Meritocracy Across Countries[*]

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Abstract

We study the micro sources and macro consequences of worker–job matching across countries with large income differences. Using internationally comparable data on over 120,000 individuals in 30 countries, we document that workers' skills align more closely with their jobs' skill requirements in higher-income countries, indicative of more meritocratic labor market matching. We interpret this fact through an equilibrium matching model with cross-country differences in three fundamentals: (i) endowments of worker skills and job requirements determining match feasibility; (ii) technology determining the returns to matching; and (iii) idiosyncratic frictions capturing how nonproductive traits affect matching. A development-accounting exercise based on the model, estimated separately for each country, shows that variation in matching frictions explains only a small share of cross-country output gaps. However, improved worker–job matching substantially amplifies the gains from adopting frontier endowments and technology.

Keywords: Multidimensional Skills, Sorting, Matching, Misallocation, Development Accounting

JEL Codes: E24, J24, O11

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1 Introduction

Labor is the primary factor of production around the world. At the same time, workers differ in their talents as much as jobs vary in the tasks they require. Political philosophy and the social sciences have a long tradition of examining how to allocate people to positions based on merit related to their skills, rather than on subjective factors unrelated to productivity.[1] That tradition has examined, within particular settings, how to promote meritocracy in the labor market to improve economic efficiency and the barriers that stand in its way.

This paper studies this phenomenon across countries in the context of economic development. To this end, we analyze cross-country differences in the matching of workers to jobs. We ask why labor markets in some countries closely match workers with the jobs that fit their skills, while in others the alignment is weaker, and what the aggregate consequences of these differences are. We utilize microdata on worker skills and job skill requirements, along with an equilibrium model, to quantify the contribution of worker-job matching to cross-country income differences. Our approach integrates matching theory (Becker, 1973) into a development accounting framework (Hall and Jones, 1999; Hsieh and Klenow, 2010). In doing so, we innovate upon micro analyses of worker-job matching by assessing the aggregate consequences of mismatch across a large set of countries along the development spectrum. We also innovate on macro analyses of development accounting by modeling both workers and jobs as heterogeneous production inputs, whose sorting patterns affect aggregate output.

Central to our analysis are internationally comparable microdata from the Survey of Adult Skills as part of the Programme for the International Assessment of Adult Competencies (PIAAC), a representative sample of over 120,000 working-age individuals across 30 middle- and high-income countries. These data have two unique features. First, they measure workers' numeracy and literacy skills using internationally comparable tests. Second, they elicit from each respondent the numeracy and literacy skills required for their job. The former circumvents the long-standing issue in research on economic development that the quality of education is not comparable across countries. The latter allows us to dispense with the restrictive assumption that different countries have the same job-level skill requirements. We leverage both of these strengths of our data when measuring worker-job matching patterns across countries.

We begin by constructing an empirical measure of mismatch in the labor market, defined as a country's average distance between workers' skills and the skill requirements of their job. Our

[1] The idea of selecting the best men to run the State goes as far back as Confucius in the East and Plato in the West.

central empirical finding is that in high-income countries workers' skills more closely align with the skill demands of their jobs, that is high-income countries exhibit stronger skill-based sorting or, equivalently, less worker-job mismatch.

Our goal is to account for this phenomenon within a structural model. We focus on three explanations: First, countries may differ in the endowments of worker skills and job requirements. If skill supply and demand are more closely aligned in richer countries, tight worker-job matching becomes more feasible. Second, countries may differ in their match output technology—broadly defined to include not only machinery and equipment but also management practices and the organization of labor—which shapes the wage returns to worker-job matches. If technology features greater complementarities between worker skills and certain job skill requirements in richer countries, there are stronger incentives to sort along these dimensions. Third, countries may differ in the prevalence of idiosyncratic matching frictions, which capture the importance of workers' and jobs' unproductive traits—e.g., social networks, family ties, and wealth—in the matching process.[2]

To quantify the relative importance of these mechanisms, we develop an equilibrium model of worker-job matching that integrates tools from the theory of matching (Choo and Siow, 2006) under multidimensional skill heterogeneity (Lindenlaub, 2017; Lindenlaub and Postel-Vinay, 2023) into a development accounting framework (Klenow and Rodríguez-Clare, 1997; Hsieh and Klenow, 2010). In the model, each country's labor market is characterized by the three fundamentals described above: the endowments of worker skills and job skill requirements, technology, and idiosyncratic matching frictions. In a given country, workers who differ in multidimensional skills and gender match with jobs that differ in multidimensional skill requirements and productivity to generate output. Workers may choose to remain nonemployed, and jobs may choose to remain idle. Worker-job matching maximizes total match surplus, which is competitively split into workers' wages and jobs' profits. Importantly, total match surplus consists of the sum of match output net of outside options, determined by the productive attributes of workers and jobs, and idiosyncratic factors unrelated to productivity. We refer to the latter as "frictions" in the sense that they lead to deviations from the output-maximizing worker-job allocation, though we attach no normative meaning to them. The importance of these frictions is guided by a country-specific dispersion parameter of idiosyncratic match components that enter the total match surplus.

[2]The prevalence of family firms is associated with poor management of firms in both low- and high-income countries (Bertrand and Schoar, 2006; Bloom and Van Reenen, 2010). Additionally, poverty, limited access to credit, corruption, networks, and nepotism distort occupational choices and management practices in low-income settings (Beaman and Magruder, 2012; Bandiera et al., 2017; Abebe et al., 2021; Akcigit et al., 2021; Weaver, 2021; Amodio et al., 2024).

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

To confront our model with the data, we first prove that all model parameters are identified based on the information contained in the PIAAC microdata. The main challenge is to separately identify a country's technology and matching frictions, since both affect the worker-job allocation and wages. Building on Salanié (2015), we solve this issue by showing that the extent of matching frictions in each country is identified based on residual wage dispersion conditional on worker skills and job skill requirements. Intuitively, through the lens of our model, this residual wage dispersion can be rationalized only through idiosyncratic matching frictions, which give rise to dispersion in total match surplus (and thus in wages) within a worker-job match type. Having pinned down the extent of matching frictions—and given that the distributions of workers' skills and jobs' skill requirements are directly taken from PIAAC microdata—a country's technology is then identified based on the observed sorting patterns between workers and jobs. Intuitively, the strength of worker-job sorting that is not accounted for by matching frictions must be driven by the returns to sorting, determined by technology. To our knowledge, this is the first application to the labor market context that disentangles technology from matching frictions in this way.

We separately estimate the model for each of the 30 countries in our data by matching moments on worker-job sorting and residual wage dispersion that are informed by our identification argument. Our estimates suggest large cross-country differences in the three model fundamentals. Higher-income countries not only have more productive worker skills and job skill requirements but also better alignment between these two endowments. They also have stronger complementarities between skills and skill requirements in production and less severe matching frictions. The estimated model fits the data well in terms of targeted moments and also accounts for the cross-country variation in output per worker.

Based on the estimated model, we compute the matching index—i.e., the ratio of actual to potential output—for each country to quantify the output losses from worker-job mismatch. Consistent with our empirical evidence, poorer countries have a lower matching index, suggesting a systematic link between economic development and output losses due to worker-job mismatch.

In our main development accounting exercise, we quantify the sources of cross-country differences in worker-job mismatch and the consequences for aggregate output per worker. To this end, we use the estimated model for several counterfactuals, eliminating cross-country differences in one or more of the three fundamentals—endowments, technology, and matching frictions. We find that differences in technology and endowments account for most of the variation in aggregate output across countries. Giving all countries access to the same frontier technology reduces the cross-country variation in output per worker by 52 percent. In turn, if all countries had the same highly skilled workforce and jobs that demand those skills, the cross-country variation in output would be 26 percent lower. Jointly adopting the frontier technology and endowments explains 95 percent of cross-country differences in output per worker, which suggests strong complementarities between different fundamentals in economic development. In contrast, idiosyncratic factors associated with deviations from the output-maximizing worker-job allocation play a relatively modest role: Assigning all countries the relatively low labor market frictions of the frontier country reduces cross-country output differences by only 12 percent. Improving the matching between workers and jobs by eliminating frictions yields limited benefits for lower-income countries where inferior skill endowments and technology keep the returns to worker-job matching low.

While we find that differences in technology and endowments dominate differences in matching frictions as determinants of cross-country differences in aggregate output, this does not imply that improvements in endogenous worker-job matching are unimportant. On the contrary, a significant portion (34 percent) of the gains from adopting frontier technology and endowments arises from enhanced sorting, since these factors both encourage more skill-based matching and boost its returns. Improvements in worker-job matching thus constitute an important amplification channel for economic development. Our findings imply that policy interventions designed to increase the *returns* to skill-based sorting are more powerful than those that focus on minimizing idiosyncratic matching frictions in lower-income countries. Investments in technology may yield the highest payoffs, especially when including not only equipment and machinery but also management practices that affect firms' hiring strategies and human capital development (Bloom and Van Reenen, 2010). We show robustness of these results to an alternative estimation strategy, in which we do not attribute all of a country's residual wage dispersion to matching frictions.

We end with a comparison to conventional development accounting exercises. Although existing approaches recognize the importance of cross-country heterogeneity in human capital and technology—broadly defined here to include differences in capital—they overlook the role of match quality differences in explaining aggregate output. We show that ignoring cross-country heterogeneity in worker-job sorting leaves approximately 40 percent of the output gap across countries unexplained. Accordingly, accounting for variation in match quality across countries may play a crucial role in closing the residual gap of cross-national output differences.

To summarize, this paper advances our understanding of the role of matching workers with jobs in economic development. We bring to development accounting a combination of rich microdata on worker skills and job skill requirements as well as tools from the theory of two-sided matching, which have predominantly been applied to advanced countries (Bagger and Lentz, 2018; Lise and Postel-Vinay, 2020).[3] Previous accounts for cross-country income inequality have emphasized differences in human capital (Erosa et al., 2010; Jones, 2014; Lagakos et al., 2018; Hendricks and Schoellman, 2018, 2023), physical capital (Young, 1995), and especially technology (Caselli and Coleman II, 2006; Caselli, 2017; Comin and Mestieri, 2018; Rossi, 2022). We contribute to growing evidence on the role of input misallocation in development, which is traditionally hidden in total factor productivity (TFP). While recognizing that firms are heterogeneous, such studies have traditionally focused on whether certain firms have too much or too little *homogeneous* labor or capital (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Buera et al., 2011; Midrigan and Xu, 2014; Gopinath et al., 2017). Because workers and jobs differ within and across countries, understanding how the *matching* between *heterogeneous* workers and *heterogeneous* jobs affects aggregate outcomes across countries is of prime importance. This is the contribution of our paper.

2 Data

2.1 Sources

Our main data source is the Survey of Adult Skills of the Programme for the International Assessment of Adult Competencies (PIAAC), administered by the Organisation for Economic Co-operation and Development (OECD). The PIAAC surveys were conducted between 2012 and 2018 and cover a representative sample of working-age adults in 38 middle- and high-income countries; see Supplementary Appendix SA.1 for details (available for download here).[4] A unique feature

[3]In turn, Roy-Fréchet one-sided assignment models have been applied to study worker-job allocation in both developed economies (Hsieh et al., 2019) and development contexts (Lagakos and Waugh, 2013; Young, 2013; Adamopoulos et al., 2022, 2024; Gottlieb et al., 2025a). These approaches, however, assume a frictionless worker assignment and thus do not allow for the analysis of matching frictions. In contrast, our approach allows for frictions that can be backed out since the productive attributes on both sides of the labor market—workers and jobs—are observed in our data.

[4]Earlier work using the PIAAC has studied workers' skills and educational attainment (e.g., Autor, 2014; Hanushek et al., 2015; Cooper and Liu, 2019) *separately* from jobs' skill requirements and task contents (e.g., Caunedo et al., 2023). In contrast, our analysis concentrates on the matching between worker skills and job skill requirements.

of these data is their detailed account of both workers' skills and their jobs' skill requirements in multiple dimensions that are assessed in a comparable way across countries. Importantly, worker skills are directly measured using standardized tests rather than self-reports or proxies such as educational attainment. This bypasses the problem of unmeasured variation in school quality in development accounting (Caselli, 2005) and enables global comparisons of human capital, as in Martellini et al. (2023).[5] Similarly, job skill requirements in PIAAC are measured based on respondents' job contents in each country, consistent with recent measures by Caunedo et al. (2023) who highlight the country-specific nature of jobs' skill demands.

2.2 Sample Selection

We restrict our analysis to individuals between the ages of 20 and 59 with nonmissing information for key variables (i.e., numeracy and literacy skill scores, employment status, and hourly wage), which are available for 30 countries. We discard the self-employed, for whom there exists no reliable wage information.[6] Importantly, our sample covers both formal and informal workers, the latter making up a substantial part of many countries' total employment (Ulyssea, 2020).

2.3 Worker Skills and Job Skill Requirements

Worker Skills. A notable strength of PIAAC is that it assesses test scores in multiple skill domains for each respondent in each country. Here, we focus on numeracy and literacy skills, which are important cognitive skills available in most PIAAC countries.[7] In each skill domain, the standardized tests are designed to assess proficiency levels by assigning tasks that range from easy to challenging. Raw test scores are reported on a scale from 0 to 500. To put these into context, the lowest numeracy proficiency level comprises scores below 176 and corresponds to the ability to do "counting, sorting, performing basic arithmetic operations with whole numbers or money, or recognizing common spatial representations." At the other end of the spectrum, the highest numeracy proficiency level comprises scores above 375 and involves "complex representations and abstract and formal mathematical and statistical ideas, possibly embedded in complex texts." Similarly, literacy proficiency levels range from the ability to "read brief texts on familiar topics" to

[5] Appendix Figure A16 shows that PIAAC test scores and years of schooling are positively but imperfectly correlated. Correlation coefficients range from 0.13 to 0.63 and show a positive association with GDP per capita across countries, consistent with educational quality increasing with economic development (Martellini et al., 2023).

[6] Panel A of Appendix Figure SA7 demonstrates that self-employment is much less common in the countries of our sample than in the world's lowest-income countries.

[7] A few countries also report problem-solving skills in technology-rich environments, as related to the use of Information and Communications Technology (ICT).

the capacity to "search for and integrate information across multiple, dense texts" (OECD, 2019).

The top two panels of Figure 1 show the distributions of raw numeracy skills (panel A) and raw literacy skills (panel B) within each country, where we highlight Ecuador and Norway as our sample's lowest- and highest-income countries, respectively. There is significant dispersion in both skill domains within each country. At the same time, average skills tend to be greater in higher-income countries; see also the top two panels of Appendix Figure A15.

The following points underline the usefulness of these worker skill measures. First, we demonstrate that they possess empirical content, as evidenced by their market valuations. To this end, we estimate a Mincerian wage regression augmented by the numeracy and literacy test scores in PIAAC. Appendix Table A2 shows that there are significant wage returns to these skills. Controlling for years of schooling and work experience, the elasticity of wages with respect to the numeracy (literacy) skill score is sizable, namely 0.28 (0.17). Also controlling for occupation-level skill requirements—see below for details on how these are constructed—this elasticity declines by around one quarter of its initial magnitude, to 0.21 (0.12). Thus, the skill premium arises partly from sorting of higher-skilled workers into more demanding occupations and partly from wage variation conditional on sorting. These results suggest that these cognitive skills are highly relevant worker characteristics, though they are not the only ones—a point we revisit below.

Second, we provide evidence that the PIAAC skill measures reflect deep-rooted cognitive ability and not just unobserved traits accumulated with labor market experience. To this end, we compare the PIAAC skill measures for our working-age population with the results of cognitive tests among 15-year-old students in the Program for International Student Assessment (PISA). Appendix Figure SA1 shows strong positive correlations between skill scores in PIAAC and PISA in all domains, ranging from 0.69 for literacy to 0.85 for numeracy. This suggests that the skills tested by PIAAC are persistent across time and age, which motivates our assumption of treating them as fixed factors in our model below.

Job Skill Requirements. Another notable strength of the PIAAC is that it asks respondents about numeracy and literacy skill use in their job. We use this information to build *occupation-level* skill requirements in each skill domain and *for each country*. This allows us to mimic the structure of the popular US Occupational Information Network (O*NET) database, separately for each of the 30 countries in our sample.[8]

[8] International information on skill and task contents of jobs is rare. For certain regions (e.g., ESCO for the European Union) and certain individual countries (e.g., SINO for Mexico), similar databases exist, but we are not aware of a

To obtain occupation-level skill requirements, we first measure job skill requirements for each respondent individually. For each task, we create a dummy equal to 1 if the worker ever performs it and 0 otherwise, multiply it by the task's difficulty weight obtained from the OECD, and sum across all tasks in a domain (numeracy and literacy); see Supplementary Appendix SA.2 for details. Dividing by the total possible weight in that domain gives an index that captures both the breadth and depth of the tasks performed by the worker. For example, if a worker uses a calculator (i.e., a numeracy task with difficulty weight 1) and creates budgets (i.e., a numeracy task with difficulty weight 3), but does not perform any other numeracy tasks at work, whose total difficulty weight across the full task list is 16, then we assign the job held by this individual a numeracy skill requirement of $0.25 = (1 + 3)/16$. Separately for each country, we then aggregate job skill requirements to the *occupation level* by averaging the individual-level skill requirements across all workers in the same occupation, defined at the two-digit level of the International Standard Classification of Occupations (ISCO-08).[9] This procedure renders a scalar numeracy and a scalar literacy skill requirement for each occupation in each country, both contained in the interval $[0, 1]$.

The bottom two panels of Figure 1 show the distributions of raw skill requirements in the domains of numeracy (panel C) and literacy (panel D) within each country, again highlighting Ecuador and Norway. As with skills, there is significant dispersion in skill requirements within each country, but on average, jobs are more demanding in higher-income countries; see also the bottom two panels of Appendix Figure A15.

To validate our measures of skill requirements constructed from PIAAC, Appendix Figures SA3 and SA4 show the constructed numeracy and literacy skill requirements across broad occupation groups in all countries. Reassuringly, in all of our countries, our skill requirements for high-skilled occupations like managers and professionals (i.e., major groups 1 and 2 in the ISCO-08 classification) are higher on average than the skill requirements for low-skilled occupations like plant and machine operators (i.e., major groups 8 and 9 in the ISCO-08 classification).

An advantage of our measure of skill requirements is that it is directly comparable across countries while allowing for the same job to be done with a different mix of skills in different places. This approach is preferable to using U.S. O*NET task data for all countries in our sample, since job-specific skill use changes across stages of economic development (Atencio-De-Leon et al., 2025). Having country-specific measures of job characteristics is particularly important for

concerted effort to harmonize these in order to create internationally comparable data as provided by PIAAC.

[9] For two countries, namely Estonia and Finland, ISCO codes are reported only at the one-digit level, so we compute occupational skill requirements at the one-digit level for them.

measuring worker-job skill mismatch, which we do not want to be driven by unobserved cross-country differences in the task content of jobs.

