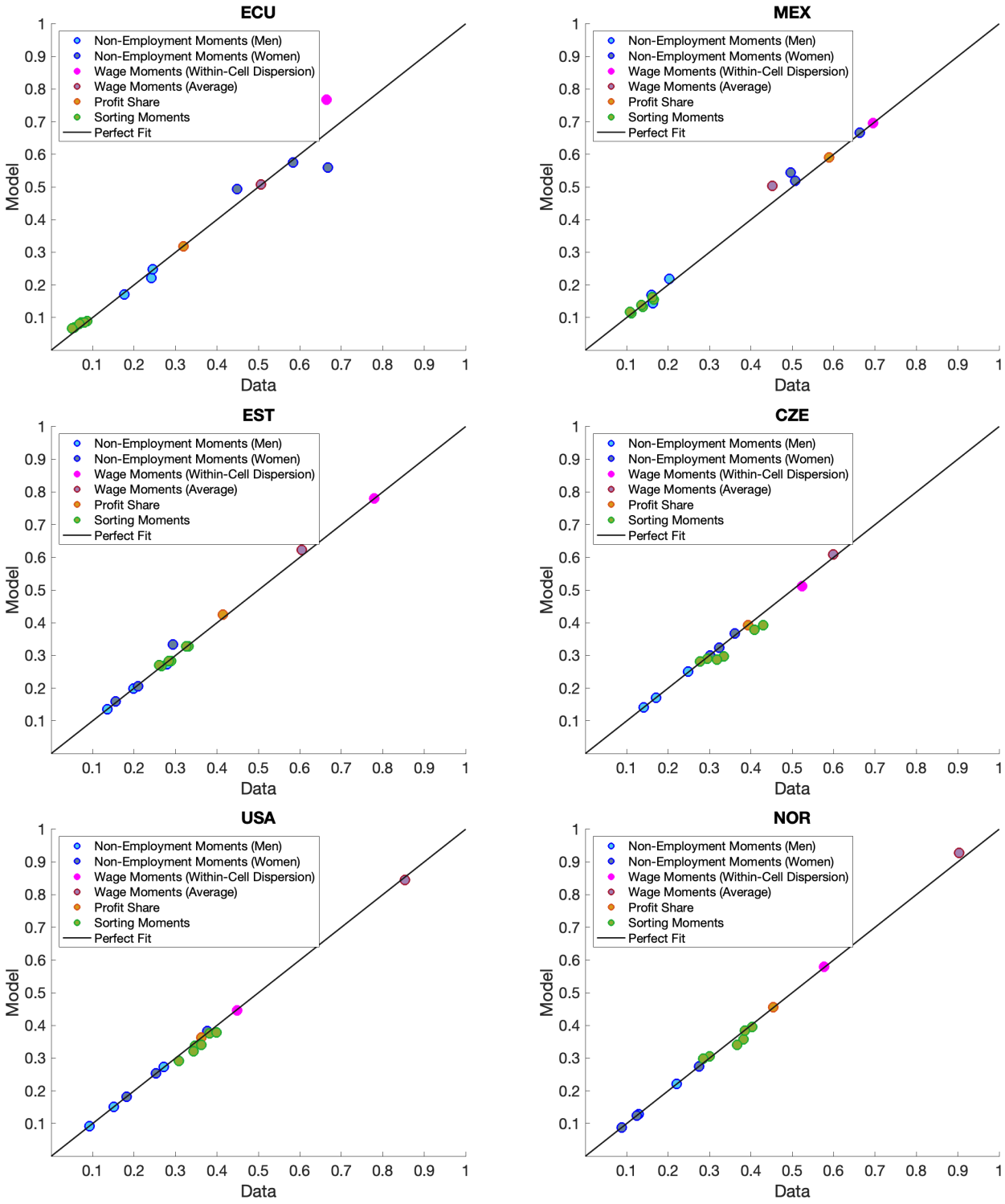
Model Validation Based on Untargeted Moments. We are interested in whether the estimated model accounts for cross-country heterogeneity in key outcomes related to worker-job mismatch that were untargeted in our estimation, including aggregate output, wage inequality, and skill returns.

The top panels of Figure 10 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. Similarly, the production function of higher-income countries features stronger worker-job complementarities in most dimensions that induce positive assortative worker-job sorting—see Figure 7.

The middle panels of Figure 10 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 lower-income countries' workforces are tilted toward workers with 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 10 show that our model reproduces the empirical pattern of

Figure 9: 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.2 for how the moments are constructed. The mean log wage (purple markers) is scaled by a factor of 1/3.5 to fit it into the same figure with the other moments. *Source:* PIAAC, OECD, and model simulations.

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 part of the development spectrum covered by the PIAAC data. Our goal is to understand the sources of these cross-country differences in the misallocation of talent as well as their implications for important outcomes across countries such as those documented above. To illustrate these cross-country differences in worker-job sorting patterns, we first capture talent misallocation 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.

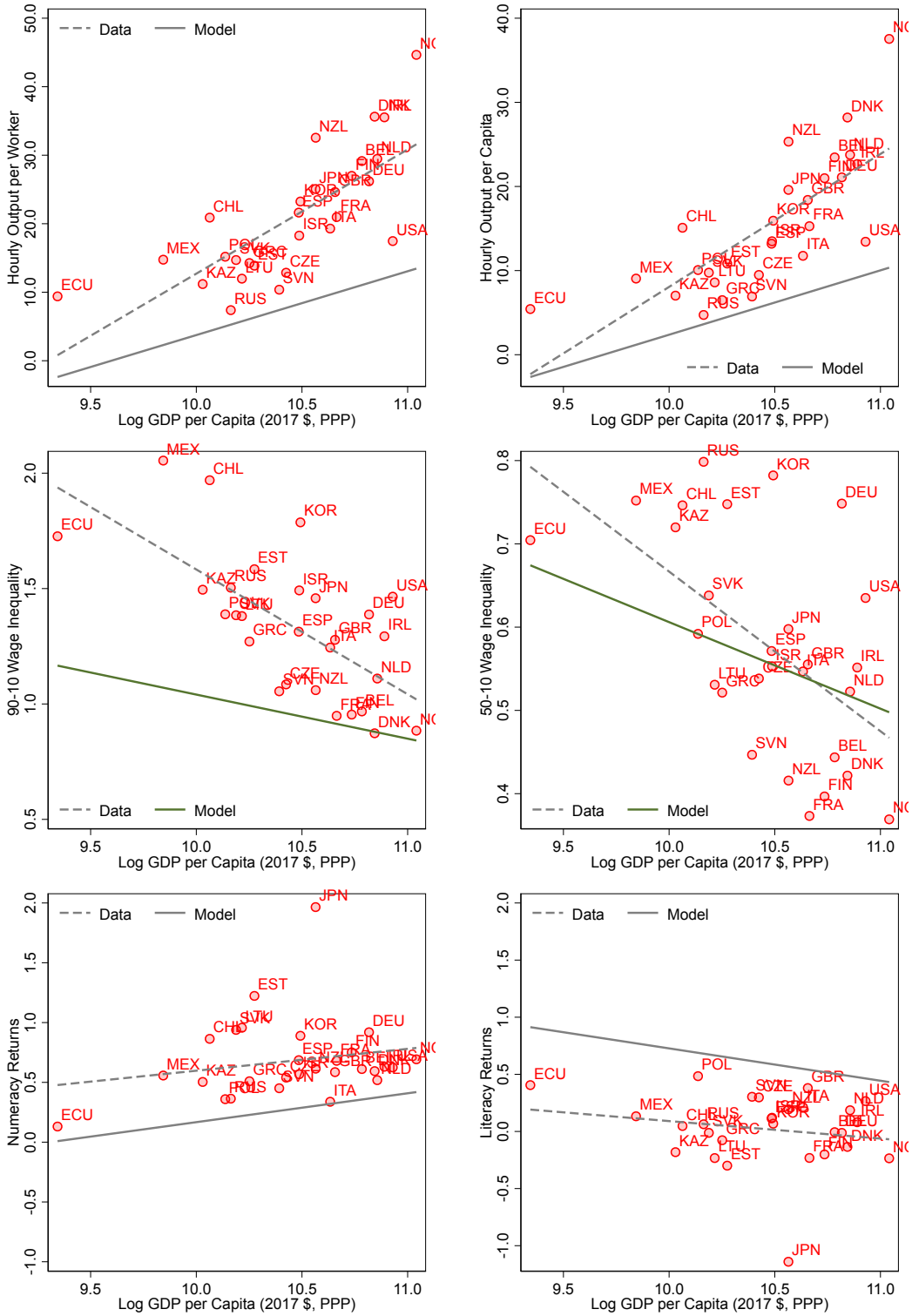
As an example, compare Ecuador—the lowest-income country in our data—with Norway—the highest-income country in our data. The left and middle panels of Figure 11 show that Ecuador displays considerably more overlap in worker skills across different job types. In other words, workers are less assortatively matched in Ecuador than in Norway. The right panels of Figure 11 highlight generalize the relationship between worker-job mismatch across all 28 countries in our data. 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 compared to lower-income countries.

To summarize the model-implied patterns of worker-job matching and talent misallocation, we construct for each country a *meritocracy index*, defined as a country's actual (i.e., estimated) output relative to its potential output without matching frictions (i.e., $\sigma \to 0$). Figure 12 shows the model estimates of this 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. In other words, Ecuador loses about twice as much output, or 80 percent of its potential, due to its high degree of matching frictions and resulting worker-job mismatch compared to Norway, whose output would be around 40% higher in a frictionless world.