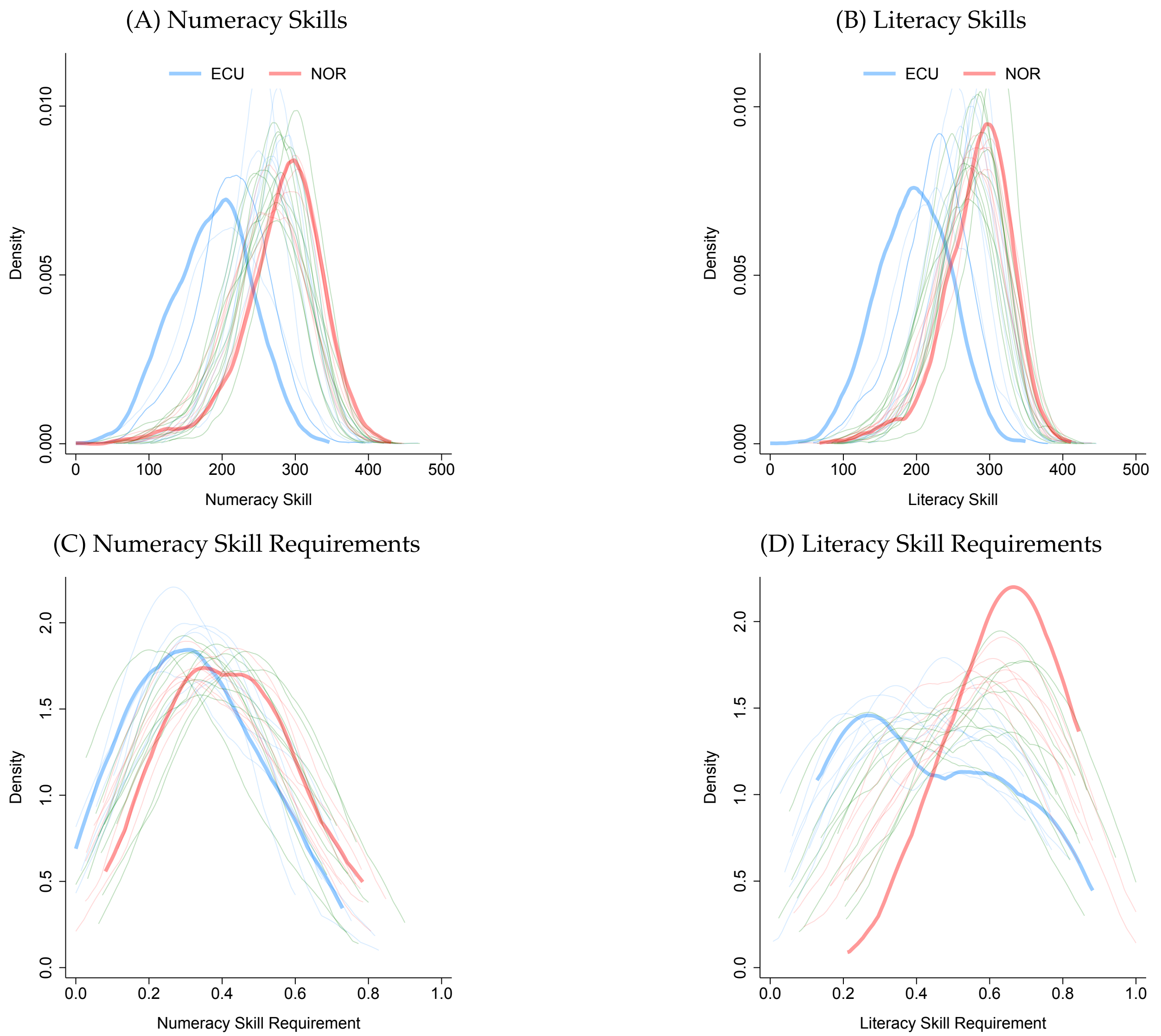
One potential concern with our measure of skill requirements is that it is endogenous to the skills of the worker who performs the job. For example, if a given worker is idiosyncratically underskilled (or overskilled) relative to the numeracy-related tasks their job requires, then that worker may end up reporting that their job requires little (or a lot of) numeracy skills, leading us to underestimate true mismatch. We address this endogeneity concern in two ways. First, we average the individual-level skill requirements across all workers in the same occupation, thereby breaking the mechanical link between idiosyncratic worker skills and self-reported job skill requirements. Second, for the U.S., we find that PIAAC-based numeracy and literacy requirements are highly correlated with O*NET-based numeracy and literacy measures across occupations; see Appendix Figure SA2. O*NET measures combine self-reports from workers with assessments by independent experts, the latter offering a presumably more objective perspective. Interestingly, and making a strong case for our use of the PIAAC survey, we find a weaker correlation between the skill requirements reported in PIAAC and those from O*NET in lower-income countries once O*NET measures are mapped onto occupations across all countries. Nevertheless, we show that our main empirical findings in Section 3 are qualitatively unchanged when we apply the US-based skill requirements from O*NET to all countries in our sample.

A second potential concern with our skill requirements from PIAAC is measurement error in the self-reported skill-use variables. If respondents in lower-income countries had noisier recall of job characteristics when interviewed, then such measurement error would mechanically lead us to infer more worker-job mismatch there, and the opposite if respondents in higher-income countries had noisier recall. However, if this were the case, we would also expect the within-occupation variation in skill requirements to vary systematically across countries. Reassuringly, Appendix Figure SA5 shows that the within-occupation variation in skill requirements is similar across countries in our sample.

2.4 Summary Statistics

Our sample comprises 120,448 observations that represent over 718 million individuals in 30 countries. Table 1 presents some key summary statistics. Panel A shows general country characteristics. The data cover middle- to high-income countries and span a substantial part of the development spectrum, with GDP per capita ranging from Ecuador at 10,700 dollars (2012 PPP) to Norway at

Figure 1: 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). Each thin solid line represents one country, with the thick lines highlighting the lowest and highest income countries, Ecuador and Norway, respectively. *Source:* PIAAC.

58,447 dollars (2012 PPP)—a ratio of around 5.5. The share of women in the population and the age distribution are relatively homogeneous across countries. Hourly wages show a range similar to that of GDP per capita, with a factor of 6.8 between the lowest- and highest-wage countries. Finally, the dataset contains an average of 4,246 observations per country, which is sizable but also imposes practical limits on data splitting in our analysis.

Panel B shows labor supply characteristics. There are marked cross-country differences in worker skills. The average respondent scores about half of the possible points on each of the skill tests. Moreover, the range of average skill scores across countries is substantial, spanning from approximately 190 in the lowest-scoring country to around 300 in the highest-scoring country. Finally, there is significant cross-country variation in years of schooling and employment shares.

Panel C shows labor demand characteristics. A notable fact is the scarcity of large firms (i.e., establishments) in lower-income countries, which, along with lower skill requirements in those countries, suggests substantial cross-country variation in the nature of jobs.

To inspect the coverage and representativeness of our data, we compare the PIAAC, in which participation is incentivized, along important dimensions with nationally representative data from the Jobs of the World Database (JWD; see Bandiera et al., 2022) and the Luxembourg Income Study (LIS), both within and across countries.[10] First, we confirm the representativeness of PIAAC within countries for important labor market outcomes such as the occupational composition (Appendix Figure SA6) as well as the share of workers in paid jobs, education, labor force participation rates, and hourly wages (Appendix Figure SA7). Second, we compare the sample of countries on the PIAAC with a wider range of countries across the development spectrum. The PIAAC countries fall in the upper tercile of all countries ranked by GDP per capita, as do their shares of workers in salaried jobs, average years of education, the ratio of female to male labor force participation, and average hourly wages.

3 Worker-Job Matching across Countries

We now document cross-country differences in worker-job matching. Our main finding is a novel empirical fact: In higher-income countries, workers' skills are more closely aligned with job skill requirements—i.e., there is less mismatch.

For the empirical analysis of worker-job sorting, we rescale worker numeracy and literacy skills as well as job skill requirements to the unit interval, aligning their units while preserving the shape of the original distributions.[11]

We begin with a simple illustration of our main finding. We select two occupations that are both very common and have different skill requirements: teachers (i.e., ISCO code 23) and truck drivers (i.e., ISCO code 83). Across all countries in our sample, teachers are the most common occupation within the relatively high-skilled ISCO major groups 1 ("Managers") and 2 ("Professionals"), while truck drivers are the most common occupation within the relatively low-skilled

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

[11] To do so, we subtract from each variable its minimum and divide by its range, separately in each country.

Table 1: Summary Statistics across Countries

	Mean	SD	Min	Max
Panel A: Country Characteristics				
GDP per Capita (2012 $, PPP)	35,126	11,571	10,701	58,447
Population (millions)	23.96	52.54	0.35	284.44
Share of women	0.53	0.02	0.50	0.56
Age	39.01	1.20	35.91	40.81
Hourly wage	14.66	6.21	3.72	25.18
Number of observations	4,246	994	2,854	7,159
Panel B: Labor Supply				
Numeracy skill	261.15	23.77	186.21	293.67
Literacy skill	265.85	21.70	195.37	302.88
Years of schooling	12.77	1.01	10.50	14.90
Employment-to-population ratio	0.71	0.09	0.45	0.82
Panel C: Labor Demand				
Numeracy skill requirement	0.38	0.06	0.27	0.56
Literacy skill requirement	0.51	0.08	0.35	0.65
Share of workers in firms with > 50 employees	0.29	0.08	0.10	0.42

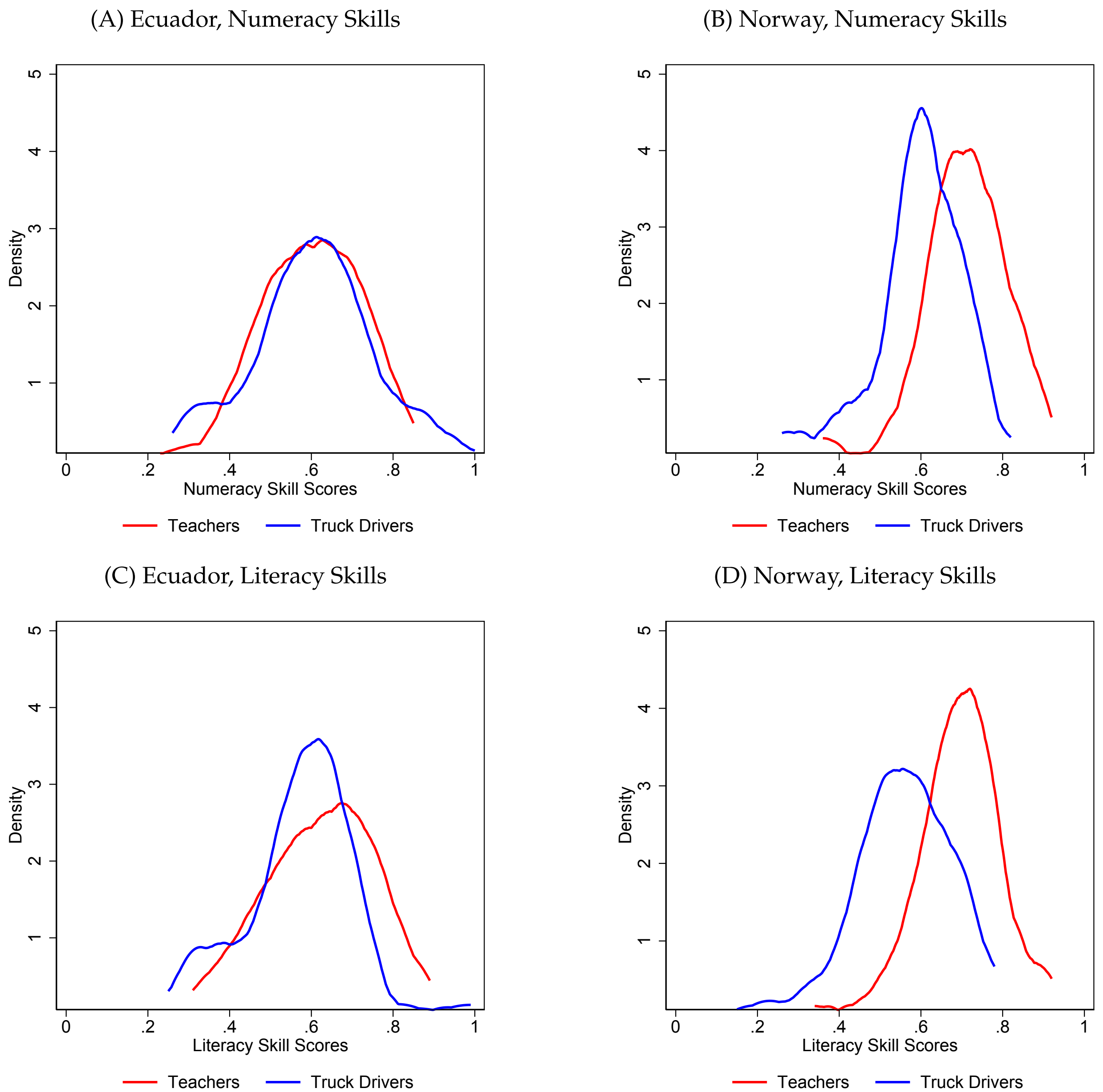
Note: This table shows summary statistics for the PIAAC data across the 30 countries included in our analysis. Panel A shows basic country characteristics; panel B labor supply statistics; and panel C labor demand statistics. Columns represent the mean, standard deviation, minimum, and maximum of the country-level *averages* for each variable. Statistics are weighted by population weights provided by PIAAC. Source: PIAAC.

ISCO groups 8 ("Plant and Machine Operators and Assemblers") and 9 ("Elementary Occupations"). Notably, teachers' skill requirements exceed those of truck drivers by around 1.5 standard deviations in numeracy and 2.2 in literacy in all countries, including Ecuador and Norway.

Figure 2 illustrates that skill-based sorting across occupations rises with economic development. Panel A shows that in Ecuador, the poorest country in our sample, the distributions of numeracy skills for teachers (red) and truck drivers (blue) almost completely overlap, essentially indicating the absence of any skill-based sorting across these occupations. Similarly, Panel C shows that there is only a low degree of occupational sorting based on literacy skills in Ecuador. In contrast, for Norway, the richest country in our sample, Panels B and D show that there is stronger skill-based sorting across occupations in the numeracy and literacy domains, respectively. This example illustrates that the allocation of workers to jobs differs across countries, which is not mechanically driven by cross-country differences in the marginal distributions of worker skills or job skill requirements. The same patterns generalize to all 30 countries in our sample.[12]

[12] Appendix Figure B17 systematically compares the skill distributions of teachers and truckers across countries by plotting the ratio of the lowest skill quartile among teachers to the highest skill quartile among truckers for each country: Richer countries exhibit a larger skill gap, and thus more skill-based sorting, between teachers and truckers.

Figure 2: Teachers vs. Truckers: Greater Skills Gaps in Higher-Income Countries

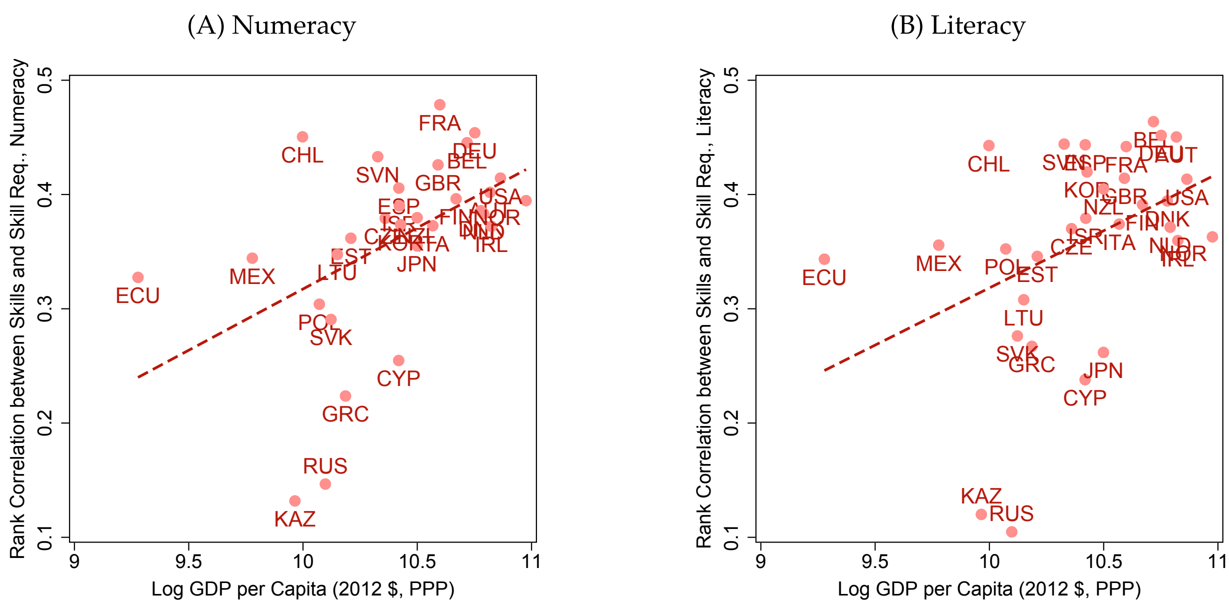


Notes: This figure depicts the distribution of numeracy (top panels) and literacy (bottom panels) skill scores for teachers (ISCO code 23; red lines) and truck drivers (ISCO code 83; blue lines) for Ecuador (left panels) and Norway (right panels). Both skills and skill requirements are rescaled at the country level to have the common support of $[0, 1]$ by subtracting the minimum value and dividing by the range of the variable in each country. *Source:* PIAAC.

Naturally, part of the observed mismatch between worker skills and job skill requirements arises due to misalignment between a country's worker qualifications relative to its job characteristics. If, for example, a country must fill a certain number of high-skill-requirement teacher jobs but its education system fails to produce enough high-skilled graduates for these positions, then allocating some lower-skilled individuals into teaching positions may be necessary, given the available talent and job pools. On the other hand, part of the observed mismatch may reflect a lack of sorting, leading workers into poorly matched jobs even when ideal jobs exist. We first investigate the latter form of mismatch by conditioning on the available workers and jobs in a country.

To this end, Figure 3 shows the country-specific rank-rank correlations between a worker's skills and their job's skill requirements, separately for numeracy (Panel A) and literacy (Panel B). A Spearman's rank correlation coefficient of 1.0 indicates perfectly assortative matching based on the relevant skill—i.e., the worker with the highest numeracy skills is allocated to the job with the highest numeracy requirements, the second-highest skilled worker is in the job with the second-highest skill requirements, and so on. In both skill domains, the Spearman rank correlation between workers' skills and their jobs' requirements increases from around 0.12 in some of the lower-income countries (e.g., Kazakhstan, Russia) to around 0.47–0.50 in some of the higher-income countries (e.g., France, Germany, Belgium). Thus, in a unidimensional sense, the extent of skill-based matching between workers and jobs is increasing in economic development.

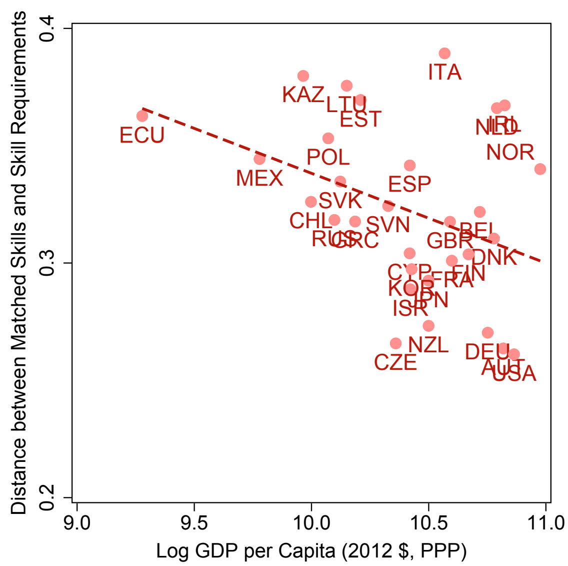
Figure 3: More Correlated Skills and Skill Requirements in Higher-Income Countries



Notes: This figure plots the Spearman rank correlation between workers' skills and their jobs' skill requirements against log GDP per capita (2012 \$, PPP) for each country. Panel A (B) shows the correlation for numeracy (literacy) skills and numeracy (literacy) requirements. Both skill and skills requirements are rescaled at the country level to have the common support of $[0, 1]$ by subtracting the minimum value and dividing by the range of the variable in each country. *Source:* PIAAC.

When considering the realistic case of matching under multi-dimensional heterogeneity—the typical situation in labor markets—complex trade-offs shape the strength of sorting across different dimensions, which are impacted not only by the productive returns to matching but also by the endowments, namely the fit between the economy's skill supply and demand (Lindenlaub, 2017). To account for this wider range of determinants of worker–job matching, we go beyond the unidimensional rank correlation and construct a simple yet intuitive measure of multidimensional worker-job skill mismatch: the average Euclidean distance, or L^2 norm, between a worker's skills and their job's skill requirements.[13] This distance measure takes on the value 0 if workers' skills perfectly match their jobs' skill requirements and $\sqrt{2} \approx 1.41$ when workers' skills are at a maximum distance from their jobs' skill requirements. By plotting the mean distance across all worker-job matches in a country against GDP per capita, Figure 4 reveals a novel empirical fact: Worker-job skill mismatch decreases with GDP per capita. Put differently, the alignment between worker skills and their job requirements strengthens with economic development.

Figure 4: Less Worker-Job Skill Mismatch in Higher-Income Countries



Notes: This figure plots the average Euclidean distance between the vector containing each worker's numeracy and literacy skills and the vector containing their job's numeracy and literacy skill requirements, against GDP per capita. Both skill and skill requirement scores are rescaled at the country level to have the common support of $[0, 1]$ by subtracting the minimum value and dividing by the range of the variable in each country. *Source:* PIAAC.