7 Sources and Consequences of Talent Misallocation

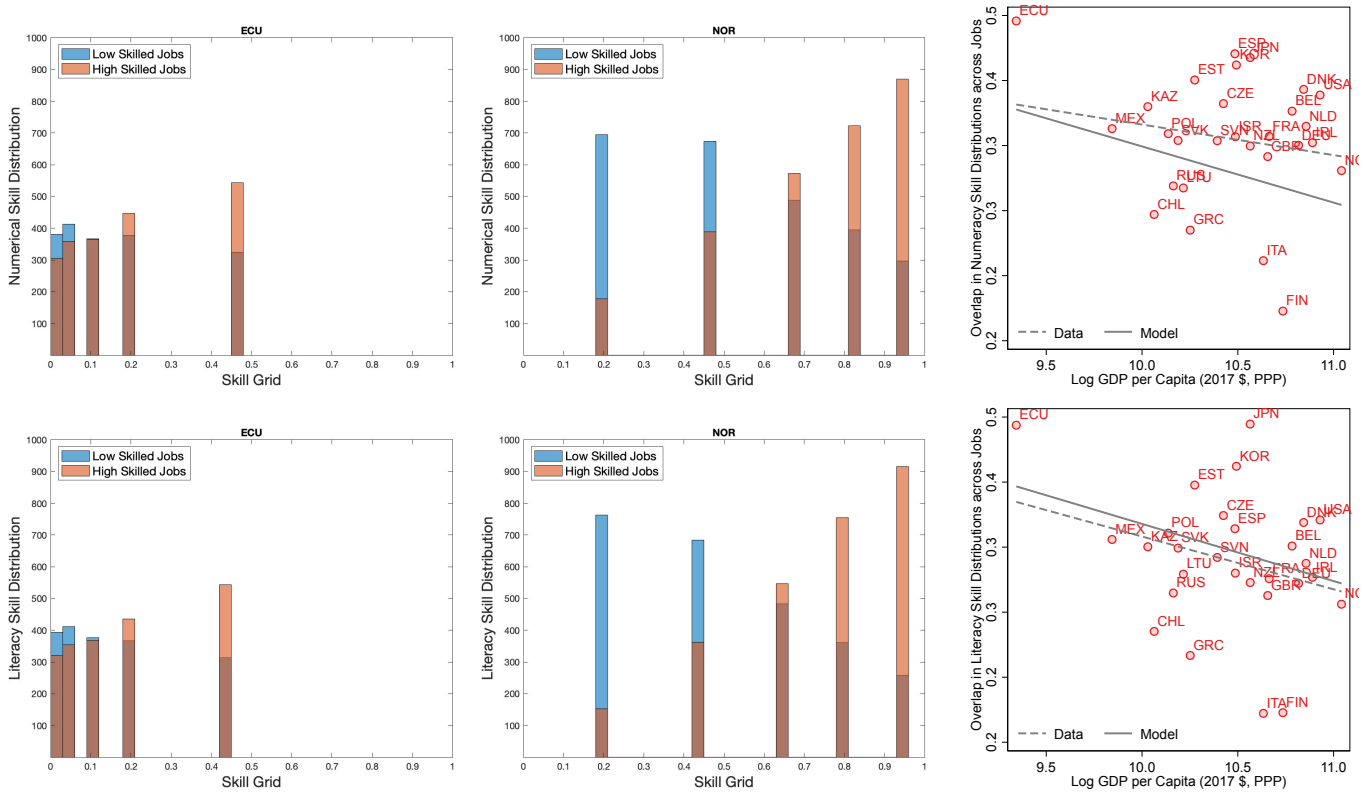
Our analysis proceeds in two steps. In the first step, we study the sources of talent misallocation by asking: How do some countries end up more meritocratic—i.e., with a meritocracy index closer to unity in Figure 12 above? We consider three codeterminants of the allocation of talent. First, a lower level of σ, or less dispersion in labor wedges is associated with more assortative worker-job matching, thereby leading to actual output closer to its potential. Second, a technology that puts greater relative weight

Figure 10: Model Validation Based on Untargeted Moments across Countries



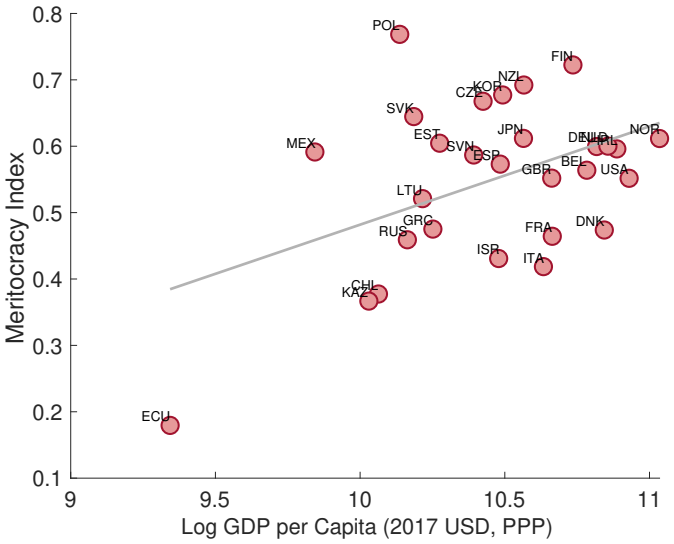
Notes: This figure shows the fit of the model vis-à-vis the data based on a set of untargeted moments against GDP per capita across countries. See Appendix A.2 for details on how the untargeted moments are constructed. Each red marker represents one country in the data. Dashed lines indicate the linear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

Figure 11: Talent Misallocation 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 overlap between blue and red bars. See Appendix A.2 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.

Figure 12: Meritocracy across Countries



Notes: This figure plots the meritocracy index, defined as a country's actual (i.e., estimated) output relative to its potential output without matching frictions (i.e., $\sigma \to 0$) against GDP per capita across countries in the estimated model. Each red dot represents one country in the estimated model. The gray solid line indicates the linear best fit. *Source:* Model simulations.

on worker-job complementarities in various dimensions yields greater returns to labor market sorting, which in turn improves the talent allocation. Third, better alignment in the economy's endowments of worker skills and job skill requirements is associated with less mismatch due to demand and supply considerations.[18]

In the second step, we study the consequences of talent misallocation by asking: How does worker-job mismatch affect key outcomes across countries at different development stages? To assess the extent to which misallocation of talent is a quantitatively important hurdle for development, we consider two factors. First, improving the allocation of talent in a lower-income country while keeping all else fixed increases aggregate output toward its potential without matching frictions (i.e., $\sigma \to 0$). Second, the returns to improving the allocation of talent depend on how far potential output is from current output, which in turn is a function of a country's technology as well as its endowments of worker skills and job skill requirements. If a country's potential output without matching frictions (i.e., $\sigma \to 0$) is low because of factors unrelated to the allocation of talent (e.g., mismatch between endowments of worker skills and job skill requirements, bad production technology), then matching frictions may account only for a small share of the overall cross-country differences in aggregate output.

We consider a sequence of counterfactual simulations based on the estimated model in order to gain a deeper understanding of both the sources and the consequences of talent misallocation across countries.

[18]Note that in the second and third cases, 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.

7.1 Decomposing Cross-Country Differences in Talent Misallocation and Aggregate Outcomes

In this section, 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 talent misallocation 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 other countries the production function of the highest-income country in our sample, namely Norway.[19] We then recompute each country's equilibrium under the new technology and reassess cross-country differences in (i) meritocracy, (ii) aggregate output, and (iii) wage inequality. Figure 13 shows outcomes (i)–(iii) in the baseline model and under the simulation of a counterfactual that assigns all countries the frontier technology of Norway. The left panel shows tha this counterfactual leads to an increase in meritocracy across countries. Intuitively, an increase in the returns to positive assortative matching induced by adopting the frontier technology leads to an equilibrium reduction in misallocation of talent. As a result, the middle panel shows that hourly output per worker increases by a roughly constant level across countries, which implies that cross-country inequality in output decreases sharply.[20] Interestingly, the middle panel also shows that these effects are primarily driven by the direct effect of technological change, rather then the indirect effect that works through improvements in worker-job matching. At the same time, wage inequality within countries increases across the board, and more so in lower-income countries. This is because some workers (e.g., those with higher numeracy and literacy skills) benefit relatively more from the new production technology than others. This result reflects strong worker-job complementarities that fuel the demand for skilled workers in high-income countries like Norway, while high-skilled workers are in particularly scarce supply in low-income countries like Ecuador.

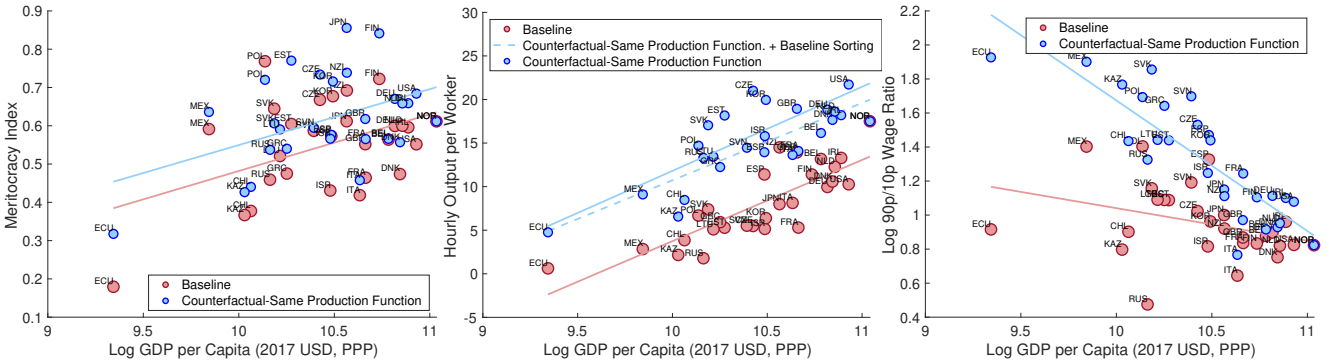
From this exercise, we conclude that giving all countries access to the same frontier production technology would significantly boost output in all places, thereby reducing cross-country inequality, while, at the same time, increasing domestic wage inequality, especially in lower-income countries.

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 14 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

[19] 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.

[20] For example, the coefficient of variation of hourly output per worker across countries decreases by 41 percent—see the right panel of Figure 18.

Figure 13: 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 pattern at its baseline. *Source:* Model simulations.

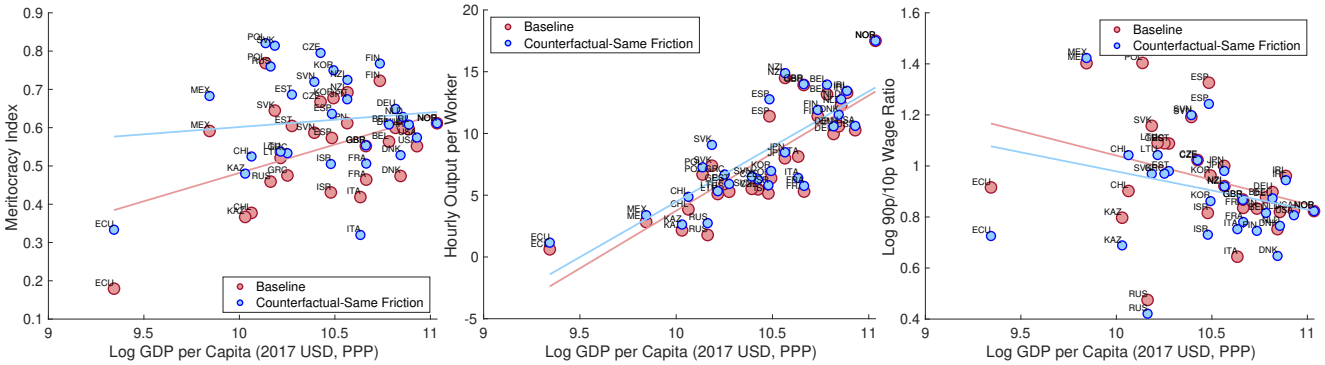
to potential. However, given the initially large cross-country heterogeneity in productivity, the middle panel shows that this effect has a modest impact on cross-country differences in hourly output per worker.[21] Contrary to the previous counterfactual that equalized technology across countries, the right panel shows that equalizing frictions tends to reduce wage inequality over all and disproportionally soin 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 in turn feeds into a reduction in overall wage dispersion. These effects are higher in lower-income countries, where frictions are more pronounced to begin with.

From this exercise, we conclude that equalizing matching frictions across countries has limited effects on aggregate output and leads to a mild reduction in domestic wage inequality, and more so in lower-income countries. That the returns to improving the allocation of talent are limited is because these countries are constrained by other factors, including production technology as well as the endowments of worker skills and job skill requirements. From this, we learn that the efficiency of the allocation of talent, technology, and endowments are strong complements in accounting for cross-country differences in aggregate output and wage inequality.

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 15 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. The left panel shows that this leads to a pronounced increase in meritocracy in lower-income countries, reflecting the fact that the returns associated with frontier distributions of worker skills and job skill requirements swamp matching frictions in lower-income countries. In fact, the effects of assigning the Norwegian endowments of skills and skill requirements to the rest of the

[21] Indeed, the coefficient of variation of hourly output per worker across countries decreases by a modest eight percent—see the right panel of Figure 18.

Figure 14: Counterfactual Imposing Norway's Matching Frictions across Countries

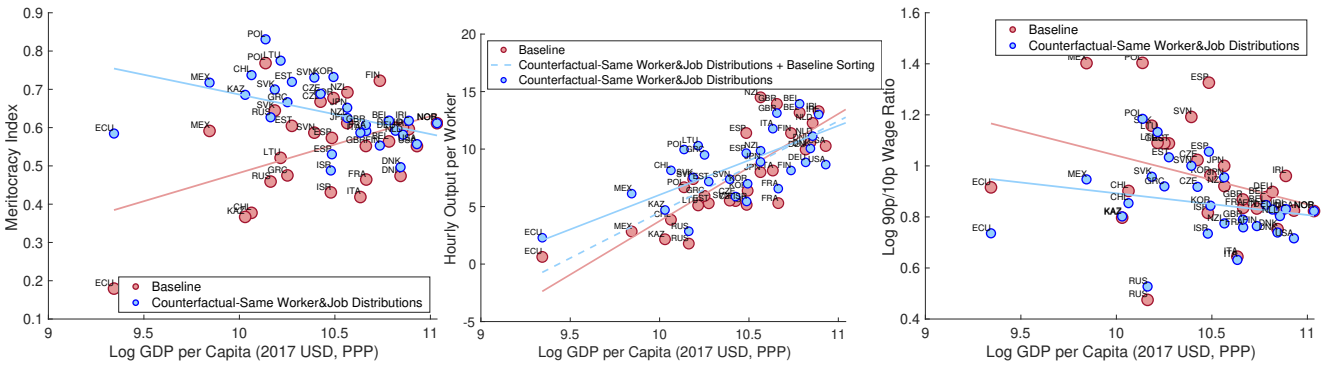


Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian matching frictions in all countries on the meritocracy index (left panel), hourly output per worker (middle panel), and wage inequality (right panel). Red circles represent the baseline model estimates for each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

world are so large that the cross-country slope of the meritocracy index flips to negative. The middle panel shows that counterfactual skill and skill requirements also lead to sizable output gains, especially in lower-income countries. In turn, around two thirds of these output gains are due to the improved allocation of talent, as output gains are only around one third under baseline worker-job sorting patterns. The right panel makes the point that the largest reduction in domestic wage inequality is attained under this simulation of counterfactual worker skills and job skill requirements, 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 talent and resulting economic outcomes across countries, though large cross-country gaps in aggregate output remain.

Figure 15: Counterfactual Imposing Norway's Worker Skills and Job Skill Requirements across Countries

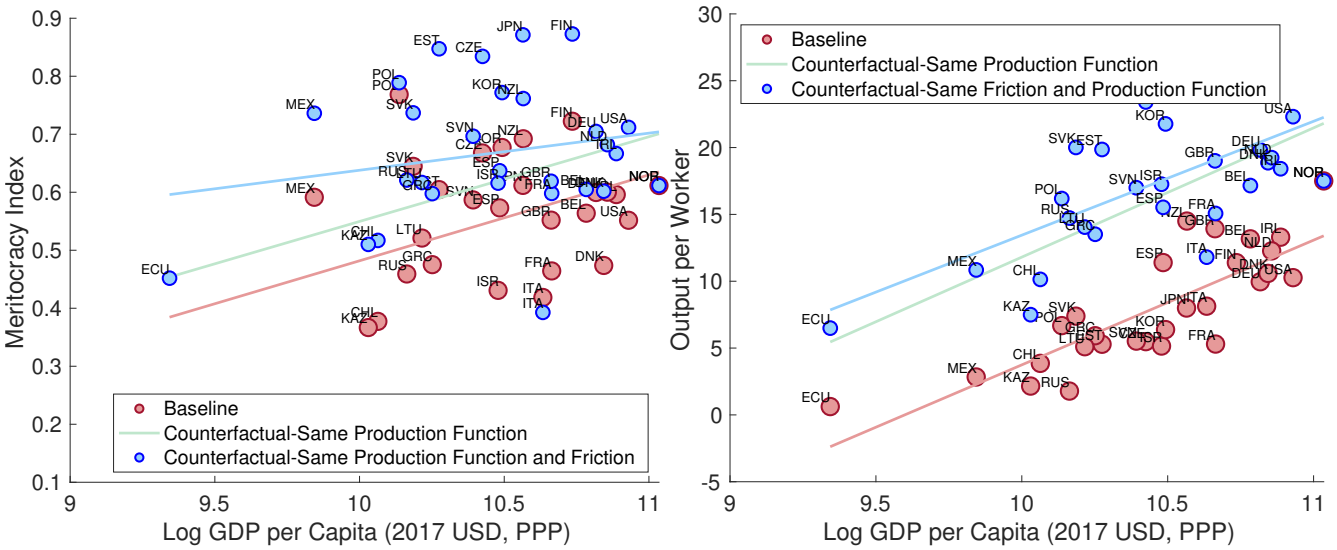


Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian distributions of worker skills and job skill requirements in all countries on the meritocracy index (left panel), hourly output per worker (middle panel), and wage inequality (right panel). Red circles represent 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 pattern at its baseline. *Source:* Model simulations.

The Role of Complementarities. Each of the previous three counterfactuals isolated the effects of one primitive—the production function, matching frictions, and endowments of worker skills and job skill requirements—at a time on cross-country differences in key outcomes. While each of the three primitives played an important role in shaping specific outcomes, the effects of changing one of them in isolation ignores the effects of complementarities between the three primitives. In this section, we highlight the complementarities between technology, frictions, and endowments. The insight emerging from this analysis is that the returns to improving the allocation of talent 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 16 shows the results of simulating a dual counterfactual that adopts Norway's production function and matching frictions simultaneously. Relative to the baseline 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). Similarly, output per worker increases by an additional 20 percent over and above the baseline counterfactual that changes only the production function.[22] As such, the gains from improving the technology and frictions are greater than the sum of the parts. Intuitively, improving the allocation of talent has greater returns when there is appropriate technology that rewards more assortative labor market matching.

Figure 16: Counterfactual Imposing Norway's Production Function and Frictions across Countries



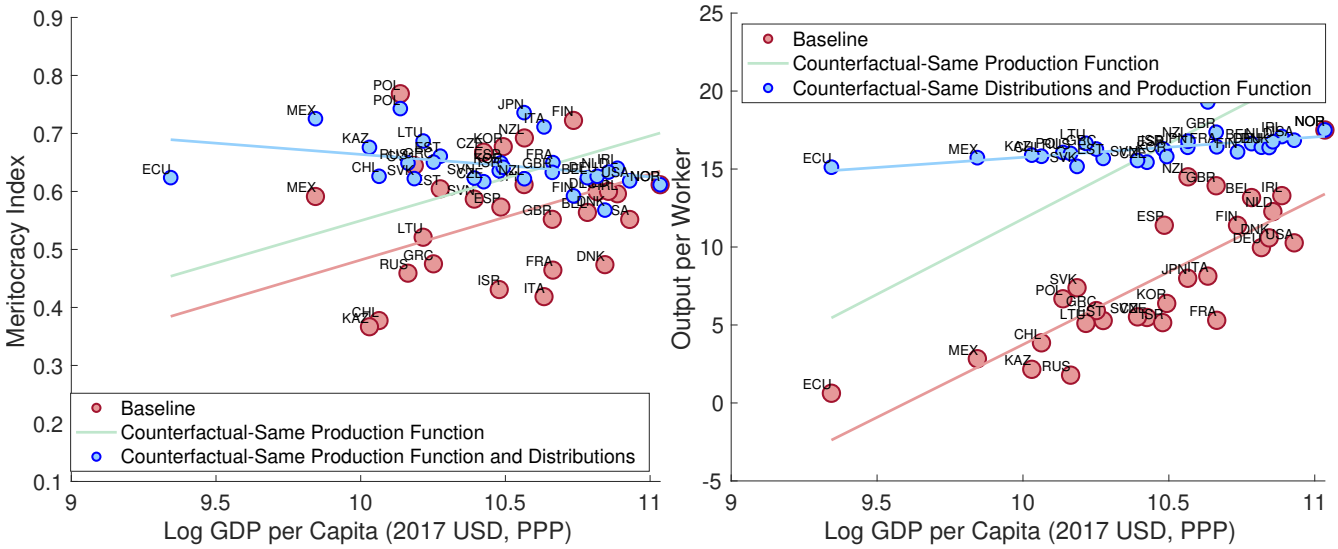
Notes: This figure shows the model-based counterfactual effects of implementing the Norwegian production technology and matching frictions simultaneously in all countries on the meritocracy index (left panel) and hourly output per worker (right panel). Red circles represent the baseline model estimates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

Second, Figure 17 shows the results of simulating a dual counterfactual that adopts Norway's production function in addition to the distributions of worker skills and job skill requirements simultane-

[22] Figure 25 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.

ously. The interaction effects between the technology and endowments are substantial. The meritocracy index (left panel) increases substantially among lower-income countries and becomes much flatter across the development spectrum. Similarly, output per worker (right panel) increases sharply among low-income countries, much more than the two individual counterfactuals would suggest.[23] 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 relatively lower-income countries. As a result, this dual counterfactual closes 91 percent of the cross-country gap in output per worker.