We show that this empirical cross-country pattern of mismatch is robust to alternative measurement strategies. First, Appendix Figure B19 shows that this pattern—based on the Euclidean distance between worker skills and their jobs' skill requirements—is robust to different measurement choices. Panel A shows a similar relation between mismatch and GDP per capita if we use the most detailed level of ISCO occupation codes available in each country. Panel B shows that

[13] Of course, any empirical measure of worker-job matching only provides a first look at the data. Below, we will develop an equilibrium model of worker-job matching, in which the trade-offs inherent to multidimensional matching are spelled out and mismatch is precisely defined as the distance between actual and optimal worker-job allocation.

using the individual-level reports of job skill requirements yields similar results. Panel C shows a qualitatively similar relation when we apply the skill requirement measures from the US O*NET to all countries. Finally, panel D shows that our result is robust to transforming worker skills and job skill requirements into country-specific z-scores before computing the Euclidean distance.

Second, Appendix Figure B18 shows alternative measures of worker-job match quality. Panel A shows the share of "perfect matches," which refers to both workers and their jobs falling into the same quintile in each dimension of the country-specific distribution of skills and skill requirements. Panel B shows the share of "good matches," which refers to worker skills lying no more than one quintile away from the corresponding skill-requirement quintile in the country-specific distributions.[14] Both measures are positively correlated with GDP, supporting our finding of more skill-based matching in richer countries.

Finally, the stronger skill-based sorting in high-income countries is not driven by cross-country differences in worker sorting across sectors, which is well known to vary with structural transformation along the economic development path. Specifically, Appendix Figure B20 shows that worker-job mismatch is decreasing in GDP per capita in all three major sectors: agriculture, manufacturing, and services, the latter making up the lion's share of economic activity in all of our countries; see Appendix Figure B21.

So far, our analysis emphasized the sorting of workers into jobs conditional on being employed. However, rates of nonemployment (i.e., being unemployed or out of the labor force) are substantial, especially in lower-income countries. As a result, the skill-based selection into employment also matters. Appendix Figure E26 shows each country's degree of selection into employment, measured by the ratio of the average skills of employed and nonemployed individuals. We find a positive selection into employment in all countries, meaning that the employed are on average more skilled than the nonemployed everywhere, but the degree of positive selection is stronger in higher-income countries. Taken together, our findings suggest that higher-income countries are characterized by more skill-based matching—not only in terms of worker-job sorting conditional on employment, but also in the selection of workers into employment.

There are three fundamental reasons that potentially underlie the observed pattern of stronger worker-job matching in higher-income countries. First, countries' endowments may differ in that both skills and skill requirements are at comparatively low levels in lower-income countries, or

[14] Specifically, we map each worker (job) into a set of country-specific quintiles, $\{1,2,3,4,5\}^2$, representing their numeracy and literacy skills (skill requirements). A worker-job match is said to be "perfect" if the L^1 norm between the worker and the job in the quintile space is zero and "good" if its distance in each dimension is no more than 1.

there is less overlap between skill supply and skill demand. For instance, a poor fit between workers' skills and jobs' skill requirements implies that a tight worker-job matching on skills is not feasible. To illustrate with the earlier example, suppose the numeracy skill requirement for teachers is similar across countries, but the endowment of numeracy skills is lower in poorer countries. In that case, the small observed difference in skills between truckers and teachers simply reflects that few individuals possess the skills required for teaching jobs.

A second reason is that countries' production technology—which determines the returns to skill-based matching—differs. Technological differences may explain weaker skill-based sorting in lower-income countries if their production functions feature weaker worker–job complementarities, due to producing lower-quality goods, using less sophisticated equipment and machines, or organizing firms less efficiently. As a consequence, good matches are less valuable in lower-income countries and therefore command a lower wage premium. Returning to the earlier example, differences in the production technology imply that the observed lack of sorting in Ecuador may stem from the limited financial incentive for skilled workers to take up teaching positions.

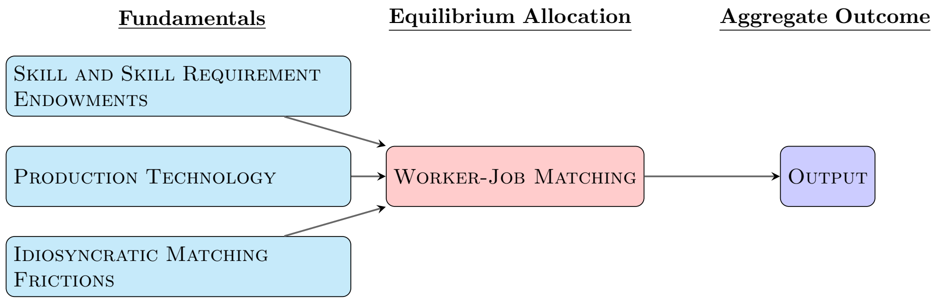
The third determinant of labor market sorting relates to frictions in the matching process that limit the extent to which workers choose jobs based on skills alone. These idiosyncratic, skill-unrelated matching reasons—such as social connections, family wealth, corruption, and discrimination at the hiring stage—may be more relevant in low-income countries, leading to less skill-based matching there. Returning to our earlier example, it is possible that more prevalent nepotism in Ecuador limits the extent to which the most suitable workers obtain teaching positions.

We now develop an equilibrium model in which countries differ along these dimensions—endowments, technology, and frictions—that jointly determine worker-job matching in the labor market. We use this framework for development accounting to quantify the relative importance of these factors in shaping worker-job matching and, via this channel, variation in aggregate output.

4 An Equilibrium Model of Worker-Job Matching

Motivated by our empirical facts, we now study the micro determinants and aggregate consequences of worker-job matching. To this end, we adapt the equilibrium matching framework of Choo and Siow (2006) with multidimensional skill heterogeneity, as in Lindenlaub (2017), to study the allocation of workers to jobs, which is determined by three country-specific fundamentals. First, the *endowments* of worker skills and job skill requirements guide match feasibility. Second, *technology* determines the output-related returns to worker-job matching. Third, *idiosyncratic*

Figure 5: Model Overview for a Given Country



Notes: This figure provides a schematic overview of our model for a given country. On the left are three country-specific fundamentals. In the center is the resulting equilibrium allocation of workers to jobs. On the right is our outcome of interest.

matching frictions impede the output-maximizing worker-job allocation. We are interested in how these three factors shape worker-job matching and, thereby, aggregate output across countries. Figure 5 provides a schematic model overview and applies to each of our countries.

4.1 Environment

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

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

Technology. Each worker-job match produces output $f(x, y)$ that depends on worker attributes x and job attributes y. We normalize the output of matches involving the lowest worker skill type $\underline{x} := (\underline{x_n}, \underline{x_\ell})$, where $\underline{x_n} := \min x_n$ and $\underline{x_\ell} := \min x_\ell$, to $f(\underline{x}, y) = 0$ for all job types y.[15] The payoff of an unmatched worker of type x is $f_{x\emptyset}(x)$, where the subscript $y = \emptyset$ indicates the worker's choice to remain nonemployed. Similarly, the payoff of an unmatched job of type y is $f_{\emptyset y}(y)$, where the subscript $x = \emptyset$ indicates the job's choice to remain idle. Workers' outside options depend on both skills and gender, which allows for gender-specific comparative advantage in home production. From here on, we assume $f_{\emptyset y}(y) = 0$.[16]

Idiosyncratic Matching Frictions. Idiosyncratic matching frictions lead to deviations from the output-maximizing worker-job allocation, along both the intensive margin (i.e., the matching of employed workers) and along the extensive margin (i.e., selection into employment). Specifically, matching is guided not only by systematic factors affecting match output but also by idiosyncratic factors capturing unproductive reasons for matching, which are transferable, contribute to match surplus, and whose importance depends on the extent of matching frictions. We denote by δ_{iy} the idiosyncratic match quality worker i generates with job type $y \in \mathcal{Y} \cup \emptyset$ and by δ_{xk} the idiosyncratic match quality job k generates with worker type $x \in \mathcal{X} \cup \emptyset$.[17] We assume that these idiosyncratic match components follow an Extreme Value (EV) Type I, or Gumbel maximum, distribution:[18]

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

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

While we refer to the idiosyncratic match components, δ_{iy} and δ_{xk}, as reflecting "matching

[15]This normalization will prove useful for identifying match output below.

[16]In theory, jobs' values of remaining idle may vary freely, akin to workers' values of nonemployment. In practice, though, the lack of information on vacancies by job type in conventional data prevents us from identifying this object. Our assumption could be motivated by the free entry of jobs, which drives the value of an idle job to zero and circumvents the need to identify $f_{\emptyset y}(y)$.

[17]Our interpretation of the idiosyncratic match components is standard (Browning et al., 2014), but a reasonable alternative is to cast them in terms of job preferences: δ_{xk} reflects the preference of *individual job k* for a worker of type x while δ_{iy} reflects the preference of *job type y* for an individual worker i, as discussed in Galichon and Salanié (2021).

[18]We tractably model idiosyncratic heterogeneity in lieu of search frictions (e.g., Mortensen, 2003), which is a natural choice given our cross-sectional data.

frictions," we think of them as a reduced form for any reason that prevents the output-maximizing matching pattern, with no normative meaning attached. This may reflect distortionary reasons for mismatch, such as nepotism (Akcigit et al., 2021), corruption (Weaver, 2021), and discrimination (Hsieh et al., 2019), but it may also reflect benign reasons, such as workers' valuations of nonwage job aspects (Morchio and Moser, 2025). Regardless of their specific interpretation, idiosyncratic match components are separate from skill-related reasons for worker-job sorting. Our interest lies in their distribution, guided by the scale parameter σ, that rationalizes observed worker-job matching patterns in a given country. In this sense, we conduct a positive accounting exercise within an equilibrium model, in the spirit of the literature on distortionary wedges in other areas of macroeconomics (e.g., Hopenhayn, 2014; Restuccia and Rogerson, 2017).

4.2 Matching

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

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

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

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

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

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

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

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

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

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

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

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

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

4.3 Equilibrium Definition and Properties

In equilibrium, workers and jobs choose their payoff-maximizing matches in such a way that demand and supply for each type of match balance, i.e., the equilibrium frequency of type (x,y) matches is given by

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

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

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

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

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

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

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

Combining the relative choice probabilities of jobs of type y, $\mu^J(x,y)/\mu^J(\emptyset,y)$, and of workers of type x, $\mu^W(x,y)/\mu^W(x,\emptyset)$, with labor market clearing (5), we obtain the following expression for the systematic surplus of match (x,y); see Appendix C for all derivations in this section:

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

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

We now turn to how the match surplus is split between workers and jobs. In equilibrium, systematic wages $w(x,y)$ are derived using workers' relative choice probabilities $\mu(x,y)/\mu(x,\varnothing)$, market clearing, and matching frequencies $\mu(x,y)$ from (7):

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

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

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

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

Systematic wages are not directly observed in the data. We next focus on the empirically relevant idiosyncratic wages, $\tilde{w}(x_i,y_k)$, which correspond to the observed wages in our data. These wages are based on total match surplus (6)—i.e., the sum of systematic match surplus $s(x,y)$ in (7) and agents' idiosyncratic match components δ_{xk} and δ_{iy}. The latter is the reason why there is wage variation within type (x,y) matches across workers indexed by i and across jobs indexed by k. We show in Appendix C that, under our assumption that—prior to any wage payment—all workers are indifferent between jobs of a given type y, the idiosyncratic wage of worker i of type x in a match with job k of type y takes the typical form (see also Galichon and Salanié, 2021):

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

That is, worker i receives a payoff that consists of the systematic wage, $w(x,y)$, which pertains to any match between a type x worker and type y job, as well as worker i's idiosyncratic contribution to the match, given by match component δ_{iy}. Intuitively, a higher value of δ_{iy} reflects a stronger idiosyncratic contribution of worker i to match surplus with a job of type y. Since there is a unique worker i with that idiosyncratic component but many jobs of type y, competition among type y jobs for worker i drives his wage up to the point of enjoying the full *value* of the idiosyncratic match component, δ_{iy} (i.e., the δ_{iy}'s are fully monetized).[19] In turn, job k of type y receives the residual surplus from matching with worker i of type x in the form of idiosyncratic profits $\tilde{v}(x_i, y_k)$.

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

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

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

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

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

Thus, finding an equilibrium is equivalent to solving the system of $|\mathcal{X}| + |\mathcal{Y}|$ equations (12)–(13) in the same number of unknowns. In our model, the assumptions from Theorem 3 in Galichon et al. (2019) are satisfied.[20] This guarantees that an iterative procedure operating on (12)–(13) monotonically converges to a solution for $(\mu(x, \emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset, y))_{y\in\mathcal{Y}}$, based on standard results on the convergence of monotone bounded sequences. This algorithm, called the Iterative Projective Fitting Procedure (IPFP), provides a computationally efficient solution to high-dimensional matching problems. Plugging the solution for $(\mu(x, \emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset, y))_{y\in\mathcal{Y}}$ into $M_{xy}(\mu(x, \emptyset), \mu(\emptyset, y))$, we

[19] We make two additional remarks. First, we assume that idiosyncratic wages $\tilde{w}(x_i, y_k)$ are monetary and equal in value to the sum of the systematic wage $w(x, y)$ and the worker's idiosyncratic match component δ_{iy}. To finance these monetary payouts, we can think of some—unmodeled—financial endowment that is constant across jobs; see Appendix C for more details. Second, equilibrium wages in our model result from a surplus split and are therefore augmented by the worker's idiosyncratic match component, δ_{iy}, which is fully transferable between worker and job and thus raises the worker-job surplus—unlike the standard logic of compensating differentials (Rosen, 1986).

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

obtain the equilibrium matching frequencies $(\mu(x,y))_{x\in\mathcal{X},y\in\mathcal{Y}}$. Similarly, plugging the solution for $(\mu(x,\emptyset))_{x\in\mathcal{X}}$ and $(\mu(\emptyset,y))_{y\in\mathcal{Y}}$ into (8) and (10), we obtain the equilibrium values of systematic wages $w(x,y)$ and idiosyncratic wages $\tilde{w}(x_i,y_k)$. This demonstrates that an equilibrium exists.

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

4.4 Measuring Skill-Based Matching

Our model allows us to measure the degree to which the matching between workers and jobs maximizes an economy's output. Denote a country's parameters by $\theta := \left(G, H, m^J, f, f_{x\emptyset}, f_{\emptyset y}, \sigma\right)$, the actual worker-job match frequencies by $\mu(x,y)$, and the hypothetical worker-job match frequencies in the frictionless case with $\sigma \to 0$ by $\mu^*(x,y)$, which accounts for both the optimal selection of workers into employment and the optimal allocation of employed workers to jobs. The following definition makes our notion of matching efficiency in the labor market precise.

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

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

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

A lower degree of idiosyncratic matching frictions (i.e., lower σ) leads to more output-based sorting between workers and jobs, which is guided by the technological returns to productive attributes (x, y). This pushes $\mu(x, y)$ closer to $\mu^*(x, y)$, and thereby narrows the gap between actual and potential output and increases the matching index, $\mathcal{M}(\theta)$. The matching index is maximized (i.e., $\mathcal{M}(\theta) = 1$) in a frictionless economy (i.e., $\sigma \to 0$), regardless of a country's specific endowments or technology.[21] By contrast, $\mathcal{M}(\theta) < 1$ when idiosyncratic factors unrelated to productivity influence the worker-job allocation (i.e., $\sigma > 0$). Importantly, in this case, technology and endowments affect the incentives to sort on skills and thereby the difference between actual versus potential output and $\mathcal{M}(\theta)$.

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

Endowments also affect the incentives for skill-based sorting for a given level of matching frictions, $\sigma > 0$. First, scaling up worker skills or job requirements raises the systematic surplus component linked to productive attributes relative to the idiosyncratic surplus component, and thereby strengthens sorting on skills relative to idiosyncratic factors. Second, better alignment between worker skills, $G(x)$, and job requirements, $H(y)$, promotes skill-based sorting, as workers are more likely to seek matches that fit their skills when more suitable jobs are available. Once more, these forces push $\mu(x, y)$ closer to $\mu^*(x, y)$, thereby narrowing the gap between actual and potential output and increasing the matching index $\mathcal{M}(\theta)$.[22]

In sum, the matching index, $\mathcal{M}(\theta)$, captures how closely a country's actual worker-job matching—determined by the mix of endowments, technology, and matching frictions—aligns with the optimal benchmark. In this sense, our analysis extends existing studies of factor misallocation to labor markets with two-sided heterogeneity, where a richer set of underlying forces matters.

5 Identification

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

$$\theta = \left(G(x), H(y), m^J, f(x, y), f_{x\emptyset}(x), \sigma \right),$$

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

[22] Greater technological returns or more aligned/productive endowments—by (effectively) changing $f(x, y)$ and also $\mu(x, y)$ and $\mu^*(x, y)$—affect both actual and potential output. In simulations, however, the increase in actual output in the numerator dominates the change in potential output in the denominator of $\mathcal{M}(\theta)$.

where $G(x)$ is the distribution of worker types, $H(y)$ is the distribution of job types, m^J is the relative job mass, $f(x, y)$ is the production function, $f_{x\emptyset}(x)$ is the value of nonemployment, and σ is the dispersion of idiosyncratic match components, which we interpret as the degree of idiosyncratic matching frictions. Since we do not observe vacant jobs, we assume that the distributions of filled and unfilled jobs are identical in a given country.[23]

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

Proof. See Appendix D.1. □

The intuition underlying the identification of each group of parameters—endowments, technology, and matching frictions—in Proposition 1 can be summarized in three steps.

First, regarding endowments, $G(x)$ and $H(y)$ are distributions over observable worker and job types, so they are identified based on the empirical shares of worker skills and job skill requirements.[24] In turn, the relative job mass, m^J, is identified based on the aggregate profit share.[25]

Second, to identify the scale parameter of idiosyncratic matching frictions, σ, we use the fact that match transfers are observed in the labor market context—contrary to conventional marriage market applications, for which this parameter needs to be normalized (e.g., Choo and Siow, 2006). Specifically, building on the insights of Salanié (2015), we demonstrate that σ is identified based on wage dispersion across individuals in the same (x, y) match.[26] In a frictionless case (i.e., $\sigma \to 0$), the law of one price requires that any individuals of the same worker type x in the same job type y must earn the same wage, so there is no wage dispersion within a given (x, y) match. In an economy with frictions (i.e., $\sigma > 0$), the idiosyncratic match components δ_{xk} and δ_{iy} result in differences in idiosyncratic match surplus, and thus total match surplus across type x workers who match with type y jobs. As a result, there is wage dispersion within a given (x, y) match, which is strictly increasing in σ and unaffected by all other model parameters. Therefore, the empirical within-(x, y)-cell wage dispersion identifies σ.

Third, technology $(f(x, y), f_{x\emptyset}(x))$ is identified based on observed matching patterns. Intuitively, the frequencies of matches between workers of type x and jobs of type y are driven by

[23] As is well known due to Heckman (1979), identifying the population distribution of market participants in the presence of endogenous selection into observable states requires additional assumptions.

[24] Based on the specified assumptions, we can identify $H(y)$ of the distribution of *filled* jobs.

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

[26] Hsieh et al. (2019) follow a similar approach to identify their Fréchet shape parameters.

systematic returns in form of match output $f(x, y)$ and idiosyncratic matching frictions σ. Thus, given σ, we can use information on who matches with whom to identify the production function, $f(x, y)$.[27] Intuitively, the strength of worker-job sorting that is not accounted for by matching frictions must be driven by the returns to sorting, which are determined by technology. In turn, consider the outside option of workers, $f_{x\emptyset}(x)$, which is identified for each worker type x based on the worker's choice probability of nonemployment relative to that of a match with some job type y. Since the relative choice probability depends on the observed wage in a match, the degree of matching frictions already identified above, and the worker's outside option, we can identify $f_{x\emptyset}(x)$ for each $x \in \mathcal{X}$.

The central contribution of our strategy is to separately identify two model primitives—frictions and technology—which are inherently hard to separate because common labor market moments are shaped by both. Our theory puts the spotlight on residual wage dispersion as a key empirical moment that—through the lens of our theory—allows us to differentiate between matching frictions and technology within each country.

6 Estimation

We estimate our model separately for each of the 30 countries in the PIAAC data. In doing so, we allow all model parameters, which correspond to endowments, technology, and idiosyncratic matching frictions, to differ across countries. After outlining our estimation procedure for the parameterized model, guided by the identification arguments in the previous section, we turn to the estimation results. They show that richer countries have more overlap between skill supply and demand; more productive complementarities between workers and jobs in match output; and lower matching frictions. We close by discussing identification threats in practice.