Figure 17: 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.

To conclude, the above exercises highlight important interaction effects between the primitives of an economy on labor market sorting and aggregate outcomes. From a policy perspective, this suggests that a multipronged approach is needed in order to reduce income disparities across the development spectrum. For example, adopting frontier technology would be considerably more effective for lower-income countries if at the same time they could upskill their workforce and reduce matching frictions.

Effects on Mean Output and Inequality in Output across Countries. Figure 18 summarizes the main results of our counterfactual exercises pertaining to mean output (left panel) and inequality in output (right panel) across countries. Starting with mean output in the left panel, a few observations are worth highlighting. First, by far the largest 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,

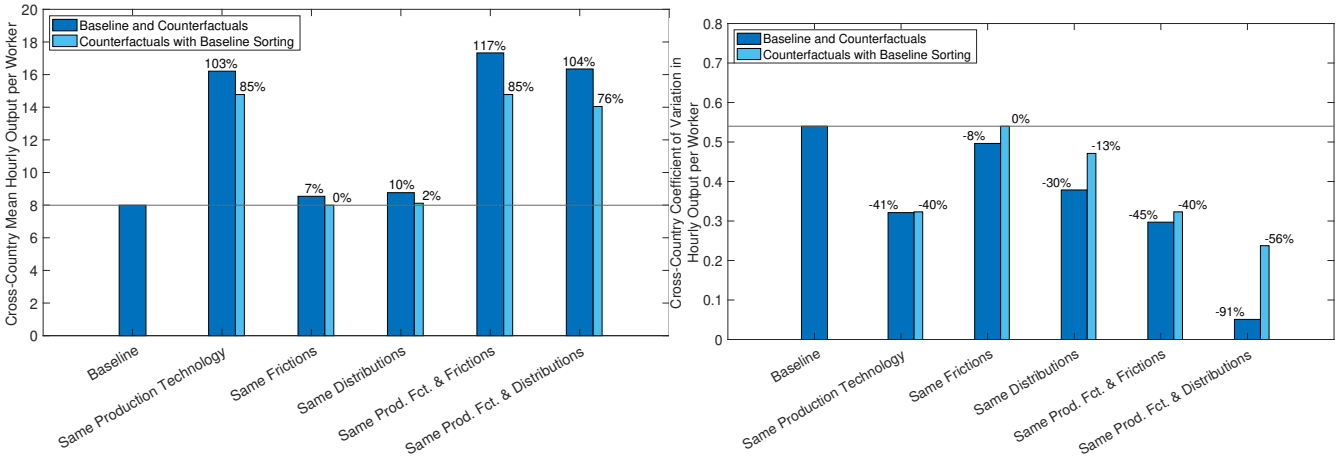
[23] Figure 25 in Appendix F.1 shows that around half of the gains in output per worker are due to an improvement in worker-job sorting induced by the adoption of the new technology and distributions.

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, the combination of technology and 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), almost half of which 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 endowments. Intuitively, the gains from improved talent allocation can be realized only if there exist profitable employment opportunities in the labor market.

Figure 18: 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 talent 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 (non-)employment outcomes of workers of different genders in relation to economic development.

To begin with, we investigate differences in the population skill distributions between men and women. Figure 26 in Appendix F.2 shows that gender skill differences are relatively muted and unlikely to be the main driver behind observed gender gaps in labor market outcomes, since skills are distributed relatively similarly across men and women in most countries. This leads us to study gender differences in outside options—estimates of which are shown in Figure 7—as the main driver behind observed gender gaps in labor market outcomes.

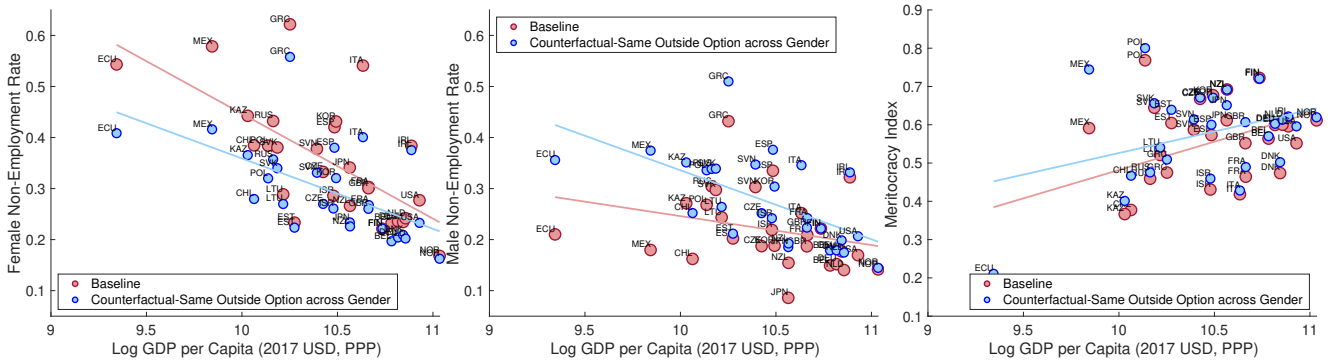
To this end, we consider two families of counterfactuals. First, we eradicate all gender differences in our model by assigning women the same outside option $f_{x\emptyset}(x)$ as men. We study the resulting extensive margin and intensive margin allocation of workers who counterfactually differ only in their numeracy and literacy skills and no economic outcomes depend directly on gender $x_g \in \{f, m\}$. On the extensive margin, Figure 19 show that nonemployment rates are up to 30 percentage points higher for women (left panel) compared to men (middle panel) among the lowest-income PIAAC countries. Among the highest-income PIAAC countries, the gap in nonemployment rates is a relatively smaller 5 percentage points.[24] Counterfactually removing gender differences in the outside option 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 around 20 percent, from 54 percentage points to 42 percentage points. 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.

On the intensive margin, the right panel of the figure shows that women entering the workforce also induces a reduction in talent misallocation that leads to a more meritocratic worker-job allocation (right panel of Figure 19). By increasing competition for jobs, this competitive effect leads to better worker-firm matching patterns, especially in lower-income countries, where there was initially more mismatch. As a result, the gradient of meritocracy across countries flattens substantially.

Figure 20 shows the effects of closing the gender gap in outside options on the aggregate nonemployment rate (left panel) and on aggregate output gains relative to the baseline (right panel). By itself, this counterfactual has little impact on the aggregate nonemployment rate (comparing the green solid line to the red solid line in the left panel) and aggregate output (green circles and green solid line in the right panel), again reflecting the effective capacity constraint due to a fixed number of jobs in the economy. If, in addition, we increase the mass of firms to the level of Norway, which effectively increases competition among firms—thereby increasing the available employment opportunities for workers—in lower-income countries, we find a striking result. 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). At

[24] There is also gendered talent misallocation on the intensive margin, which varies across countries. Figure 27 in Appendix F.2 shows that women are relatively underrepresented in high-skilled jobs in low-income countries, while the opposite is the case in high-income countries. However, compared to gender differences on the extensive margin, these differences on the intensive margin are relatively small.

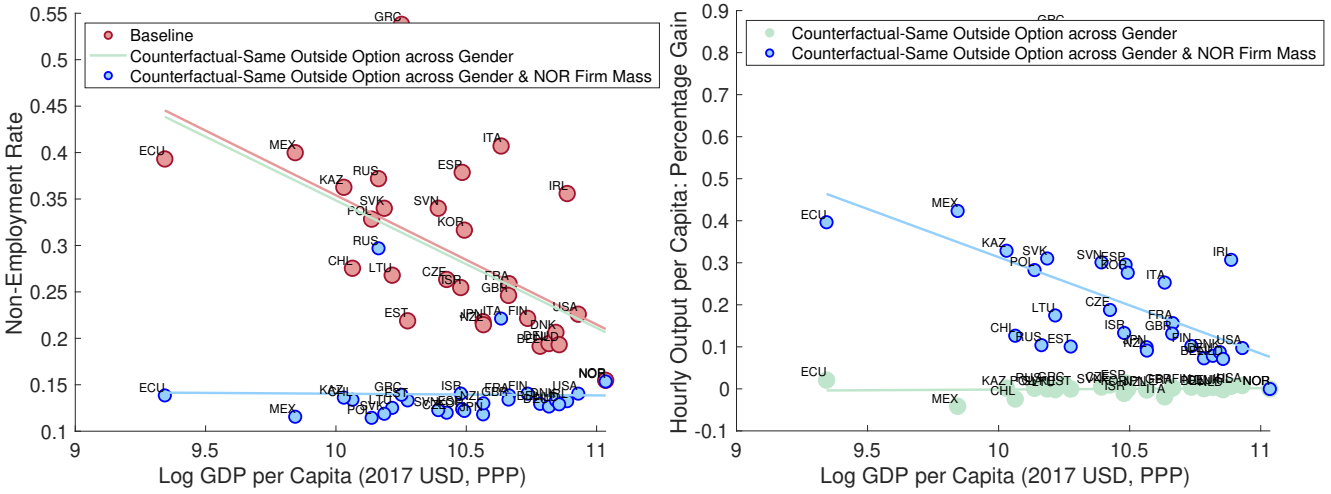
Figure 19: Misallocation of Women and Men on the Extensive and Intensive Margin



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.

the same time, the lowest-income countries enjoy up to 30 percent greater employment, leading to large gains in aggregate output. From this, we learn that the scarcity of jobs is a major obstacle to increasing female employment rates and, as a result, economic development.

Figure 20: 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.

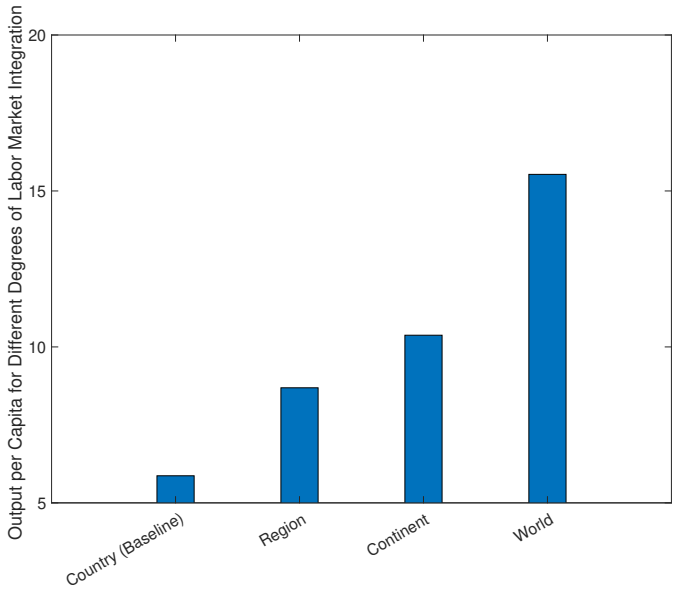
7.3 The Effects of Integrating Labor Markets across Countries

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 talent. In our baseline analysis, we took as given the boundaries of each country when considering the allocation of talent. While in most countries,

workers remain attached to their country of birth, migration is often associated with large output and welfare gains for migrants (Borjas, 1999; Martellini et al., 2023; Lagakos et al., 2018a; Hendricks and Schoellman, 2018; Schoellman, 2010). To this end, we allow for free worker flows across country borders in a sequence of counterfactuals exploring 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 associated with the highest-income country in the region.

Figure 21 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 by almost 100 percent due to. 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 21: 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

We study the extent to which workers are matched to jobs in an output-maximizing pattern. Using harmonized microdata on workers' skills and jobs' skill requirements in 28 countries, we show that labor markets in higher-income countries are characterized by greater meritocracy—i.e., more positive assortative matching between multidimensional worker skills and job skill requirements. To understand the sources of cross-country differences in talent 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 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 the production technology account for most cross-country heterogeneity in outcomes, with matching frictions playing a relatively modest role. However, a large share of the gains from adopting better skill endowments and technology are realized through improved worker-job sorting. This reflects our finding that the returns to improving the allocation of talent are constrained by the available skill endowments and technology. Therefore, we view talent misallocation as a consequence of economic underdevelopment rather than a source. We further use our model for two natural applications. First, we show that misallocation of women's talent 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 competitive jobs. Second, we show that regional labor market integration significant boosts global output through an improved allocation of talent across borders.

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Appendix for "Meritocracy"

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December 20, 2023

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. Appendix F shows additional results relating to the counterfactual analysis in Section 7 of the main paper.

A Data Appendix

A.1 Data Sources

OECD. PIAAC.

World Bank. World Development Indicators.

A.2 Variable Construction

GDP per Capita. Data Source: World Bank.

Hourly GDP per Capita and per Worker. Data Sources: PIAAC and OECD.

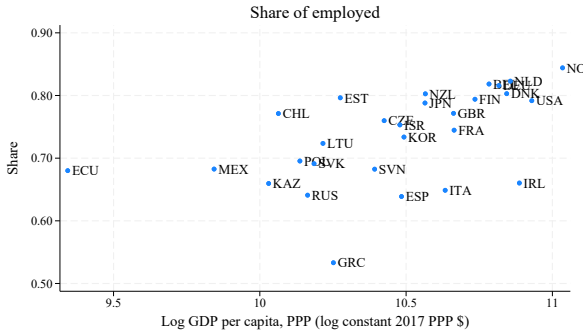
Numeracy and Literacy Skills. Data Source: PIAAC.

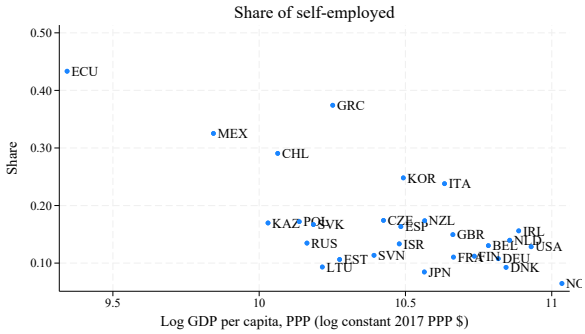
For some exercises and plots, we construct "broad" skill types—low, medium and high—as follows: We add each worker's numeracy and literacy scores, which range from (quintiles) 1–5 after our discretization, and then classify workers as "low-skill" if the sum of their scores is between 2 and 4, as "medium-skill" if it is between 5 and 7, and as "high-skill" if it is between 8 and 10.

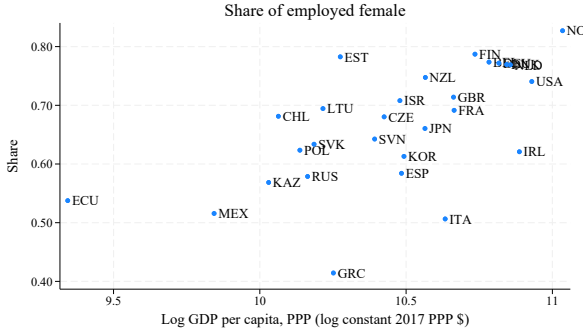
Numeracy and Literacy Skill Requirements. Data Source: PIAAC.

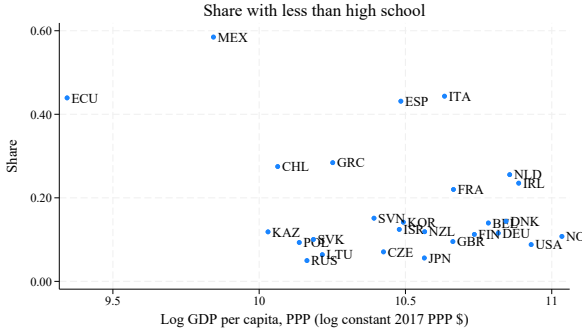
For some exercises and plots, we construct "broad" skill requirement types—low, medium and high—as follows: We add each occupation's numeracy and literacy skill requirements, which range from (quintiles) 1–5 after our discretization, and then classify occupations as "low-skill intensive" if the sum of their scores is between 2 and 4, as "medium-skill intensive" if it is between 5 and 7, and as "high-skill intensive" if it is between 8 and 10.

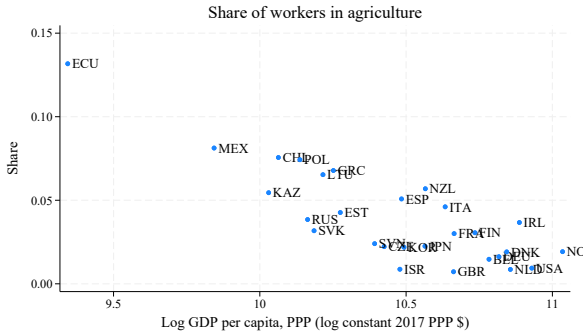
A.3 Summary Statistics

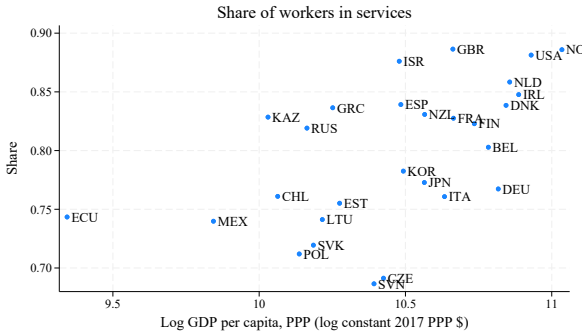

Share of employed
Share
Log GDP per capita, PPP (log constant 2017 PPP $)

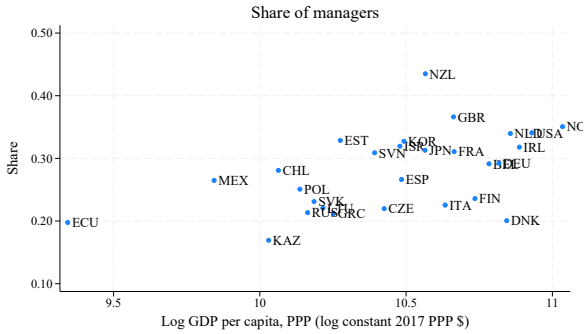

Share of self-employed
Share
Log GDP per capita, PPP (log constant 2017 PPP $)

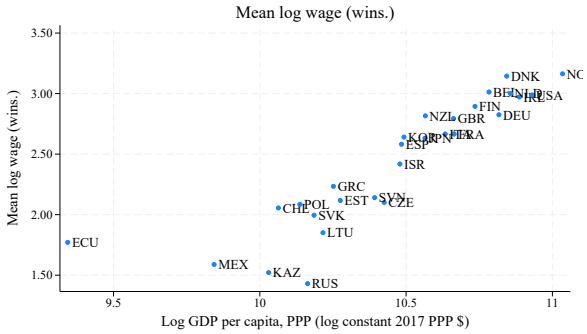

Share of employed female
Share
Log GDP per capita, PPP (log constant 2017 PPP $)

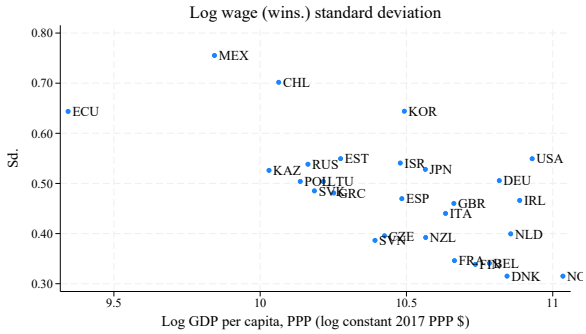

Share with less than high school
Share
Log GDP per capita, PPP (log constant 2017 PPP $)

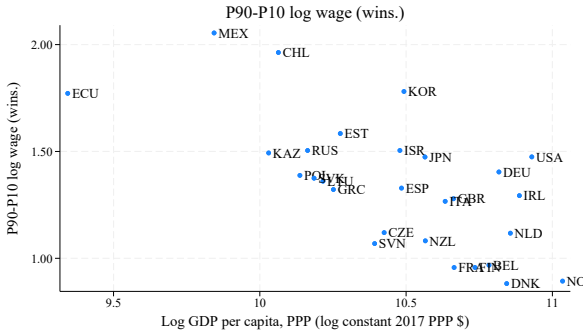

Share of workers in agriculture
Share
Log GDP per capita, PPP (log constant 2017 PPP $)