6.1 Distributional and Functional-Form Assumptions

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

Endowments. We discretize the distributions of worker skills and job skill requirements from the PIAAC microdata for consistency with our model. To allow for skills and skill requirements to

[27] Under our assumption that $f(\underline{x}, y) = 0$, the probability that a job of type y matches with a worker of type x relative to matching with the least productive worker $\underline{x}$ depends only on wages $w(x, y)$, the already-identified matching frictions σ, and match output $f(x, y)$, so we can identify $f(x, y)$ for each $(x, y) \in \mathcal{X} \times \mathcal{Y}$. Note that systematic wages $w(x, y)$ are not directly observed but can be backed out from the observed average idiosyncratic wages, $\mathbb{E}[\tilde{w}(x_i, y_k)|x, y]$ in a given (x, y) match, using properties of the EV distribution; see Appendix D for details.

be comparable within and across countries, we construct what we refer to as *global quintiles* in each dimension of worker skills (x_n, x_ℓ) and job skill requirements (y_n, y_ℓ). We first divide workers' and jobs' marginal distributions in each country into country-specific quintiles. Each country-specific quintile is then assigned the average global percentile rank of the workers or jobs it contains in that dimension, with global percentiles computed from the pooled sample of all countries. This yields discrete distributions of numeracy and literacy skills, as well as skill requirements, comprising 25 skill types and 25 skill requirement types per country. These types take values ranging from 0 to 1 while preserving differences in levels across countries. In addition, we classify workers into two genders, $x_g \in \{\text{female}, \text{male}\}$, and jobs into two firm-size groups, $y_s \in \{\text{small}, \text{large}\}$, where "small" corresponds to up to 50 employees and "large" to more than 50 employees.[28]

For workers, since we observe both nonemployed and employed individuals in the PIAAC, we can directly infer the population distribution of types. For jobs, an additional assumption regarding the distribution of idle jobs is needed since we have no information on vacancies by job type. We assume that the unobserved population of all (i.e., filled and idle) job types is congruent with the observed distribution of filled jobs in a given country. As a result, we obtain probability mass functions over 50 worker types, $g(\cdot)$, and 50 job types, $h(\cdot)$.

Technology. We assume a bilinear production function for the output produced by a type x worker in a match with a type y job:

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

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

We allow for flexible workers' outside options, $f^{rg}_{x\varnothing}$, nonparametrically estimated across six groups of workers, consisting of three broad skill groups indexed by $r \in \{\text{low}, \text{medium}, \text{high}\}$ interacted with two gender groups indexed by $g \in \{\text{female}, \text{male}\}$.[29]

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

[29] Creating broad skill groups reduces the dimensionality of the estimation routine while retaining sufficient hetero-

6.2 Estimation Procedure

Given our distributional and functional-form assumptions, there are two distributions, $(g(x), h(y))$, and 14 parameters to be estimated

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

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

We use the ratio of within-(x, y)-cell log-wage dispersion to the overall log-wage dispersion to pin down σ/A. To disentangle TFP, $A = \alpha_{nn}$, from scale parameter, σ, we additionally exploit the mean log wage in 2012 PPP dollars—which is sensitive to absolute levels—together with the observed worker-job matching patterns along the numeracy dimension.[30] We then choose five moments that reflect the worker-job matching patterns in the other dimensions to inform the production technology parameters, $(\alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell\ell}, \alpha_{\ell n}, \alpha_{\ell s})$; six skill-gender-specific nonemployment rates to pin down the six outside option values $f^{rg}_{x\varnothing}$; and the aggregate profit share to pin down the relative job mass m^J. See Appendix E.1 for the detailed construction of model and data moments, and Appendix E.2 for the estimation procedure.

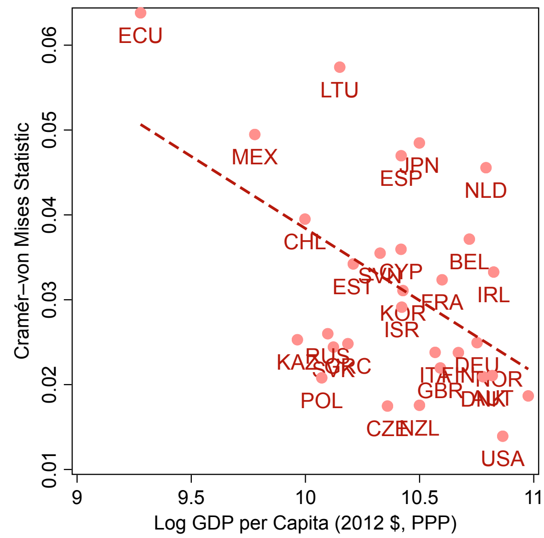
6.3 Estimation Results

Parameter Estimates. Countries differ substantially in worker skill and job skill requirement distributions. Higher-income countries have a more skilled workforce and more demanding jobs in terms of numeracy and literacy—documented in Section 2.3—and they also exhibit more overlap between skill supply and skill demand. This is reflected in a smaller distance between the

geneity to match the data. Specifically, we take the sum of worker's numeracy and literacy skill quintiles and classify workers as "low-skilled" if the sum is 2–4, "medium-skilled" if it is 5–7, and "high-skilled" if it is 8–10.

[30] Proposition SA1 (Supplementary Appendix SB.1) states a homogeneity property of our model, which implies that target moments that comprise only workers' and jobs' choice probabilities (i.e., sorting patterns), within-(x, y)-cell *log*-wage dispersion, and the profit share merely pin down the degree of matching frictions *relative* to TFP, σ/A. This is why we add the moment of the mean log wage. Note that in estimation we target within-(x, y)-cell log-wage dispersion (as opposed to level wage dispersion from the identification argument) for its scale-free, numerically robust properties.

Figure 6: Smaller Distance Between Skill Supply and Skill Demand in Higher-Income Countries



Notes: This figure plots the Cramér-von Mises distance between the bivariate distributions of worker skills and job skill requirements against log GDP per capita across countries. Skills and skill requirements are discretized into global quintiles of numeracy and literacy, yielding 25 skill types and 25 skill requirement types per country, as described in Section 6.1. Each red dot represents one country. The solid line represents the linear best fit. *Source:* PIAAC.

economy-wide bivariate distributions of skills and skill requirements, irrespective of the particular matching patterns between workers and jobs; see Figure 6 for the Cramér-von Mises distance and Appendix Figure E23 for the Kolmogorov–Smirnov distance measure.

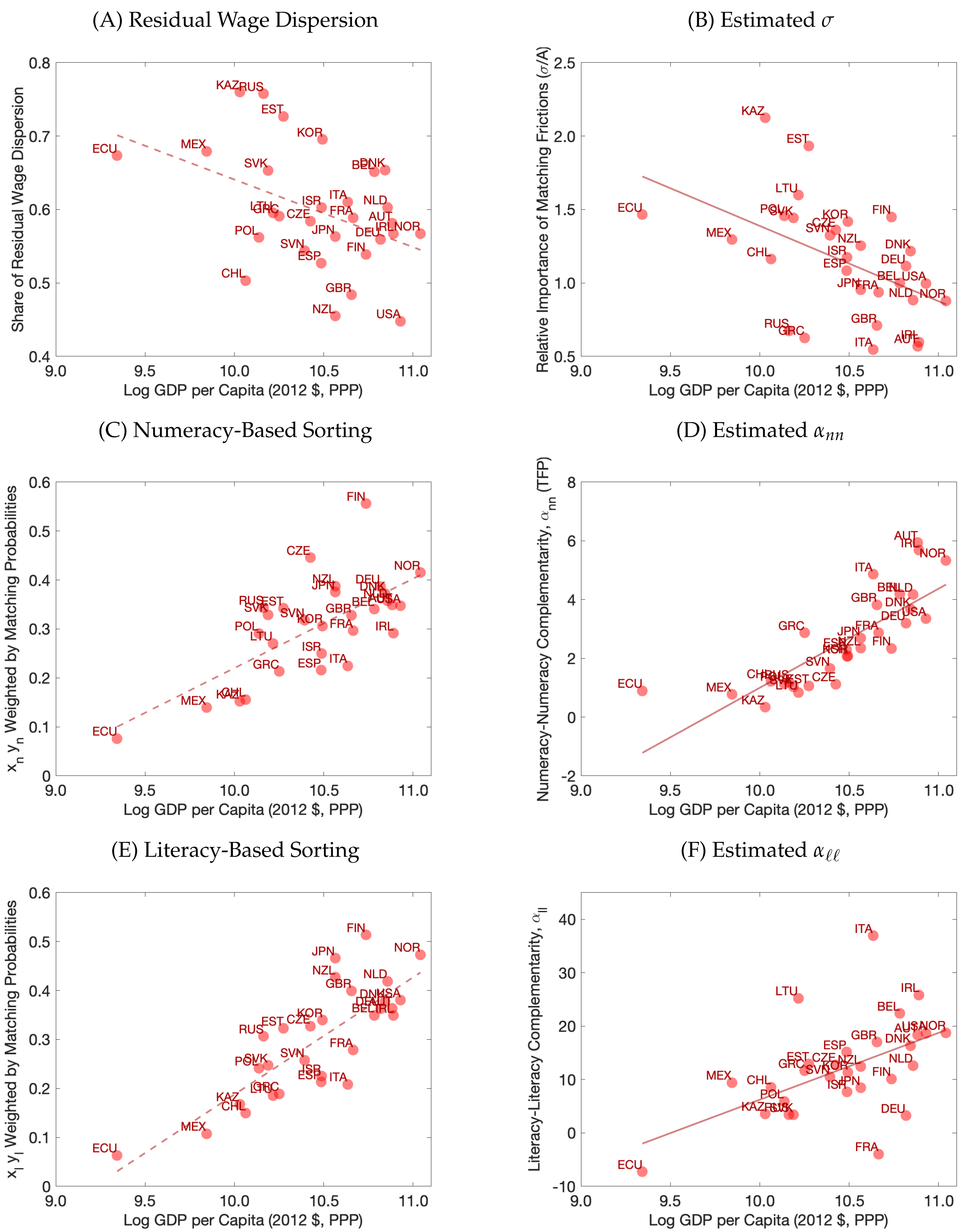
Panel B of Figure 7 shows the estimated relative importance of idiosyncratic matching frictions across countries, measured as the scale parameter of the distribution of match components relative to TFP, σ/A. This ratio captures how much weight is given to idiosyncratic factors, as opposed to productive attributes, in the matching of workers and jobs. We find that the relative importance of matching frictions is considerably higher in lower-income countries in the PIAAC survey. For example, the estimated σ/A in Ecuador, the lowest-income country, is around 50 percent higher than in Norway, the highest-income country.Through the lens of our model, this suggests that worker-job matching is guided more strongly by idiosyncratic factors in poorer countries. These estimates are informed by the empirical within-(x, y)-cell wage dispersion across countries, which is higher in lower-income countries; see panel A of Figure 7. We caution that attributing all residual wage dispersion to matching frictions likely yields an upper bound for σ in each country, a point we explicitly account for in our analysis and elaborate on in Sections 6.4 and 7.1.

Panels D and F of Figure 7 display how key production function parameters vary with log GDP per capita across countries. A clear pattern emerges: Estimated complementarities between worker numeracy skills and job numeracy skill requirements, α_{nn}, are greater in higher-income countries; and similarly for literacy complementarities, $\alpha_{\ell\ell}$. These estimates capture the stronger empirical sorting between worker and job traits in the numeracy and literacy dimensions observed in high-income countries—beyond what is already explained by lower matching frictions; see panels C and E. Appendix Figure E24 shows the remaining production function estimates.

Regarding home production, panel A of Appendix Figure E25 reports the relative value of home production—measured as the payoff from nonemployment relative to the mean value of market production—across the development spectrum for workers by broad skill group and gender. We find that the relative value of home production tends to be higher for all skills in lower-income countries, which reflects their higher nonemployment rates; see panels A and B of Appendix Figure E22. Finally, panel B of Appendix Figure E25 shows that the estimated relative mass of firms is lower in low-income countries, which suggests that their labor markets are less competitive or subject to higher entry costs. These estimates are informed by higher aggregate profit shares in lower-income countries; see panel C of Appendix Figure E22.

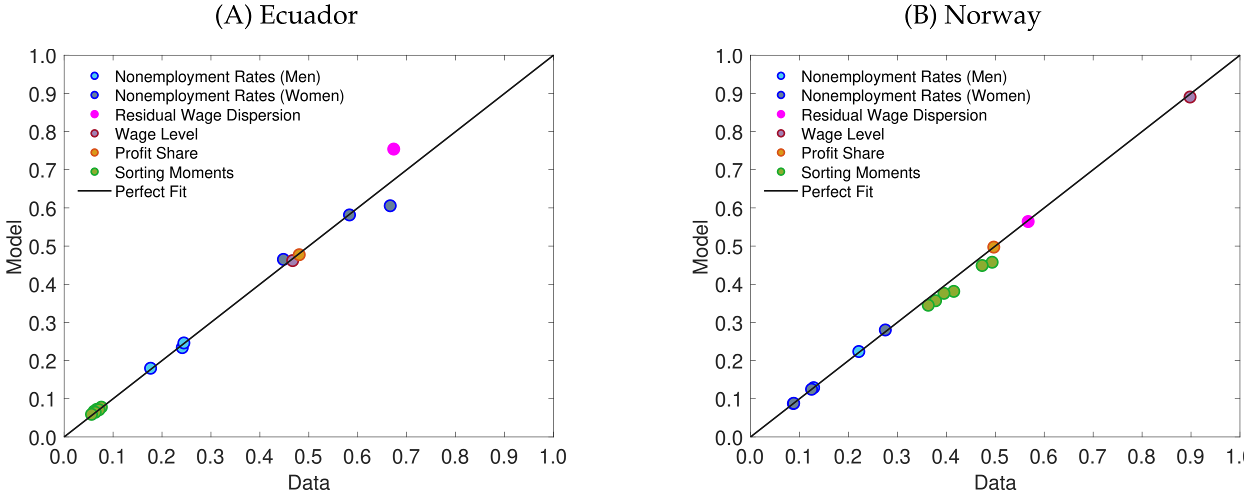
Model Fit Based on Targeted Moments. To showcase the model's fit based on targeted moments, Figure 8 focuses on the lowest-income and highest-income countries in our sample: Ecuador and Norway. The model fit for the complete set of 30 countries is reported in Appendix Figures E27 and E28. Each panel plots the model-based moments against targeted data moments, where the 15 moments are split into six categories, denoted by different-colored markers. Our parsimonious model fits the data from all countries well, with the targeted moments lined up near the 45-degree line, which indicates a perfect model fit. While not unexpected, this confirms that our estimation strategy based on the formal identification result in Proposition 1 works well in practice, which suggests that our distributional and functional-form assumptions are not overly restrictive. Several features of the model fit are worth highlighting. First, in both the data and the model, the moments related to sorting patterns (green markers) are increasing in GDP per capita, consistent with our empirical finding that there is stronger worker-job sorting in high-income countries; see Section 3. Second, the within-cell wage dispersion (pink markers) is decreasing in GDP per capita; also see panel A of Figure 7. Third, our model matches that nonemployment rates for both genders (blue markers) are decreasing in GDP per capita, especially for women. Finally, our model matches the fact that average wages (purple markers) are increasing in GDP per capita.

Figure 7: Data Moments and Estimated Model Parameters across Countries



Notes: This figure plots key data moments in the left panels and the parameter estimates they inform in the right panels. All statistics are plotted against countries' log GDP per capita. Panel A plots the share of wage dispersion not explained by the interaction between worker skills and job skill requirements in a log wage regression. Panel B plots the estimated relative importance of idiosyncratic matching frictions, measured as the scale parameter of the distribution of idiosyncratic match components relative to TFP, σ/A. Panels C and E plot the basis functions involving numeracy and literacy skills and skill requirements, capturing the correlation between the corresponding skills and skill requirements (see Appendix E.1). Panels D and F show the corresponding production function parameters, α_{nn} and $\alpha_{\ell\ell}$. Each red dot represents one country. Lines indicate the linear best fit. *Source:* PIAAC and model estimates.

Figure 8: Model Fit of Targeted Moments: Ecuador and Norway

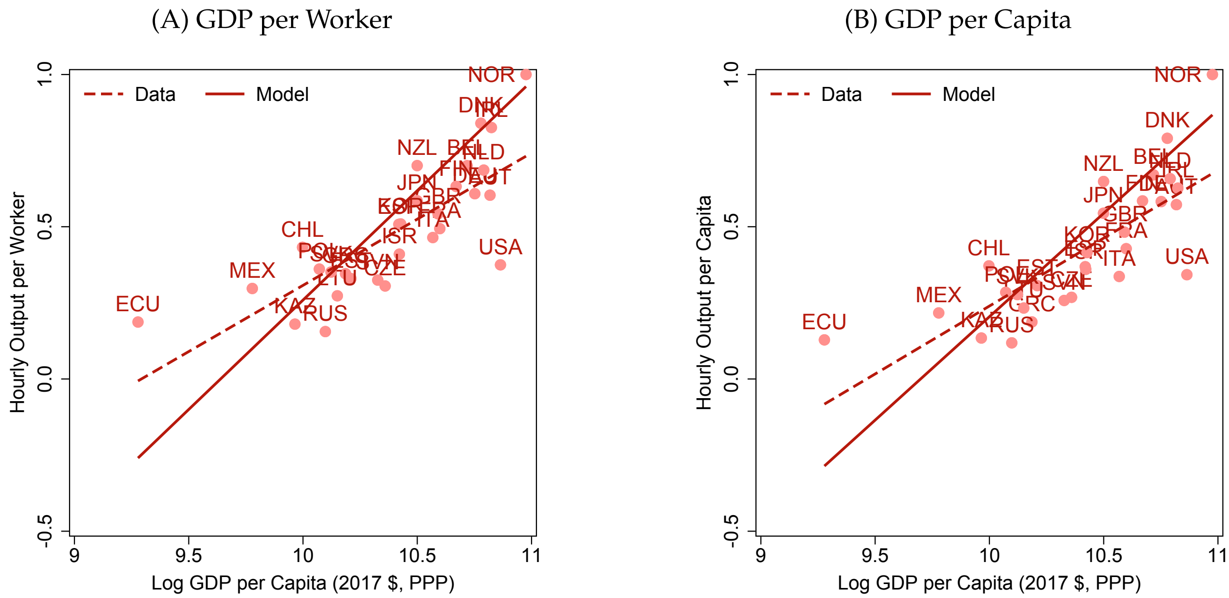


Notes: This figure illustrates model fit by plotting model moments against data moments for Ecuador (panel A), the lowest-income country in our sample, and Norway (panel B), the highest-income country. The 45-degree line indicates a perfect fit between the model and the data. See Appendix E.1 for details on the construction of moments. The purple markers show mean log wage levels scaled by a factor of 1/3.5 to fit them on the same axes as other moments. *Source:* PIAAC, OECD, Our World in Data, and model estimates.

Model Validation Based on Additional Moments. We are interested in the extent to which the estimated model—through variation in worker-job mismatch across countries—accounts for the empirical cross-country heterogeneity in aggregate output. Figure 9 shows that the model reproduces reasonably well the empirical differences in hourly output per worker or hourly output per capita. In our model, high-income countries produce more output due to a more skilled workforce, more demanding jobs, superior technology, and lower idiosyncratic matching frictions. Endowments and technology affect output directly through productivity and indirectly through their impact on worker-job mismatch, whereas frictions matter only through their effect on mismatch.

Cross-Country Differences in Worker-Job Matching. Our estimated model predicts significant differences in worker-job matching patterns across the development spectrum. Figure 10 captures the output losses from worker-job mismatch by use of matching index $\mathcal{M}(\theta)$, defined as the ratio of a country's actual to potential output. The average country's matching index is around 0.4, which reflects substantial mismatch of workers across jobs. We interpret the estimated *level* of skill-based matching in each country as a lower bound, given that our estimation strategy likely yields an upper bound on frictions in each country. However, our primary concern is not with absolute but with relative magnitudes of the matching index. We observe a significant positive *slope*, reflecting substantial cross-country variation in worker-job mismatch: Richer countries have higher matching indices. For instance, Norway's matching index is around five times as high as

Figure 9: Model Validation Based on GDP Moments across Countries



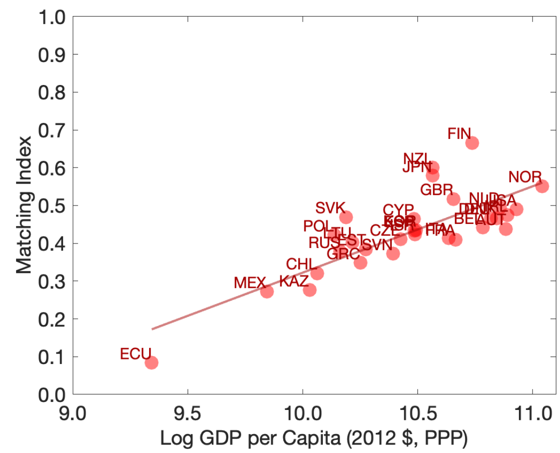
Notes: Panel A plots hourly output per worker against log GDP per capita. Panel B plots hourly output per capita against log GDP per capita. Data moments are constructed from PIAAC microdata using survey weights: Total *hourly* labor income is aggregated within country and scaled by the labor share to obtain total hourly output; we then divide by weighted workers in panel A and by the weighted population in panel B to obtain hourly output per worker and per capita, respectively. Both moments are normalized in data and model so that they equal one in Norway. Each red dot represents one country in the data. Solid (dashed) lines are linear best fits to the model (data) moments. *Source:* PIAAC, World Bank, and model estimates.

Ecuador's. That is, Ecuador could increase its output considerably more than Norway in the absence of matching frictions. These large relative output losses in Ecuador are driven by both high matching frictions and weak incentives for workers to sort across jobs, which stem from inferior endowments and a technology that lacks strong worker-job complementarities. Our findings suggest that labor markets in lower-income countries are less effective in matching workers to jobs. It is important to note that our matching index is lower in poorer countries, not only because there is more mismatch between workers and jobs conditional on employment, but also because skill-based selection into employment is weaker (Appendix Figure E26). This further widens the gap between actual and potential output, as potential output is defined based on the optimal selection of workers into employment given the scarcity of jobs.

6.4 Discussion of Identification Threats in Practice

An advantage of our approach is that it allows for the transparent identification of frictions separately from technology, as discussed above. At the same time, due to data limitations, our theoretical identification result—especially the identification of the degree of frictions, σ—might not carry over to its practical implementation in estimation.

Figure 10: Worker-Job Allocation across Countries



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

Most importantly, not all of the residual wage dispersion observed in the data (panel A of Figure 7) may be attributed to heterogeneity in unproductive factors, as our model assumes. Instead, some of this dispersion may reflect measurement error in wages or unobserved productive attributes. This implies that we likely overestimate the true extent of residual wage dispersion and, consequently, the degree of matching frictions in each country. As a result, our estimates provide an *upper bound* on the *level* of σ in each country and, therefore, also an upper bound on the share of output loss attributable to frictions. It is important to keep this in mind throughout the analysis.

Whether this potential upward bias in the estimated level of σ leads to misleading conclusions in our development accounting exercise depends on whether the *slope* of σ in GDP per capita is biased. This, in turn, hinges on whether the slope of residual wage dispersion in GDP—the data moment that pins down σ (Figure 7, panel A)—is biased. We provide several pieces of evidence suggesting that this slope is relatively stable across measurement choices. Specifically, the estimated slope of residual wage dispersion is robust when: (i) we include additional skills, such as ICT skills, available for a subset of countries in the PIAAC data (Appendix Figure E29); (ii) we saturate the wage regression with all observable productivity-related variables at our disposal (Appendix Figure E30); and (iii) we discretize skills and skill requirements more coarsely (into terciles) or more finely (into deciles) to allow for different degrees of productive heterogeneity relative to our baseline specification with quintiles (Appendix Figure E31).

With this said, we acknowledge that these empirical checks cannot fully rule out concerns about bias in the estimated gradient of σ. For this reason, in Section 7.1 we assess the robustness of our main development accounting results to alternative assumptions about the direction and magnitude of bias in the estimated frictions. We show that our central conclusions about the role of matching frictions in cross-country output differences remain largely unchanged.

7 The Role of Worker-Job Matching in Development Accounting

To quantify the determinants of labor market mismatch and its consequences for economic development, we proceed in two steps. In the first, we focus on the sources by asking: How much of the cross-country differences in labor market sorting are due to differences in endowments, technology, and idiosyncratic matching frictions? In the second step, we turn to the consequences: To what extent do worker-job sorting patterns affect aggregate output?

We demonstrate that the quantitative importance of skill-based matching for development hinges critically on the interplay between idiosyncratic matching frictions, endowments, and technology. Reducing frictions in lower-income countries (i.e., lowering σ) while fixing their technology and endowments increases aggregate output toward its potential and, thus, their matching index. However, if potential output in these countries is relatively low to begin with—due to either worse endowments of worker skills and job skill requirements or lagging technology—then the gains from improving labor market matching are limited. In this case, cross-country convergence in output requires upgrades to endowments and technology in low-income countries, which increase the returns to worker-job sorting, and thus actual output, and additionally boost their potential output. The result is a narrower gap between actual and *now-increased* potential output.[31]

7.1 Accounting for Aggregate Output Differences across Countries

We now use the estimated model for our central exercise of development accounting. We simulate several equilibrium counterfactuals to decompose aggregate output differences across countries into contributions from endowments, technology, and idiosyncratic matching frictions (see Appendix F.1 for details). For each counterfactual, we highlight the role of worker-job matching.

The Role of Endowments. To account for cross-country output differences, we first quantify the contribution of endowments. We recompute equilibrium after counterfactually assigning each country the endowments of worker skills and job skill requirements of the frontier country, Norway, which has the highest GDP per capita in our sample. This has two distinct effects, which are more pronounced in lower-income countries. First, it directly increases output as high-skilled

[31] That is, upgrades in endowments and technology increase both the numerator and the denominator of the matching index in a way that increases their ratio, and thus matching index $\mathcal{M}(\theta)$ increases.

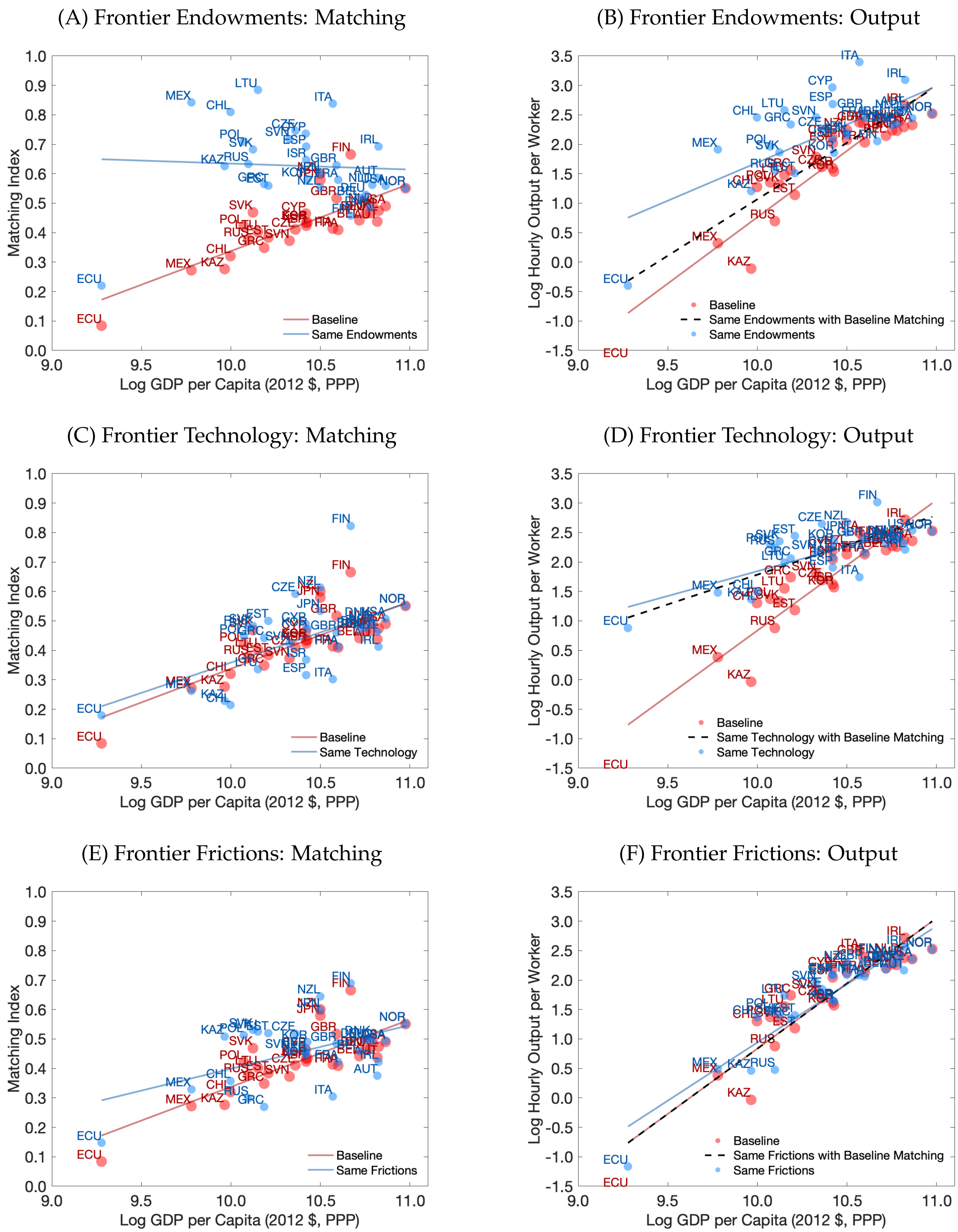
workers and jobs become more abundant. Second, for any positive level of matching frictions $\sigma > 0$, it indirectly raises output by improving the worker–job allocation. More productive worker skills and job skill requirements, together with better alignment between them, induce agents to place a greater weight on skills rather than idiosyncratic factors in the matching process.

Figure 11 depicts the results of this experiment. Panel A shows a strong increase in the matching index in lower-income countries. Panel B shows that this leads to sizable output gains, especially in lower-income countries, where log output per worker increases by around 1.4 log points. Importantly, more than half of these gains are due to an improved worker-job allocation. This is illustrated in panel B by the distance between the solid blue line and the dashed black line that shows output per worker in a partial equilibrium counterfactual when adopting frontier endowments while holding each country's matching index fixed at baseline.

The Role of Technology. Next, we assess the role of technology. We recompute each country's equilibrium after assigning Norway's technology to all countries. Figure 11 shows the results of this counterfactual. In panel C, we see improved worker-job matching in most countries. Intuitively, adopting the frontier technology with stronger worker-job complementarities increases the returns to skill-based labor market sorting, and thus reduces worker-job mismatch. Panel D shows that log hourly output per worker rises everywhere but more so in lower-income countries, with increases by around 1.7 log points over baseline. This implies a large decrease in cross-country output differences. Most of these output changes are due to the direct effect of technology improvements rather than the indirect effect of improved worker-job matching, as illustrated by the dashed black line in panel D, which fixes the matching index at its baseline.

The Role of Idiosyncratic Matching Frictions. Finally, we evaluate the impact of idiosyncratic matching frictions. Panels E and F of Figure 11 show the results of counterfactually adopting Norway's comparably low matching frictions. Panel E shows that worker-job matching improves, especially in the lowest-income countries where frictions were initially high, with increases in the matching index of around 60 percent over baseline. However, panel F shows that this has only modest effects on output differences across countries. This finding is rooted in two central insights. First, match quality in lower-income countries does not reach the levels observed in higher-income countries, even when the same matching frictions are imposed. For a given σ, workers in poorer countries face weaker incentives to sort into jobs that fit their skills either because technology constrains the returns to skill-based matching or because such jobs are simply unavailable. Second,

Figure 11: Counterfactuals: Frontier Endowments, Technology, and Matching Frictions



Notes: These panels show the model-based counterfactual effects of implementing Norway's endowments (A-B), technology (C-D), and matching frictions (E-F) in all countries on the matching index (left) and log hourly output per worker (right). Red circles depict baseline estimates with a red best-fit line across log GDP per capita. Blue circles and lines show counterfactuals. The dashed black line in the right panels indicates the linear best fit across log GDP per capita in the respective counterfactual while keeping worker-job sorting, measured by the matching index, at its baseline. *Source:* Model simulations.

increases in matching efficiency yield only modest relative output gains for these countries, as they move actual output toward a potential output that is low compared to the actual output of richer countries (see the dashed potential output line in panel A of Appendix Figure F32).

Our result highlights the central importance of other factors—i.e., the relative scarcity of workers' skills or jobs' skill requirements and technology that lacks worker-job complementarities—that constrain low-income countries and render their potential output low compared with the actual output levels of richer countries. We conclude that while idiosyncratic matching frictions disproportionally impact lower-income countries, their effects on *cross-country* output differences are relatively small. This is because strengthening worker-job sorting helps low-income countries catch up only if the returns from sorting are sufficiently high.

Complementarities. The previous counterfactuals isolated the effects of a single fundamental—endowments, technology, frictions—while ignoring any complementarities between them. We now show that the returns to worker-job matching depend on a country's entire set of fundamentals.

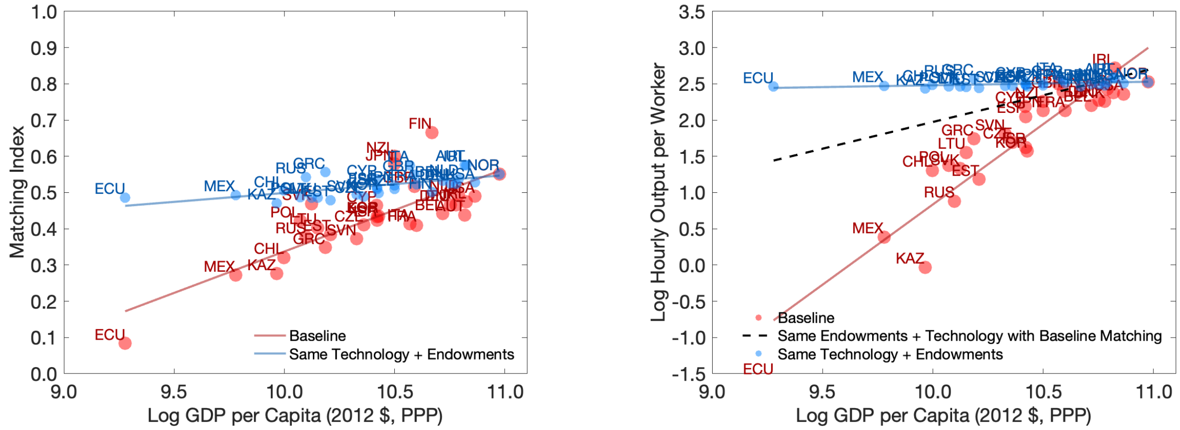
Here, we highlight the complementarity between endowments and technology, which we find to be quantitatively most important.[32] Figure 12 shows the results of counterfactually adopting Norway's endowments of worker skills and job skill requirements together with its technology in all countries. Worker-job matching, measured by the matching index in panel A, improves markedly, and more so in low-income countries. Consequently, output per worker in panel B increases overall, especially in poorer countries. Notably, output in low-income countries grows more than "the sum" of the two counterfactuals in isolation would suggest. These complementarities between endowments and technology exclusively reflect increased returns to sorting, which lead to further improvements in worker-job matching that push actual output toward the now-increased potential output (see panel B of Appendix Figure F32). As a result, this dual counterfactual essentially erases the cross-country variation in output per worker. Importantly, a substantial part of this convergence is due to improved worker-job sorting in lower-income countries, as illustrated in panel B by the distance between the solid blue line and the dashed black line that fixes the matching index at its baseline. We conclude that there are important complementarities between different economic fundamentals, and that worker-job sorting is crucial to unleash them.

Development Accounting for Aggregate Output across Countries. Summarizing our development accounting exercise, Figure 13 displays the contribution of each fundamental to cross-

[32] Appendix Figure F33 summarizes the set of all possible complementarities between our three fundamentals.

Figure 12: Counterfactual: Frontier Endowments and Technology

(A) Frontier Endowments & Techn.: Matching (B) Frontier Endowments & Techn.: Output



Notes: This figure shows the model-based counterfactual effects of assigning Norway's endowments of skills and skill requirements, as well as their technology, simultaneously to all countries on the matching index (A) and log hourly output per worker (B). Red circles represent baseline model estimates for each country, and red lines the linear best fit across log GDP per capita. Blue circles and lines represent the counterfactual outcomes. The dashed black line in panel B indicates the linear best fit across log GDP per capita in the counterfactual while keeping worker-job sorting, measured by the matching index, at its baseline. *Source:* Model simulations.

country output differences, first in isolation (panel A) and then in sequence (panel B). For each counterfactual, the solid blue bars represent the overall equilibrium effect on the standard deviation of output per worker across countries, while the hollow bars represent the partial-equilibrium effect holding fixed worker-job sorting as captured by each country's baseline matching index.

Most cross-country differences in output per worker are accounted for by differences in technology (-52 percent)—defined broadly to include not only machinery but also the organization of labor—followed by endowments (-26 percent) and matching frictions (-12 percent). While the effect of technology is mostly direct, improved worker-job allocation is key for the convergence across countries due to equalized endowments (-14, and thus more than half, out of -26 percent) and drives all of the effects due to lower frictions (-12 percent), as evident from comparing the hollow with the blue bars in panel A. Beyond these individual effects, there are strong complementarities: Jointly adopting frontier endowments and technology essentially closes the cross-country output gap (-95 percent, see the second column in panel B)—more than "the sum" of the two counterfactuals in isolation.[33] Importantly, a large share of the effects of this dual counterfactual is due to improved worker-job sorting (-34, and thus more than a third, out of -95 percent).

In summary, improved worker-job matching is crucial for harvesting the gains from improved

[33]Let g_E, g_T and g_{ET} denote the proportional reduction in the standard deviation of log output due to changes in endowments, technology, and endowments jointly with technology relative to the same baseline. Absent complementarities, the joint reduction would be $\hat{g}_{ET} = (1 + g_E)(1 + g_T) - 1$. We find, however, $|g_{ET}| > |\hat{g}_{ET}|$.

endowments and technology. Improvements in endowments and technology increase the returns to worker-job sorting, and thereby narrow the gap between actual and now-increased potential output. Conversely, the payoff from lowering idiosyncratic matching frictions, which materializes through improved worker-job sorting, are limited in economies in which inferior endowments or technology pin potential output to a low level. In this case, narrowing the gap between actual and potential output triggers little benefit in the cross-country comparison. We conclude that a greater extent of skill-based matching is crucial for economic development when driven by investments in the workforce, job upgrading, and the adoption of frontier technology. However, it plays a limited role when endowments and technology constrain the returns to worker-job sorting.

Robustness. In Section 6.4, we discussed potential reasons why the estimated matching frictions based on countries' residual wage dispersion may be biased upward. Here we show that our conclusions are robust even when allowing for substantial bias in the estimation of matching frictions, as captured by each country's dispersion parameter, σ. If the estimated slope of σ in GDP is too steep relative to the truth, matching frictions contribute even less to explaining cross-country income differences—implying that our results provide an upper bound on the role of frictions.

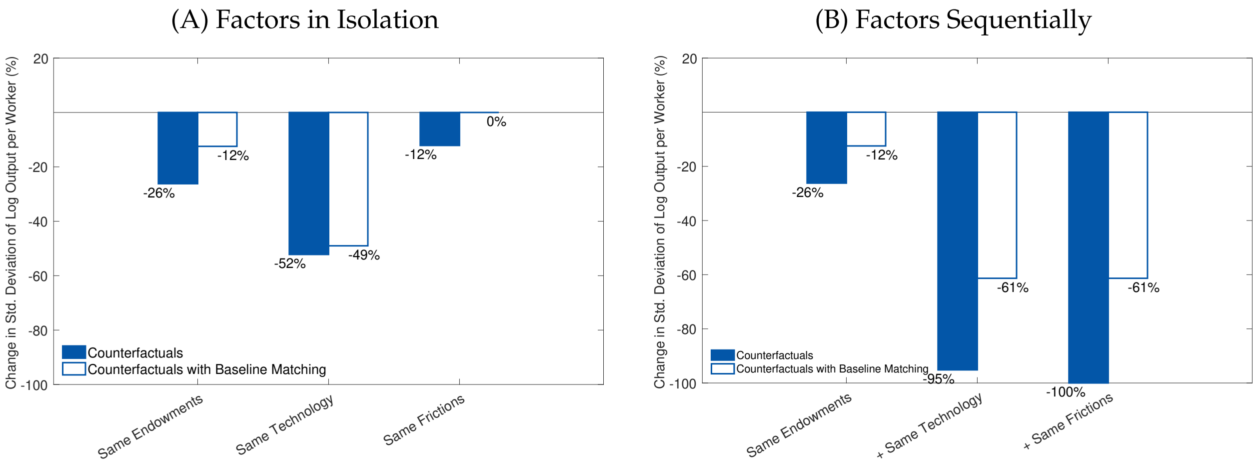
Conversely, if the estimated slope is too flat, matching frictions may play a more significant role. To investigate this case, we re-estimate the model for Norway assuming that its residual wage dispersion is substantially lower than in our baseline—set to 0.2, reflecting a scenario in which it consists only of the relatively low *frictional* wage dispersion typical of advanced countries—while keeping wage dispersion in other countries unchanged.[34] This adjustment leads to an estimated σ for Norway that is approximately 50 percent lower than in our baseline. Nevertheless, equalizing frictions across countries by applying Norway's lower σ everywhere does not alter our main conclusion that endowments and technology are considerably more important than frictions in explaining cross-country output differences. Appendix Figure F34 shows that our development accounting results from panel B of Figure 13 are virtually unchanged in this case.