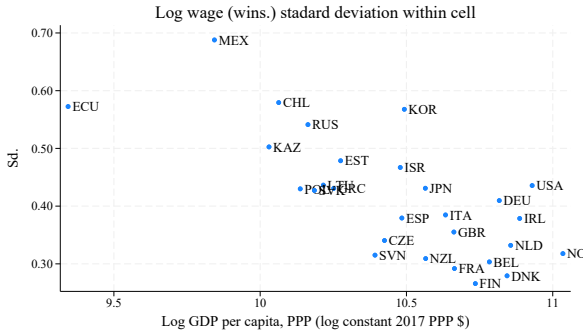

Share of workers in services
Share
Log GDP per capita, PPP (log constant 2017 PPP $)

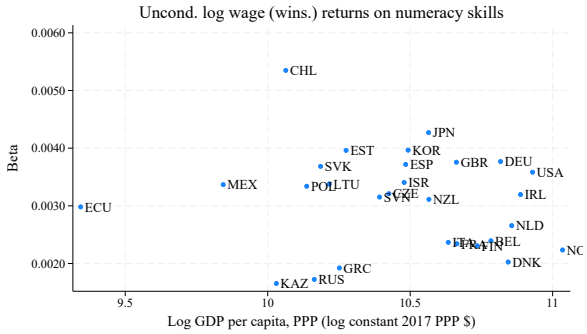

Share of managers
Share
Log GDP per capita, PPP (log constant 2017 PPP $)

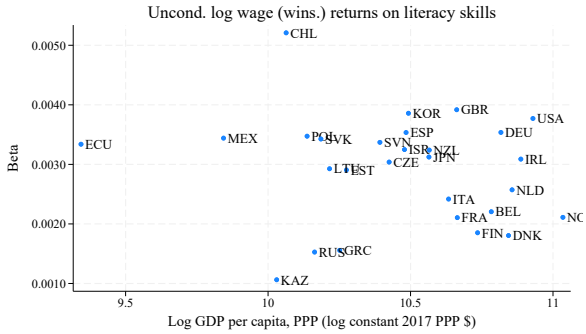

Mean log wage (wins.)
Mean log wage (wins.)
Log GDP per capita, PPP (log constant 2017 PPP $)


Log wage (wins.) standard deviation
Sd.
Log GDP per capita, PPP (log constant 2017 PPP $)


P90-P10 log wage (wins.)
P90-P10 log wage (wins.)
Log GDP per capita, PPP (log constant 2017 PPP $)


Log wage (wins.) stadard deviation within cell
Sd.
Log GDP per capita, PPP (log constant 2017 PPP $)

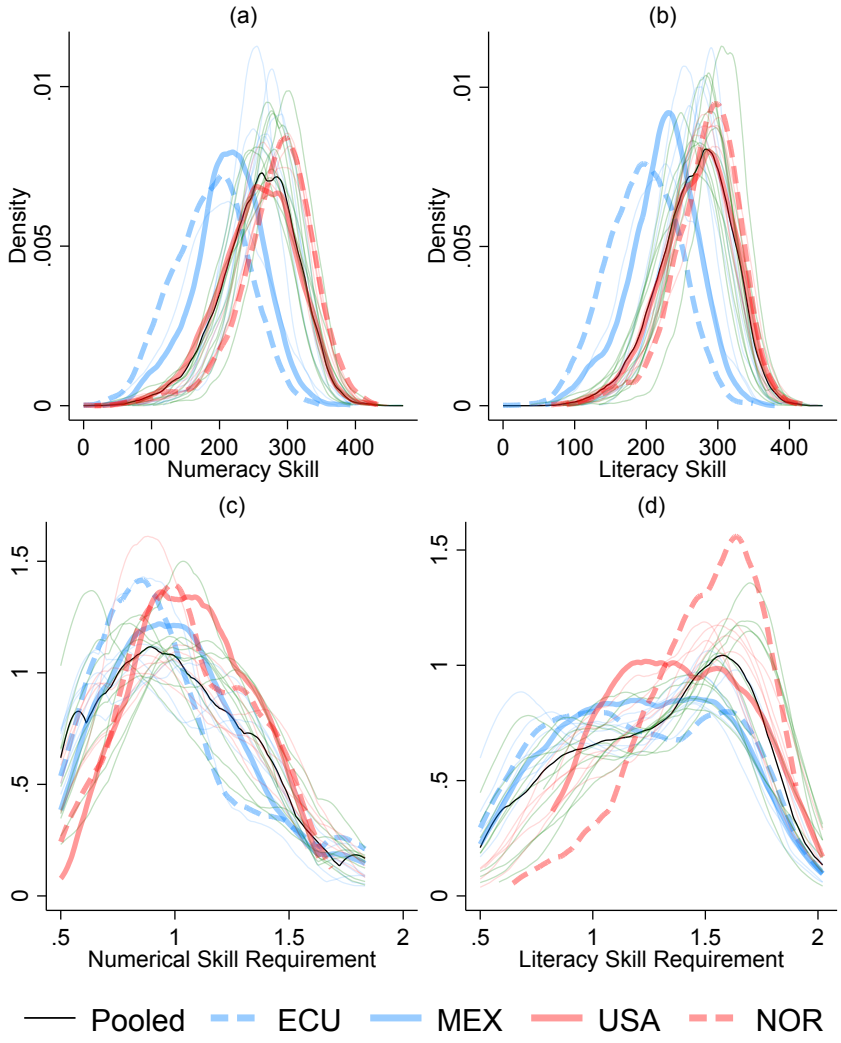

Uncond. log wage (wins.) returns on numeracy skills
Beta
Log GDP per capita, PPP (log constant 2017 PPP $)


Uncond. log wage (wins.) returns on literacy skills
Beta
Log GDP per capita, PPP (log constant 2017 PPP $)

B Facts Appendix

B.1 Distributions of Worker Skills and Job Skill Requirements

Figure 22: 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.

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

$$\log\left(\frac{\mu_{x|y}}{\mu_{\varnothing|y}}\right) = \log\left(\frac{\mu^J(x,y)}{\mu^J(\varnothing,y)}\right) = \frac{f(x_n,x_\ell,y) - w(x,y) - f_{\varnothing y}(y)}{\sigma}, \tag{19}$$

$$\log\left(\frac{\mu_{y|x}}{\mu_{\varnothing|x}}\right) = \log\left(\frac{\mu^W(x,y)}{\mu^W(x,\varnothing)}\right) = \frac{w(x,y) - f_{x\varnothing}(x)}{\sigma}. \tag{20}$$

Combining equations (19)–(20) by substituting out the wage function $w(x,y)$ and imposing labor market clearing (5), we get

$$\sigma\log\left(\frac{\mu(x,y)}{\mu(\varnothing,y)}\right) = f(x_n,x_\ell,y) - \left(\sigma\log\left(\frac{\mu(x,y)}{\mu(x,\varnothing)}\right) + f_{x\varnothing}(x)\right) - f_{\varnothing y}(y). \tag{21}$$

We solve (21) 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 (20) for the wage function $w(x,y)$ and imposing labor market clearing (5), we get

$$w(x,y) = \sigma\log\left(\frac{\mu(x,y)}{\mu(x,\varnothing)}\right) + f_{x\varnothing}(x) \tag{22}$$

Now plug in the matching frequency $\mu(x,y)$ from (11) into equation (22) to obtain the expression for the wage function $w(x,y)$ 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:

$$f(x_n,x_\ell,y) - f_{\varnothing y}(y) + \delta_{i\to k,y} + \delta_{x,k\to k} - \tilde{w}(x_i,y_k) = f(x_n,x_\ell,y) - f_{\varnothing y}(y) - w(x,y) + \delta_{xk}, \tag{23}$$

$$\tilde{w}(x_i,y_k) - f_{x\varnothing}(x) + \delta_{i\to i,y} + \delta_{x,k\to i} = -f_{x\varnothing}(x) + w(x,y) + \delta_{iy}. \tag{24}$$

In the equations above, (23) is the post-transfer surplus of job k of type y and (24) 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.

Based on equation (23) or (24) above, we can solve for the idiosyncratic wage of worker i of type x in job k of type y:

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

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

$$\delta_{x,k\to i} = 0 \quad \Longrightarrow \quad \delta_{xk} = \delta_{x,k\to k} \tag{25}$$

$$\delta_{i\to i,y} = 0 \quad \Longrightarrow \quad \delta_{iy} = \delta_{i\to k,y}. \tag{26}$$

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

D Identification Appendix

D.1 Proof of Proposition 1

Restatement of 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. Our goal is to identify all elements of the parameter vector $\theta := \left(H(\cdot), G(\cdot), \sigma, f_{x\varnothing}(\cdot), f(\cdot), m^J\right)$, which consists of the worker type distribution $H(\cdot)$ and the job type distribution $G(\cdot)$, worker's nonemployment value $f_{x\varnothing}(\cdot)$, workers' nonemployment value $f_{x\varnothing}(\cdot)$, the production function $f(\cdot)$, and the relative job mass m^J. The identification result relies on data on worker and job types, matching patterns, within-match-type wage dispersion, and the aggregate profit share. For the purpose of this proof only, 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 $y = (y_n, y_\ell, y_s)$. The proof of the identification result proceeds in five steps.

Step 1: Identification of 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. To account for the fact that we observe all (i.e., nonemployed and employed) workers but only filled (i.e., none of the idle) jobs, we assume that the distribution of filled jobs is representative of the population distribution $G(\cdot)$.

Step 2: Identification of the matching wedge distribution's scale parameter 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:

$$Var\left(\tilde{w}(x_i, y_k)|x, y\right) = \frac{\pi^2\sigma^2}{6}. \tag{27}$$

Thus, we can invert the analytical expression for the within-cell wage variance in (27) for *any* match type (x, y) to uniquely pin down the scale parameter of the distribution of matching wedges, σ.

Step 3: Identification of 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

$$\log\left(\frac{\mu(x,\varnothing)}{\mu(x,y)}\right) = \frac{f_{x\varnothing}(x) - w(x,y)}{\sigma}. \tag{28}$$

On the left-hand side (LHS) of (28), 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 (28) for the outside option $f_{x\varnothing}$ for each worker type x.

Step 4: Identification of the production function $f(\cdot)$. Considering the log relative choice probabilities of job type y matching with any arbitrary worker type x compared to that of matching with the least

productive worker type $\underline{x} := (\underline{x_n}, \underline{x_\ell}, x_g)$ based on (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

$$\log\left(\frac{\mu(x,y)}{\mu(\underline{x},y)}\right) = \frac{f(x,y) - w(x,y) + w(\underline{x},y)}{\sigma}. \tag{29}$$

On the LHS of (29), 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 (29) for the value of the production function $f(\cdot)$ for each worker type $x \in \mathcal{X} \setminus \underline{x}$ and each job type $y \in \mathcal{Y}$.