7.2 Comparison with Conventional Development Accounting

We conclude by comparing our analysis with conventional development accounting approaches, illustrated in Figure 14. Conventional development accounting recognizes cross-country heterogeneity in human capital. According to our estimates, differences in worker skills alone, while

[34] The importance of firm fixed effects in earnings regressions is closely tied to the presence of frictional wage dispersion. We proxy the latter by the share of earnings variation explained by firm effects, which in advanced countries, including Norway, is about 20 percent (Bagger and Lentz, 2018; Bonhomme et al., 2023).

Figure 13: Development Accounting for Aggregate Output



Notes: The panels of this figure summarize the results from all counterfactual simulations, in terms of their effects on the cross-country standard deviation of log output per worker, considering the different factors in isolation (A) and sequentially (B). Solid bars represent outcomes based on the counterfactual exercises. Hollow bars represent the counterfactual while keeping each country's matching index at its baseline level. Numbers below the bars indicate the percentage change relative to the baseline. *Source:* Model simulations.

holding worker-job matching fixed at baseline, account for 9 percent of the variation in output per worker across countries (first bar)—a relatively modest share, potentially due to the narrower development spectrum and thus smaller cross-country skill gaps in our sample. When we incorporate heterogeneity in technology—which we think of broadly to also encompass capital differences—the explanatory power rises sharply, accounting for 59 percent of income differences (second bar), while the matching index is still held fixed at its baseline.

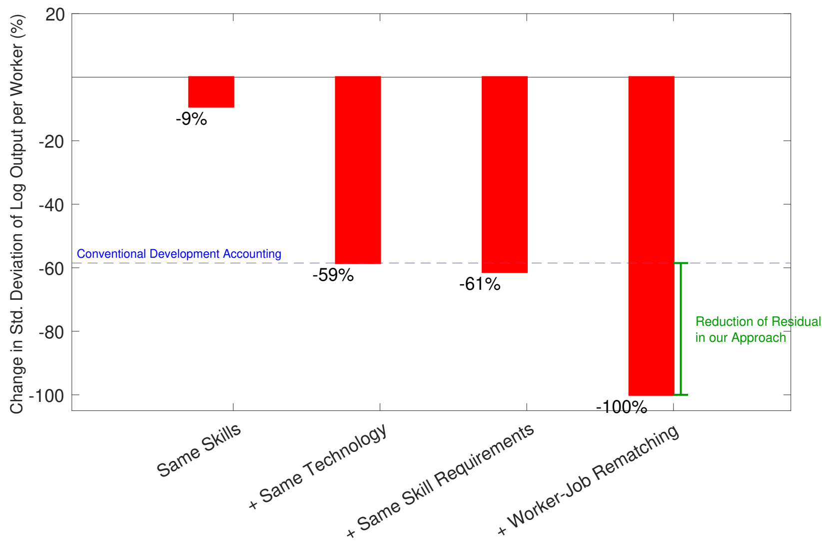
Going beyond the conventional approach, we first add heterogeneity in another structural primitive: skill requirements. This raises the explained share to 61 percent (third bar). Most importantly, the remaining gap—from 61 to 100 percent—is accounted for by endogenous worker–job matching responses to cross-country variation in endowments, technology, and frictions (fourth bar).[35] This channel, held fixed in the first three bars, is absent from existing development accounting exercises. This final step highlights the substantial role worker-job sorting can play in closing the residual gap and understanding cross-country output disparities more fully.

8 Conclusion

From family firms elevating the founder's son to CEO, to doctors inheriting their parents' occupational choices, numerous anecdotes highlight the lack of meritocracy in labor markets, particularly

[35]The fourth bar includes the effect of differences in matching frictions because their inclusion would have no impact in the partial equilibrium exercises of the first to third bars that keep the matching index in each country at baseline.

Figure 14: Comparison with Conventional Development Accounting



Notes: This figure reports the percentage reduction in the standard deviation of log output per worker across countries, when imposing four sequential counterfactuals: Norway's skills everywhere (first bar); adding Norway's technology everywhere (second bar); adding Norway's skill requirements everywhere (third bar); adding Norway's frictions everywhere as well as the endogenous adjustment of labor market sorting to all these primitive changes (fourth bar). Numbers at the bars indicate the percentage change relative to baseline. *Source:* Model simulations.

in low-income settings. This paper examines how the degree to which workers match with jobs on the basis of skills, as opposed to idiosyncratic attributes unrelated to productivity, differs across countries. We then ask why we see these patterns and what are the aggregate consequences.

We find that worker-job matching in high-income countries is closer to the output-maximizing allocation due to more aligned endowments of skills and skill requirements, stronger complementarities in production, and lower matching frictions. Furthermore, heterogeneity in technology and the endowments of workers and jobs account for most cross-country output differences, while matching frictions play a relatively modest role. From this, we conclude that the gains from improving worker-job sorting in low-income countries are constrained by their endowments and technology that keep the returns to labor market sorting low. At the same time, a large share of the gains from adopting better endowments and technology are due to improved worker-job sorting. Thus, policies aimed at improving worker-job matching alone will not effectively eradicate cross-country output differences unless combined with interventions that enhance the returns to matching. Such interventions may involve modernizing technology (e.g., by investing in modern machinery or improving management practices), upgrading the workforce (e.g., by attracting high-skilled immigrants), or upgrading jobs (e.g., by facilitating foreign investment in new industries). Finally, cross-country heterogeneity in worker-job sorting has the potential to play a substantial role in closing the residual output gap in conventional development accounting.

While our accounting exercise points to the important effects of technology and endowments on economic development—both in isolation and in combination—we were silent on the determinants of these fundamentals. If determined endogenously, interesting dynamics can emerge. For example, countries could be trapped in a high-mismatch equilibrium, in which inferior endowments and technology constrain the returns to improved worker-job matching, but investments in endowments or technology are not performed given the existing matching frictions. As such, a "Big Push" in one of the three fundamentals may jump-start a chain reaction in the others that can lead to rapid economic development (Buera et al., 2023; Engbom et al., 2025; Gottlieb et al., 2025b). Endogenizing the link between what we treated as fundamentals in a dynamic equilibrium model is a fruitful avenue for future research.

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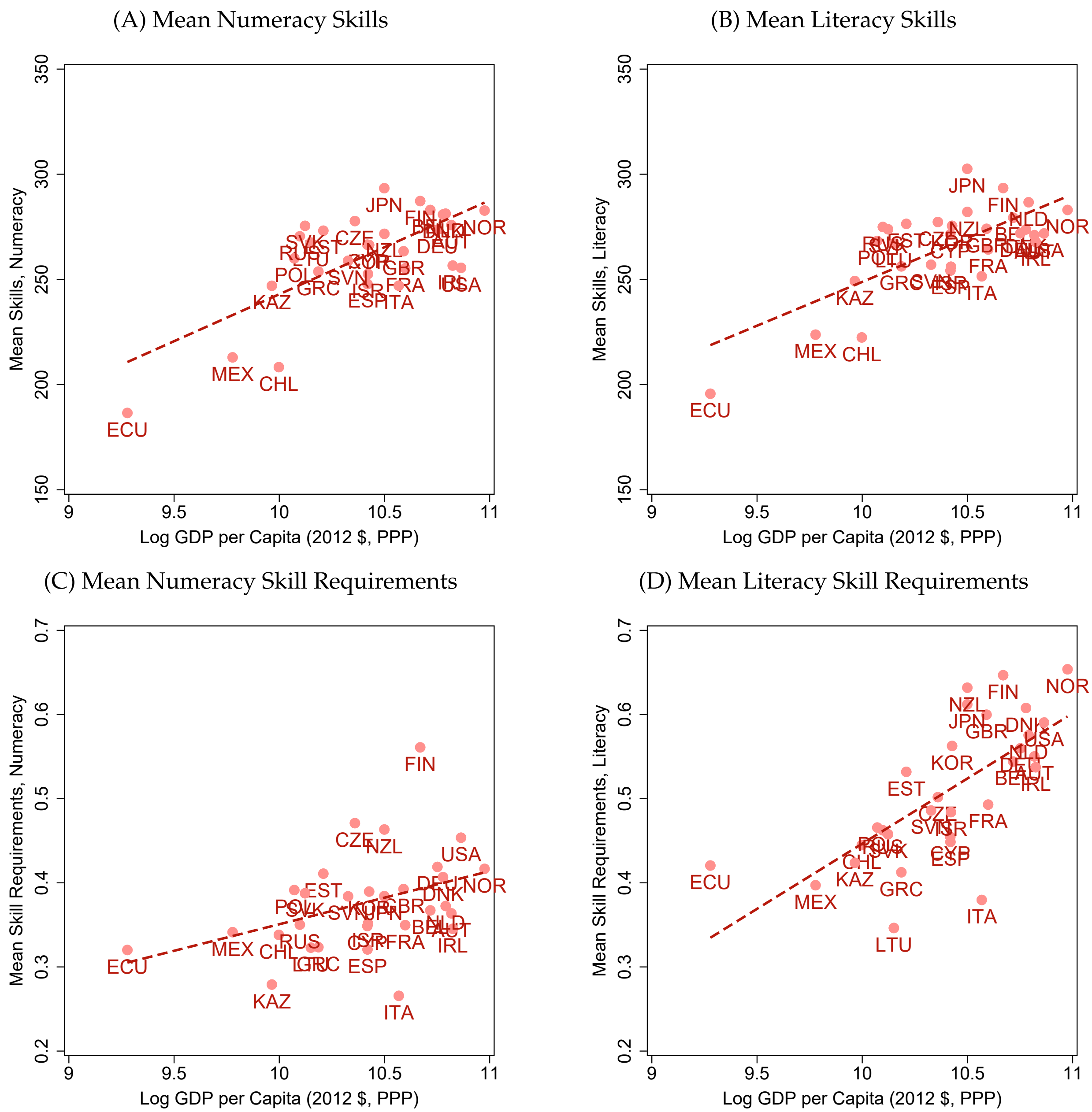
Appendix

— For Online Publication —

A Data Appendix

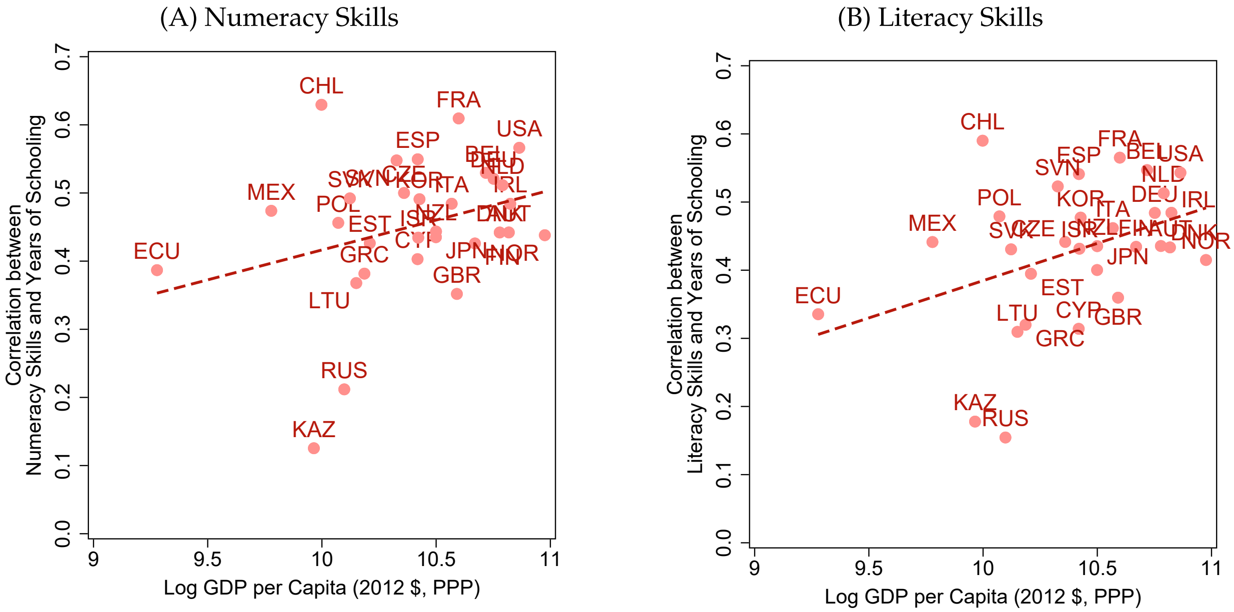
A.1 Summary Statistics

Figure A15: Mean Skills and Skill Requirements across Countries



Notes: This figure plots mean worker skills (top panels) and mean job skill requirements (bottom panels) against countries' log GDP per capita. The left panels show numeracy, and the right panels show literacy. *Source:* PIAAC.

Figure A16: Correlation between Skills and Education



Notes: This figure plots the Pearson correlation coefficient between PIAAC skill scores and years of education for each country against log GDP per capita. Panel A reports the correlation for numeracy skills and panel B for literacy skills. *Source:* PIAAC.

Table A2: Returns to Skills

	(1)	(2)	(3)
Log numeracy skill		0.284***	0.214***
		(0.0449)	(0.0414)
Log literacy skill		0.169***	0.124***
		(0.0513)	(0.0476)
Log years of schooling	0.846***	0.681***	0.448***
	(0.0186)	(0.0218)	(0.0225)
Work experience (years)	0.0261***	0.0256***	0.0234***
	(0.00151)	(0.00149)	(0.00145)
Squared work experience/1000	-0.374***	-0.357***	-0.329***
	(0.0383)	(0.0375)	(0.0365)
Log numeracy skill requirement			0.0252
			(0.0200)
Log literacy skill requirement			0.258***
			(0.0245)
Country fixed effects	✓	✓	✓
Observations	78,512	78,512	78,507
R^2	0.644	0.653	0.671

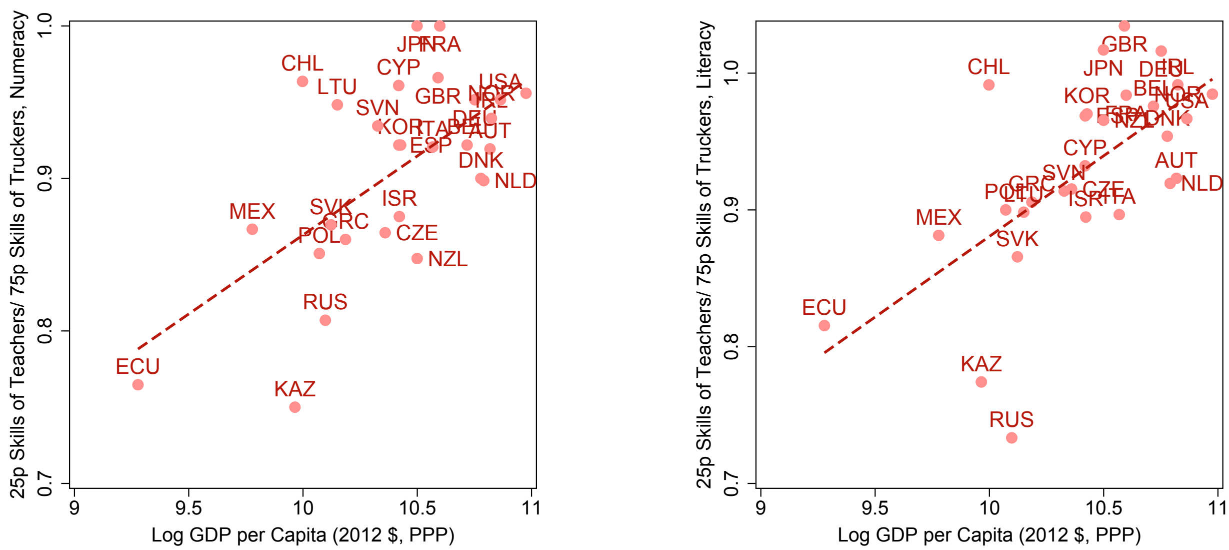
Note: This table shows estimated coefficients from Mincer regressions using individual-level PIAAC data pooled across 30 countries. The dependent variable is log hourly wage $\log w_{ic}$ of individual i in country c. We include country fixed effects λ_c and the Mincer controls $Z_{ic} = \{\log \text{years of schooling}_{ic}, \text{experience}_{ic}, \text{experience}^2_{ic}/1000, \text{female}_{ic}\}$. Regression specification (1) is: $\log w_{ic} = \gamma' Z_{ic} + \lambda_c + \varepsilon_{ic}$; (2) adds controls for log skills $(\log x_{l,ic}, \log x_{n,ic})$; (3) adds log skill requirements of worker i's occupation $(\log y_{l,ic}, \log y_{n,ic})$. Regressions are weighted by PIAAC sampling weights and use robust standard errors. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source: PIAAC.*

B Facts Appendix

B.1 Robustness: Worker-Job Mismatch

Figure B17: Teachers vs. Truckers: Numeracy and Literacy Skill Gaps across Countries

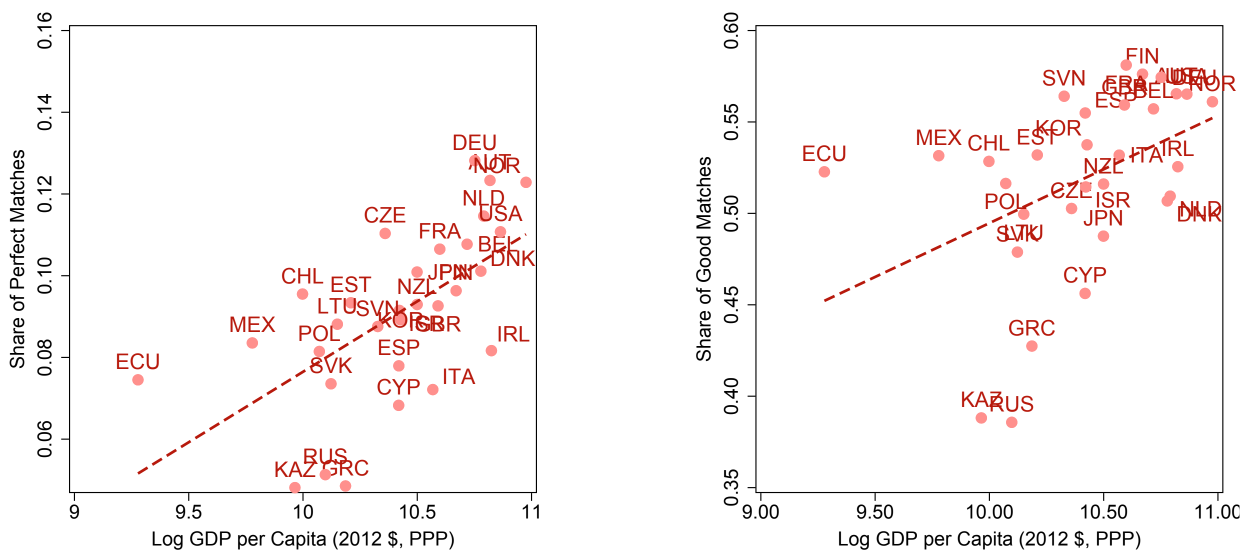
(A) Numeracy (B) Literacy



Notes: The figure plots the ratio of numeracy skills (panel A) or literacy skills (panel B) between teachers (ISCO code 23, "teaching professionals") and truckers (ISCO code 83, "drivers and mobile plant operators") against log GDP per capita. In each skill domain, this ratio is calculated as the 25th percentile of teachers' skills divided by the 75th percentile of truckers' skills within each country. Both skills and skill requirements are rescaled within each country to have the support $[0, 1]$. *Source:* PIAAC.