Step 5: Identification of 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

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

Into these expressions, we plug in

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

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

$$\widehat{\mu}(x,\emptyset) := \frac{\mu(x,\emptyset)}{m^W} = h_x \frac{\exp(f_{x\emptyset}(x)/\sigma)}{\exp(f_{x\emptyset}(x)/\sigma) + \sum_{\tilde{y}\in\mathcal{Y}} \exp(w(x,\tilde{y}))/\sigma)} \tag{30}$$
$$\widehat{\mu}(\emptyset,y) := \frac{\mu(\emptyset,y)}{m^J} = g_y \frac{\exp(f_{\emptyset y}(y)/\sigma)}{\exp(f_{\emptyset y}(y)/\sigma) + \sum_{\tilde{x}\in\mathcal{X}} \exp(f(\tilde{x}_n, \tilde{x}_\ell, y) - w(\tilde{x},y))/\sigma)}. \tag{31}$$

Note that $\widehat{\mu}(x,\emptyset)$ in (30) 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 $\widehat{\mu}(\emptyset,y)$ on the RHS of (31) are already identified under the assumption that g_y, which is the share of all (i.e., matched and idle) type y jobs in the economy, is reflected in the share of matched jobs observed in our data. Then, we can express the profit share in match (x,y) as

$$\frac{f(x_n, x_\ell, y) - w(x,y)}{f(x_n, x_\ell, y)} = \frac{\sigma\left[\log\left(\frac{\widehat{\mu}(x,\emptyset)}{\widehat{\mu}(\emptyset,y)}\right) - \log\left(m^J\right)\right] + \tilde{f}(x,y)}{2f(x_n, x_\ell, y)}. \tag{32}$$

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 (32) 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 (32) for the relative mass of firms m^J.

Summary. To summarize, we have identified all model parameters $\theta := \left(H(\cdot), G(\cdot), \sigma, f_{x\varnothing}(\cdot), f(\cdot), m^J\right)$ by sequentially following Steps 1–5 above. □

D.2 Proof of Proposition 2

Proof. Let $\lambda > 0$ be an arbitrary scalar. Indexing the wage function $w(x, y; \cdot)$ by the set of parameters $(f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma)$, it follows that

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

which proves that the wage function $w(\cdot)$ is homogeneous of degree 1 in $(f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma)$. As a corollary, the profit function $\pi(\cdot)$ can be written as

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

which proves that also the profit function $\pi(\cdot)$ is homogeneous of degree 1 in $(f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma)$. Next, note that for any variable $\delta \sim$ EV Type I$(0, \sigma)$, the cumulative distribution function $F(\cdot)$ satisfies

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

so that $\lambda\delta \sim$ EV Type I$(0, \lambda\sigma)$. Note also that we can write match-type-specific surplus $\tilde{f}(\cdot)$ as

$$\begin{aligned} & \tilde{f}(x, y; \lambda f(x_n, x_\ell, y), \lambda f_{\varnothing y}(y), \lambda f_{x\varnothing}(x)) \\ = \; & \lambda f(x_n, x_\ell, y) - \lambda f_{x\varnothing}(x) - \lambda f_{\varnothing y}(y) \\ = \; & \lambda \tilde{f}(x, y; f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y)), \end{aligned}$$

which proves that the match-type-specific surplus $\tilde{f}(\cdot)$ is homogeneous of degree 1 in $(f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma)$. Finally, total match surplus $s(\cdot)$ for a given worker i of type x and a given job k of type y can be written as

$$\begin{aligned} & s(x_i, y_k; \lambda f(x_n, x_\ell, y), \lambda f_{\varnothing y}(y), \lambda f_{x\varnothing}(x), \lambda\sigma) \\ &= \lambda f(x_n, x_\ell, y) - \lambda f_{x\varnothing}(x) - \lambda f_{\varnothing y}(y) + \lambda\delta_{xk} + \lambda\delta_{iy} \\ &= \lambda s(x_i, y_k; f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma), \end{aligned}$$

which proves that the total match surplus $s(\cdot)$ is homogeneous of degree 1 in $(f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma)$. To summarize, we have shown that the equilibrium wage functions $w(x, y)$ and $\tilde{w}(x_i, y)$, profit function $\pi(x, y)$, match-type-specific surplus $\tilde{f}(x, y)$, and total match surplus $s(x_i, y_k)$ are all homogeneous of degree 1 in $(f(x_n, x_\ell, y), f_{x\varnothing}(x), f_{\varnothing y}(y), \sigma)$. □

E Estimation Appendix

E.1 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.2 Target Moments

In this section, we describe how each of the target 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.2 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 wage dispersion within cells defined by worker skill group and job skill requirement group:
  - mean of log earnings; and
  - the unexplained variance share, $1 - R^2 = RSS/TSS$, in a regression of log earnings 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 $\tilde{f}(x, y)$ is the systematic (economic) surplus of this type of match, which we aim to estimate. A necessary assumption underlying this estimation approach is that this match surplus is linear in the parameter vector:

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

where $\boldsymbol{\lambda} \in \mathbb{R}^K$ 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, $\boldsymbol{\lambda} = \{\alpha_{nn}, \alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell n}, \alpha_{\ell\ell}, \alpha_{\ell s}\}$ 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 $\boldsymbol{\mu}$ as the average values of the basis surplus vectors:

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

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

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

E.3 Solution Algorithm

For a given parameter vector, we use the Iterative Projective Fitting Procedure (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 (17), 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.4 Details of Model Fit

Figure 23: Model Fit: Middle-Income Countries

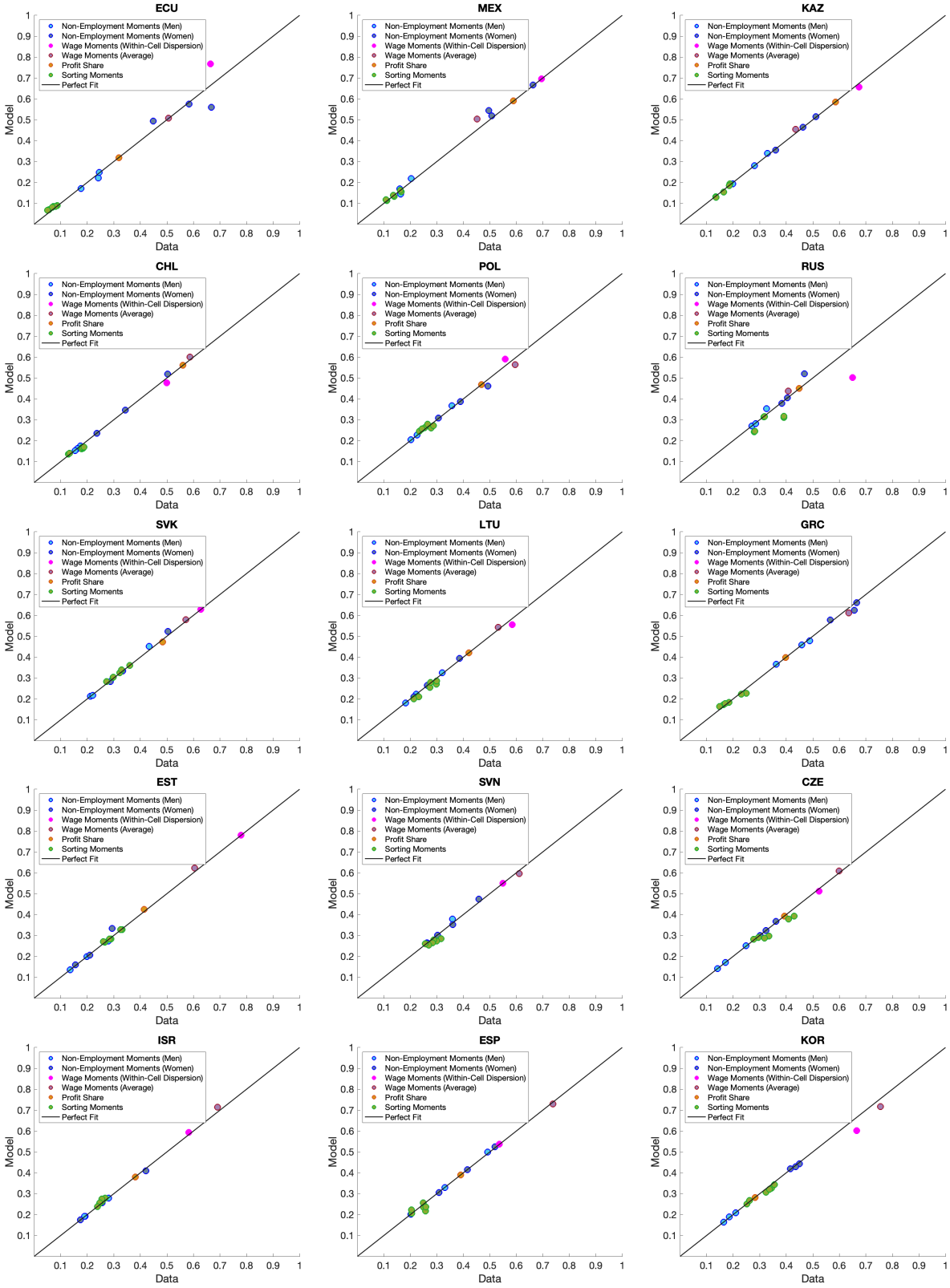
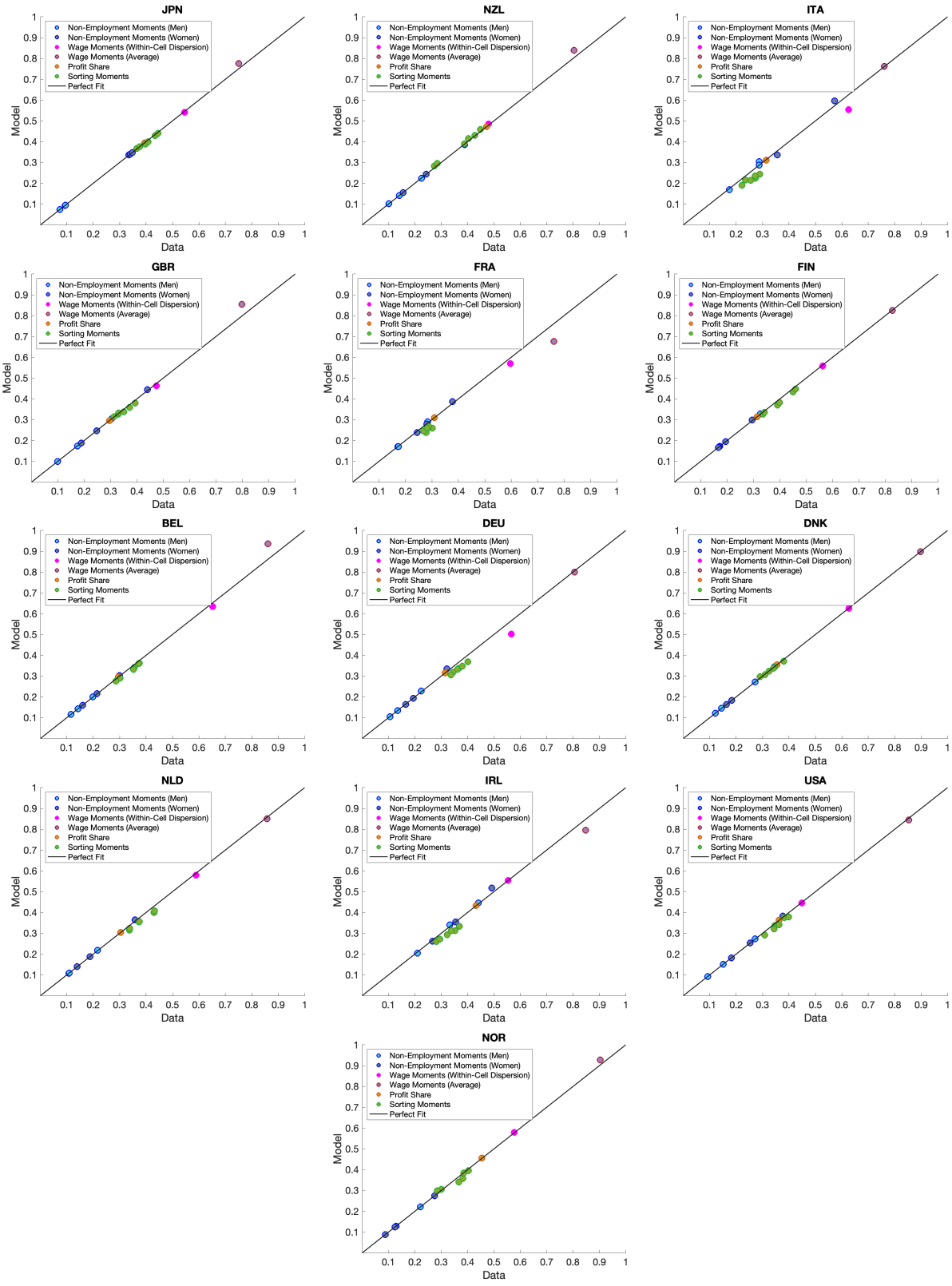