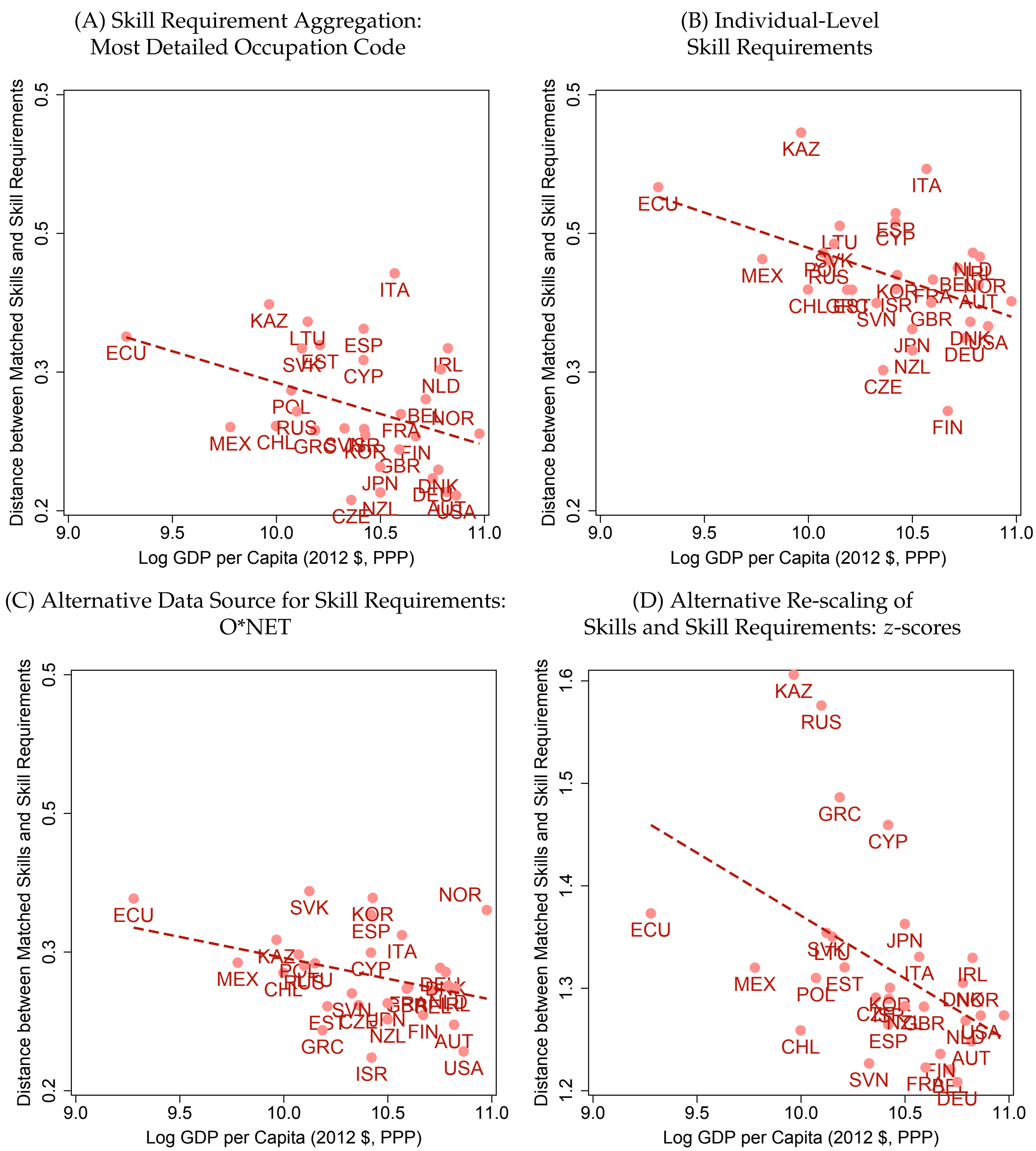
Figure B18: More Perfect and Good Worker-Job Matches in Higher-Income Countries

(A) Share of Perfect Matches (B) Share of Good Matches



Notes: This figure plots the share of "perfect" matches (panel A) and "good" matches (panel B) between workers' numeracy and literacy skills and their jobs' skill requirements against log GDP per capita. Perfect matches are those in which both numeracy and literacy skills fall in the same within-country quintile as the job's numeracy and literacy skill requirement respectively, while good matches allow a difference of up to one quintile in each skill dimension. *Source:* PIAAC.

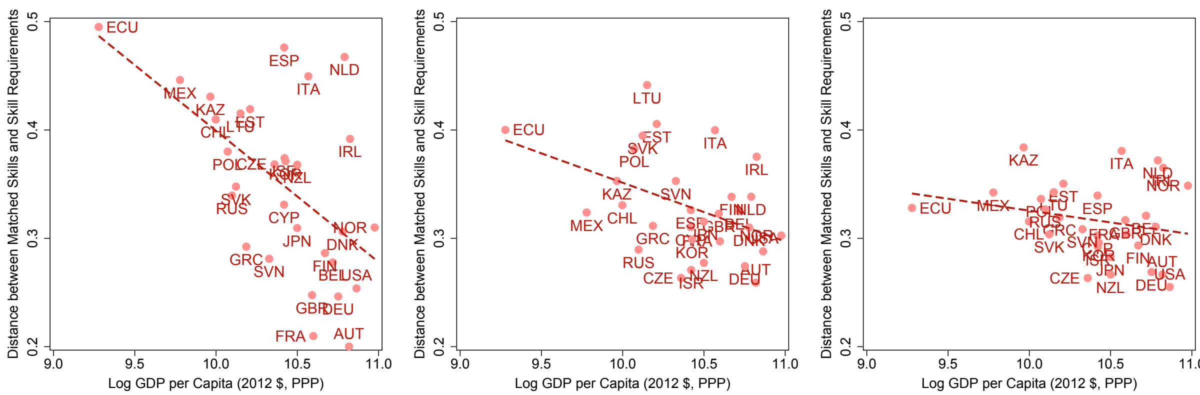
Figure B19: Worker-Job Mismatch across Countries: Robustness



Notes: This figure plots the average Euclidean distance between workers' skills (numeracy and literacy) and their jobs' skill requirements against log GDP per capita for each country. The distance statistic is shown for four alternative measurement choices of skill requirements (panels A-C) and also skills (panel D), based on: (i) local $[0,1]$-rescaling using occupation-level skill requirements at the most detailed ISCO code available for each country (panel A), (ii) local $[0,1]$-rescaling using individual-level skill requirements (panel B), (iii) local $[0,1]$-rescaling using O*NET-based skill requirements in each country (panel C), and (iv) alternative rescaling based on local z-scores (panel D). *Source:* PIAAC and O*NET.

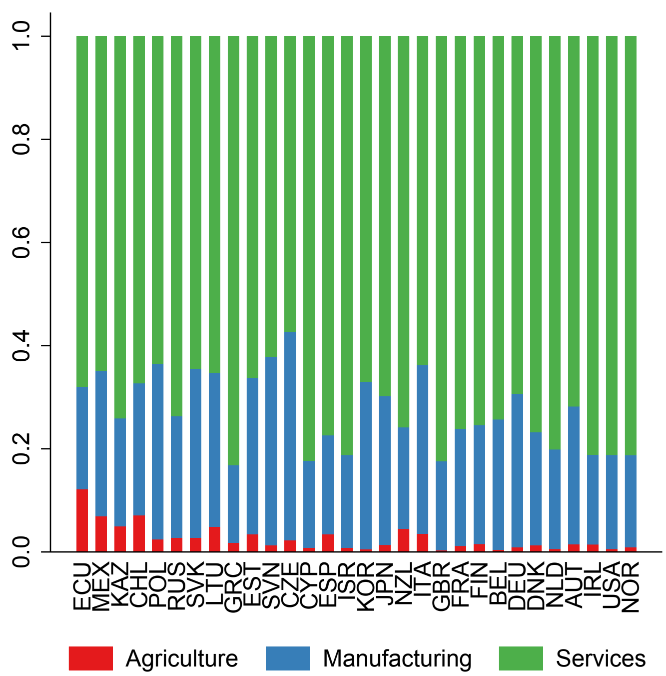
Figure B20: Worker-Job Matching by Sector: Robustness

(A) Agriculture (B) Manufacturing (C) Services



Notes: This figure plots the mean Euclidean distance between workers' skills and their job's skill requirements against log GDP per capita *by sector*: agriculture (panel A), manufacturing (panel B), and services (panel C). Both skills and skill requirements are locally rescaled to have the common support of $[0,1]$ by subtracting the minimum value and dividing by the range of the variable in each country. *Source:* PIAAC.

Figure B21: Sectoral Composition across Countries



Notes: The figure shows the share of total employment accounted for by agriculture (red), manufacturing and other industrial activities (blue), and services (green) in each country. Employment shares are computed for individuals aged 20–59 who report being employed. Industry classification follows ISIC Rev. 4 at the 1-digit level. Countries are ordered by log GDP per capita (2012 $, PPP). *Source:* PIAAC.

C Model Appendix

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

We assume that these idiosyncratic wages, $\tilde{w}(x_i, y_k)$, are monetary (i.e., paid in terms of units of the produced good), equal in value to the sum of the systematic wage $w(x,y)$ and the worker's idiosyncratic matching wedge δ_{iy}. Purely monetary payouts to workers can be ensured by assuming that, in the background, there is some—unmodeled—financial endowment K, which is constant across jobs, added to match output, and fully accrues to jobs. Jobs tap into K if $\tilde{w}(x_i, y_k)$ exceeds match output. Although, in theory, the support of δ_{iy} is unbounded and so there may not be a finite K that can ensure a monetary compensation of all workers, in practice, we estimate the model with a finite number of agents, for which $\max_i \delta_{iy} < \infty$. Thus, we can always find a large enough, but finite, firm endowment K to satisfy our assumption.

D Identification Appendix

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

D.1 Proof of Proposition 1

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

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

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

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

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

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

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

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

Step 4: Identifying the production function $f(x,y)$.

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

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

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

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

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

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

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

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

Into these expressions, we plug

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

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

$$\widehat{\mu}(x,\varnothing) := \frac{\mu(x,\varnothing)}{m^W} = \mu(x,\varnothing) = g(x) \frac{\exp(f_{x\varnothing}(x)/\sigma)}{\exp(f_{x\varnothing}(x)/\sigma) + \sum_{\tilde{y}\in\mathcal{Y}} \exp(w(x,\tilde{y}))/\sigma)}, \tag{D.4}$$
$$\widehat{\mu}(\varnothing,y) := \frac{\mu(\varnothing,y)}{m^J} = h(y) \frac{\exp(f_{\varnothing y}(y)/\sigma)}{\exp(f_{\varnothing y}(y)/\sigma) + \sum_{\tilde{x}\in\mathcal{X}} \exp(f(\tilde{x},y) - w(\tilde{x},y))/\sigma)}. \tag{D.5}$$

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

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

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

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

E Estimation Appendix

E.1 Targeted Moments

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

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

- 6 moments reflecting the nonemployment rates by broad skill group (see above on how these groups are constructed) and gender:
  - the nonemployment share among low-skilled men;
  - the nonemployment share among middle-skilled men;

- the nonemployment share among high-skilled men;
- the nonemployment share among low-skilled women;
- the nonemployment share among middle-skilled women; and
- the nonemployment share among high-skilled women.

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

- 1 moment reflecting the distribution of output between workers and jobs:
  - the share of profits in aggregate value added, computed as one minus the labor share.

- 6 moments reflecting the matching pattern between workers and jobs, using the *basis function* approach proposed by Galichon and Salanié (2021):
  - the match-share-weighted product of workers' numerical skill and jobs' numerical skill requirement;
  - the match-share-weighted product of workers' numerical skill and jobs' literacy skill requirement;
  - the match-share-weighted product of workers' numerical skill and jobs' firm size;
  - the match-share-weighted product of workers' literacy skill and jobs' numerical skill requirement;
  - the match-share-weighted product of workers' literacy skill and jobs' literacy skill requirement; and
  - the match-share-weighted product of workers' literacy skill and jobs' firm size.

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

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

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

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

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

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

In our application, these 6 basis function moments enter the joint SMM objective described below.

E.2 Estimation Procedure

Our estimation procedure solves for the parameter vector

$$\tilde{\theta}^* = \arg\min_{\tilde{\theta}} \Omega\left(\mathcal{S}^m(\tilde{\theta}), \mathcal{S}^d\right). \tag{E.1}$$

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

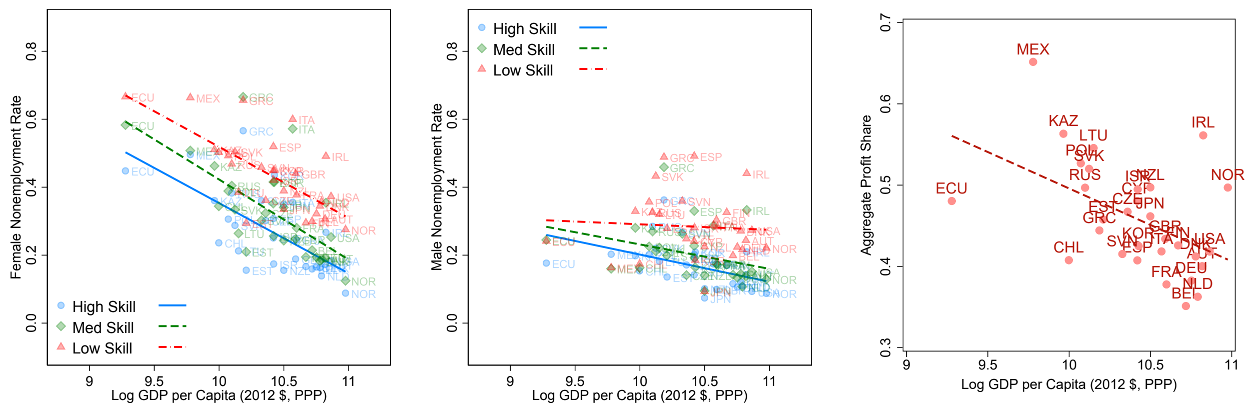
$$\Omega(\mathcal{S}^m(\tilde{\theta}), \mathcal{S}^d) = ((\mathcal{S}^m(\tilde{\theta}) - \mathcal{S}^d) \oslash \mathcal{S}^d)'\mathbf{W}((\mathcal{S}^m(\tilde{\theta}) - \mathcal{S}^d) \oslash \mathcal{S}^d),$$

where percentage deviations between model and data moments are formed through *Hadamard division*, denoted by $\oslash$. Here, $\mathbf{W}$ is a 15-by-15 weighting matrix, which we set equal to the identity matrix. We solve (E.1) by using a global optimization algorithm.

E.3 Additional Moments

Figure E22: Nonemployment Rates and Aggregate Profit Share across Countries

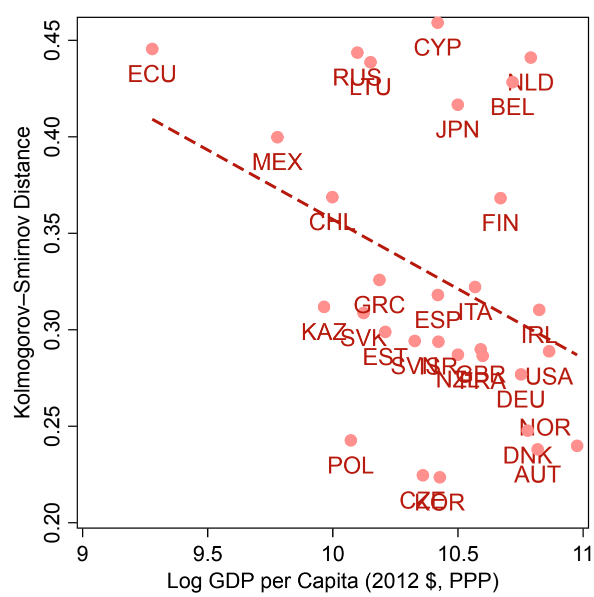
(A) Female Nonemployment Rate (B) Male Nonemployment Rate (C) Average Profit Share



Note: Panels A and B of this figure show the female and male nonemployment rates by broad skill groups across countries. See Appendix E.1 for how these skill groups are constructed. Panel C shows aggregate profit shares across countries. For each country, the aggregate profit share is computed as 1 − aggregate labor share. All statistics are plotted against log GDP per capita. *Source:* PIAAC and Our World in Data.

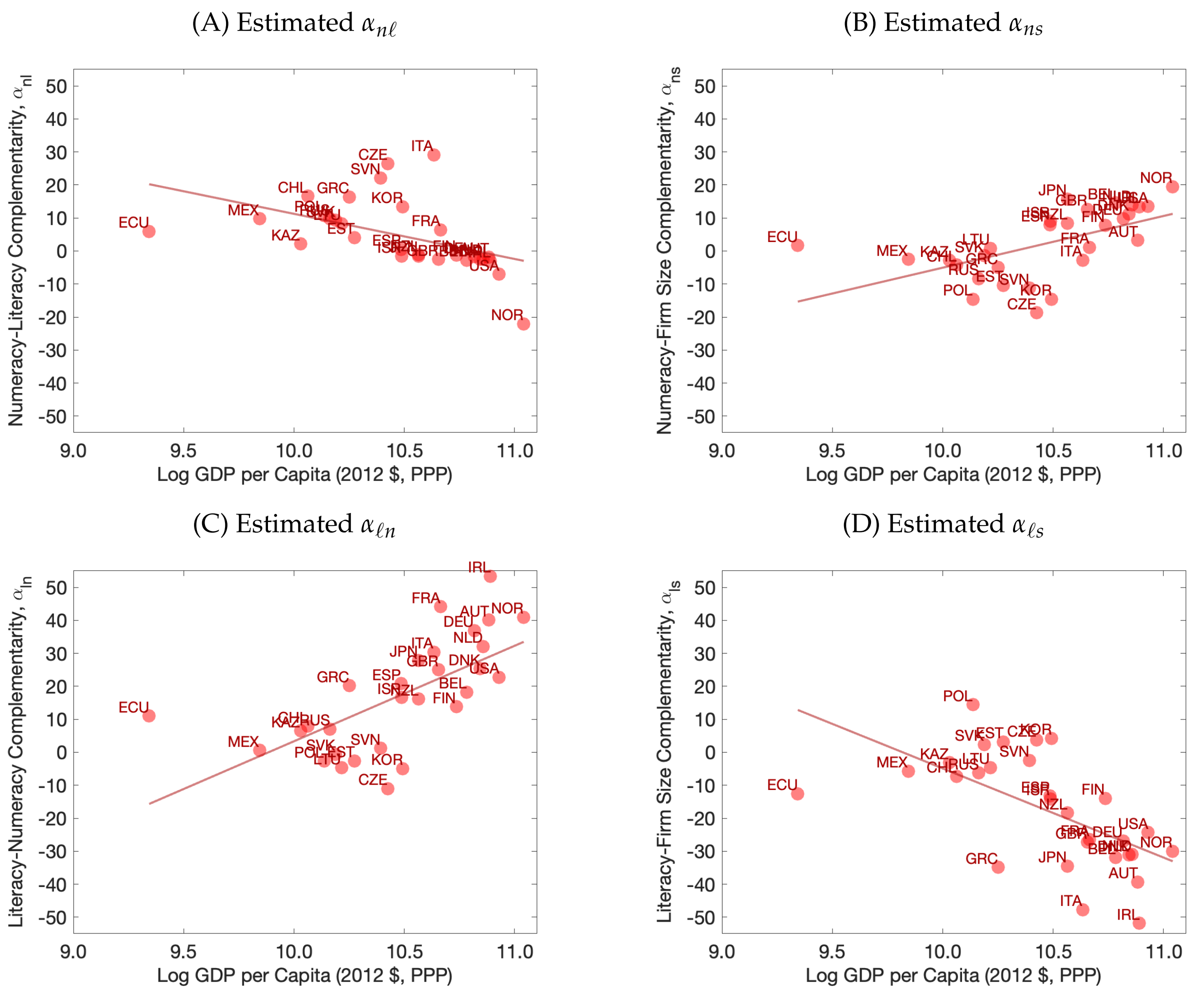
E.4 Additional Estimates

Figure E23: Distance between Skill Supply and Skill Demand Across Countries: Robustness



Notes: This figure plots the Kolmogorov-Smirnov distance between the discretized empirical bivariate distributions of worker skills and job skill requirements against log GDP per capita across countries. Skills and skill requirements are discretized into global quintiles of numeracy and literacy, yielding 25 worker types and 25 job types per country, as described in Section 6.1. *Source:* PIAAC.