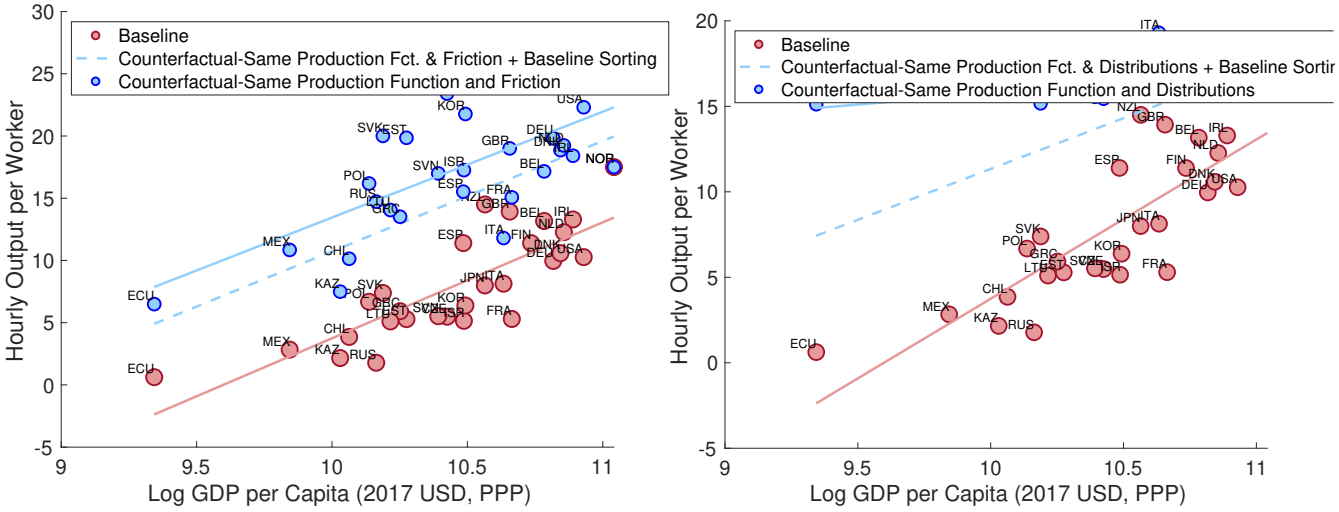
Figure 24: Model Fit: High-Income Countries



F Counterfactuals Appendix

F.1 Additional Counterfactual Simulations

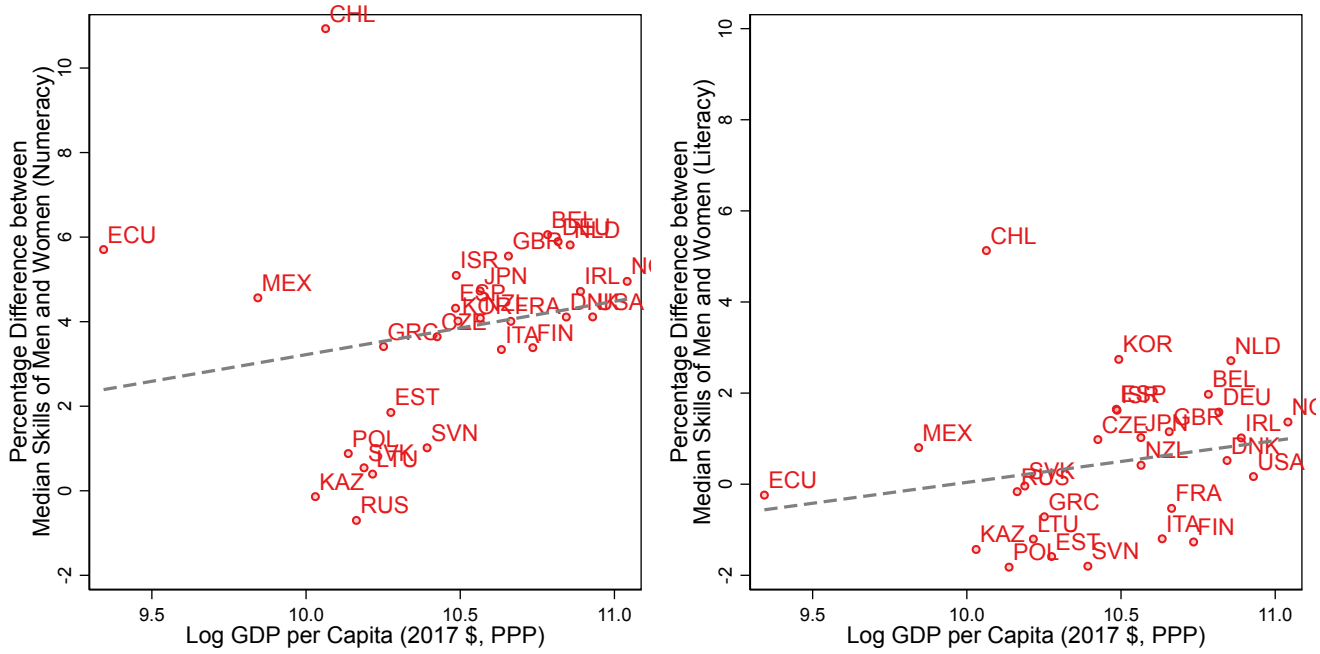
Figure 25: Counterfactual Imposing Norway's Production Function and Distributions across Countries: The Role of Worker-Job Sorting



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 the worker-job sorting pattern at its baseline. *Source:* Model simulations.

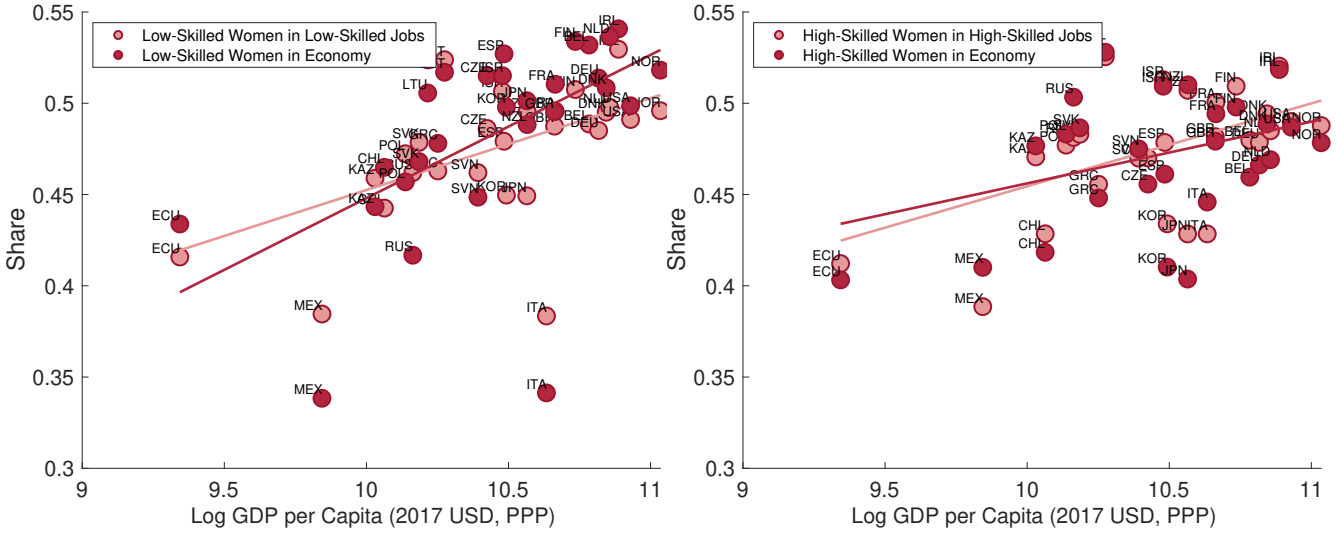
F.2 Talent Misallocation by Gender in the Data

Figure 26: 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 27: 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.2 for the definition of these broad skill groups. *Source:* Model simulations.