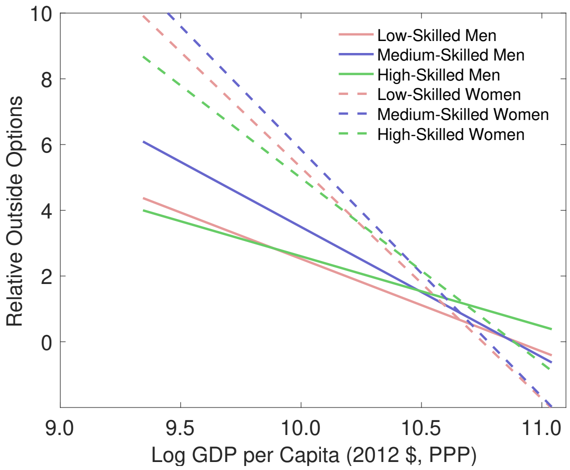
Figure E24: Additional Estimated Production Function Parameters across Countries



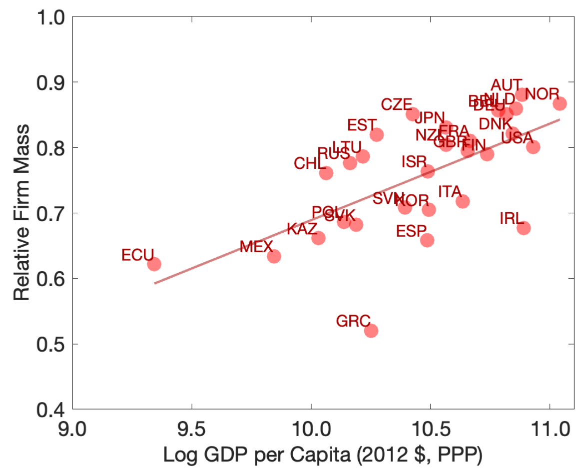
Notes: This figure plots estimates of the production function parameters $(\alpha_{n\ell}, \alpha_{ns}, \alpha_{\ell n}, \alpha_{\ell s})$ against log GDP per capita across countries. Each red dot represents one country. Solid lines indicate the linear best fit. *Source:* Model estimates.

Figure E25: Estimated Outside Options and Relative Firm Masses across Countries

(A) Outside Options



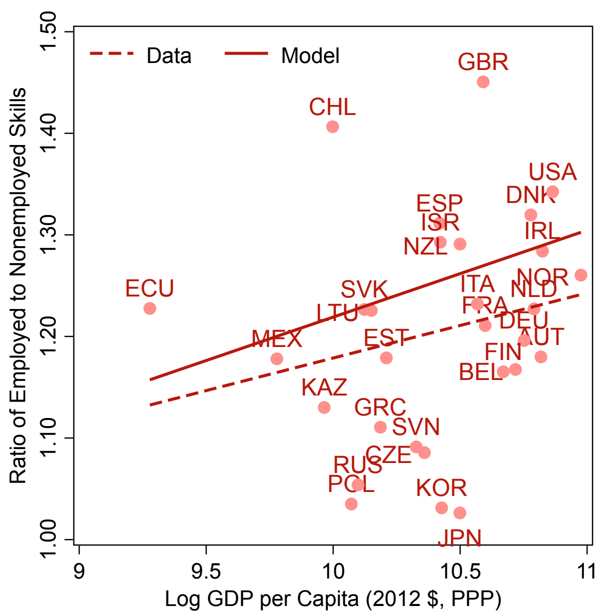
(B) Firm Mass



Notes: This figure plots estimates of outside options $f^{rg}_{x\varnothing}$ relative to the mean value of market production for worker groups defined by broad skill groups r and gender g (panel A) and the relative firm mass m^J (panel B) against log GDP per capita across countries. Each line in panel A represents the linear best fit of the outside option estimates for one broad worker group. See Appendix E.1 for the definition of the skill groups. Each red dot in panel B represents a model estimate of m^J for one country, and the solid line indicates the linear best fit. *Source:* Model estimates.

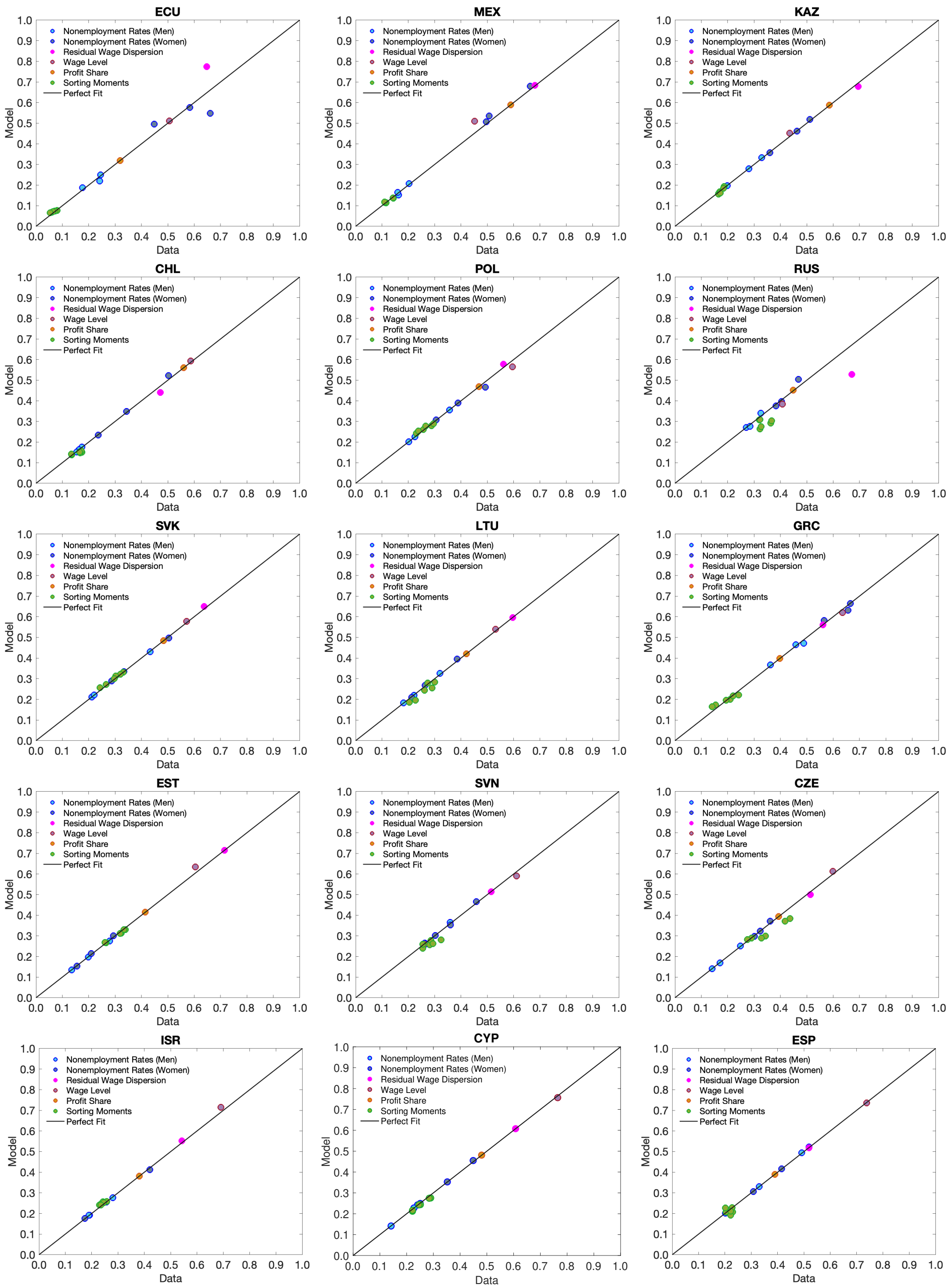
E.5 Details of Model Fit

Figure E26: Worker-Job Allocation across Countries: Selection into Employment



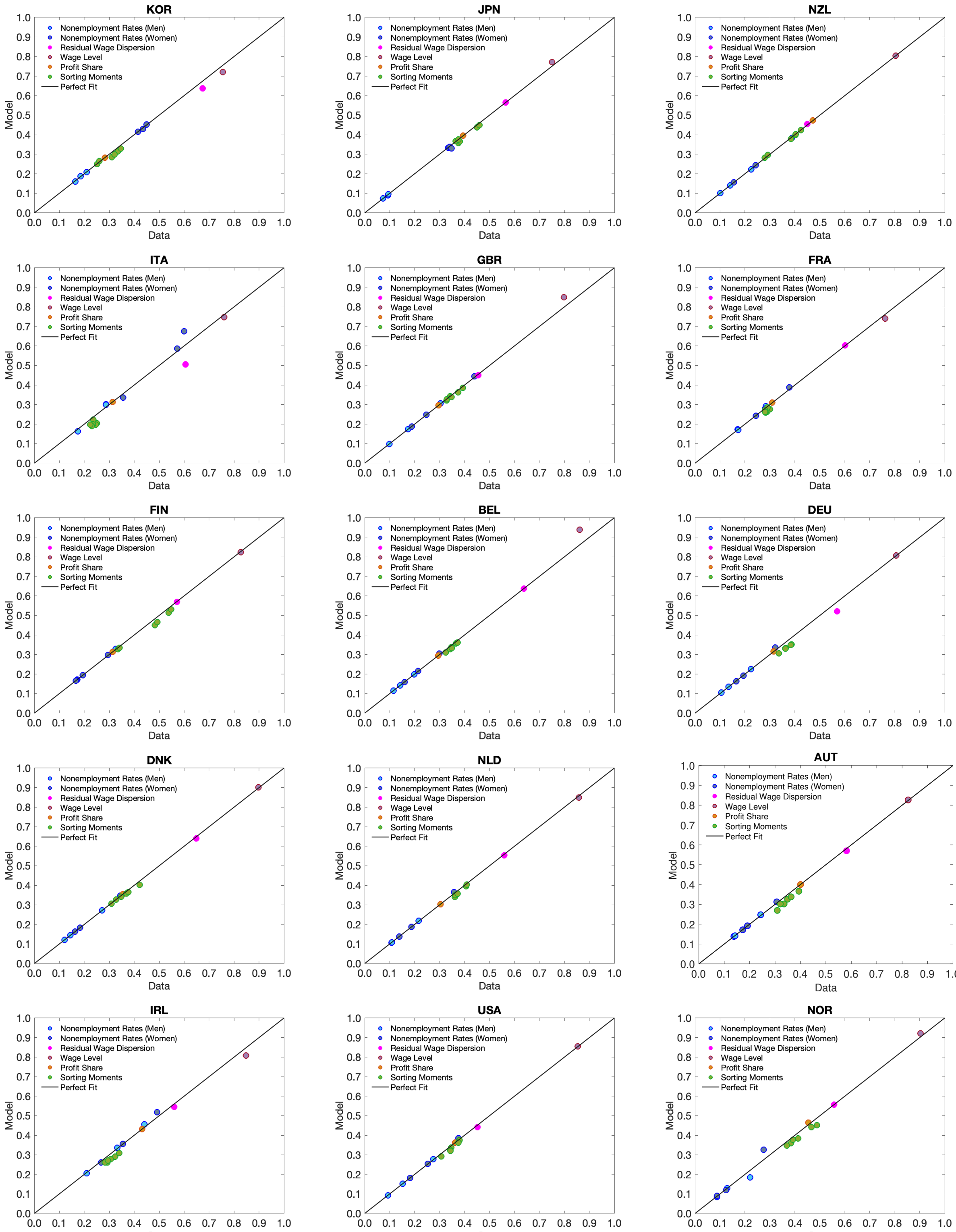
Notes: The figure plots the ratio of the average skills of employed workers and nonemployed workers against GDP per capita across countries in the estimated model and in the data. Each label represents one country in the data. The dashed line indicates the linear best data fit. The solid line indicates the linear best model fit. *Source:* PIAAC and Model estimates.

Figure E27: Model Fit for Middle- to High-Income Countries



Notes: This figure illustrates the model fit by plotting model moments against data moments for medium-income and high-income countries of the PIAAC sample. Countries are ordered by GDP per capita. For details, see Figure 8. *Source:* PIAAC, OECD, Our World in Data, and model simulations.

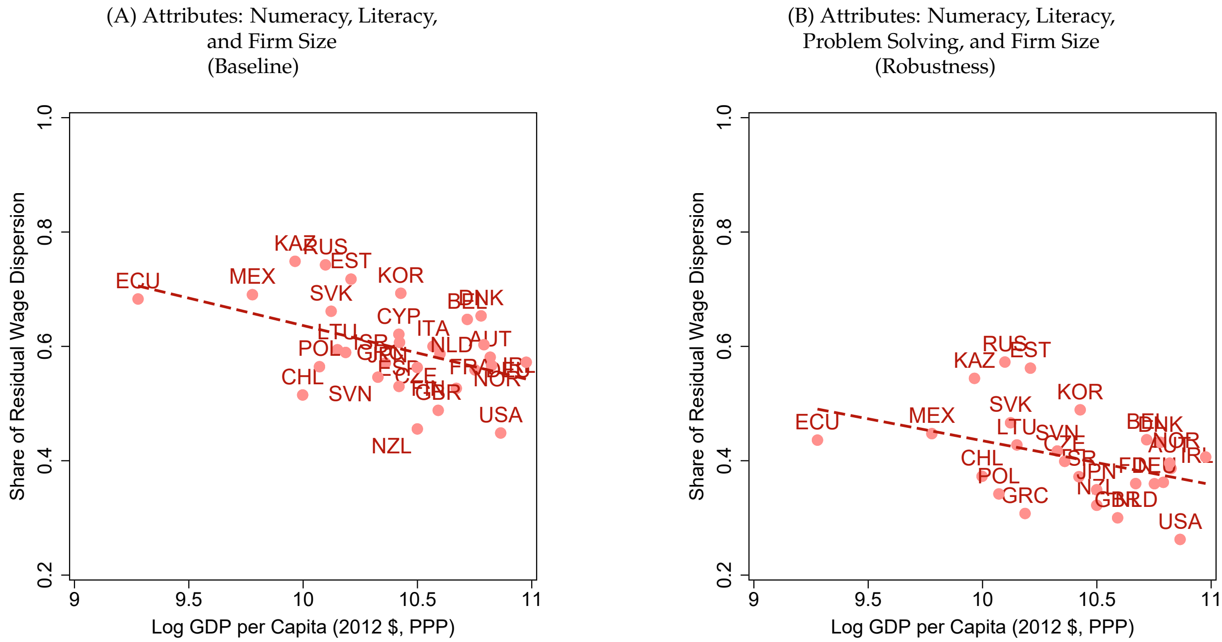
Figure E28: Model Fit for High-Income Countries



Notes: This figure illustrates the model fit by plotting model moments against data moments for high-income countries of the PIAAC sample. Countries are ordered by GDP per capita. For details, see Figure 8. *Source:* PIAAC, OECD, Our World in Data, and model simulations.

E.6 Robustness: Lower Residual Wage Dispersion in Higher-Income Countries

Figure E29: Lower Residual Wage Dispersion in Higher-Income Countries using Additional Skill and Skill Requirement Attributes

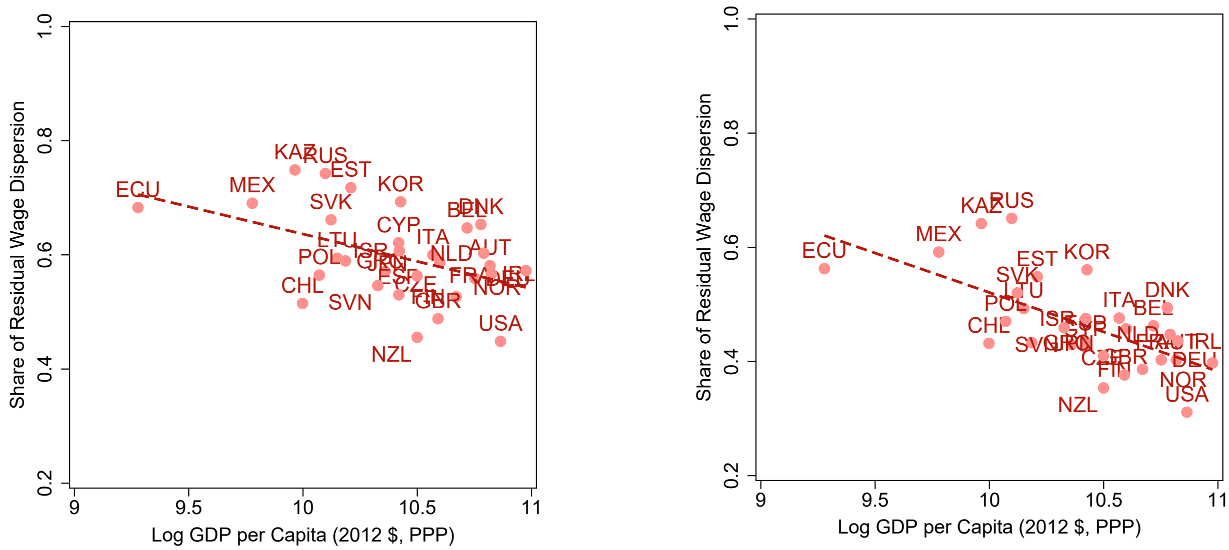


Note: This figure plots the share of dispersion in log wages not explained by cell dummies defined as the interaction between worker skills, job skill requirements, and firm size. Panel A is our baseline specification, where we use both literacy and numeracy characteristics and also firm size as controls in the log wage regression. For robustness, panel B adds problem-solving skills (ICT) and skill requirements in technology-rich environments to our baseline specification. Data on problem-solving skills is not available for Italy, France, and Spain, and thus these countries are omitted from this panel. Note that for panel B, we discretize skills and skill requirements using terciles (instead of quintiles) of the underlying distributions to avoid issues with sparse cells. *Source:* PIAAC.

Figure E30: Lower Residual Wage Dispersion in Higher-Income Countries using Additional Productivity-Related Controls

(A) No Additional Controls (Baseline)

(B) Additional Controls: Mincer Controls and Industry & Occupation Fixed Effects (Robustness)



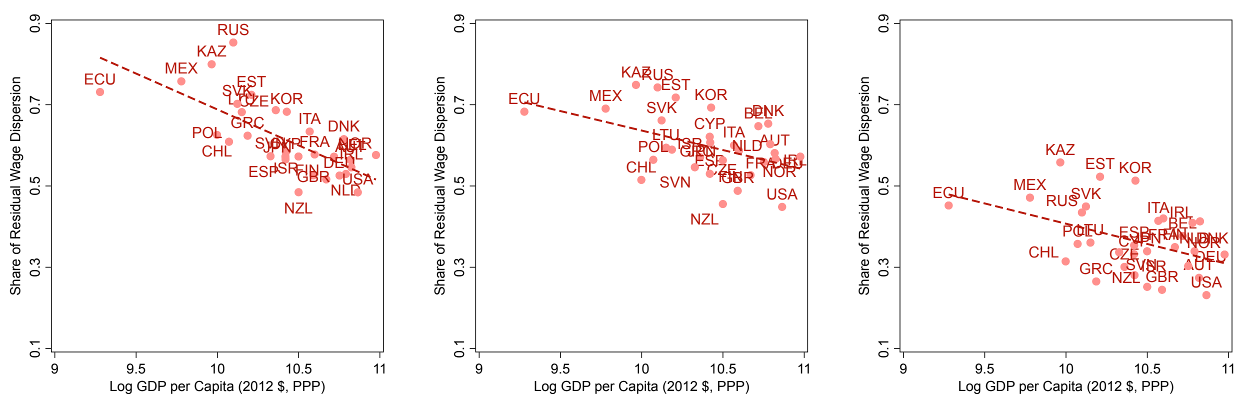
Notes: This figure plots the share of dispersion in log wages not explained by cell dummies defined as the interaction between worker skills, job skill requirements, and firm size. Panel A is our baseline specification, where we use both literacy and numeracy characteristics and also firm size as controls in the log wage regression. For robustness, panel B adds Mincer controls of education, experience, the square of experience, and gender as well as 1-digit industry and 1-digit ISCO occupation fixed effects. *Source:* PIAAC.

Figure E31: Lower Residual Wage Dispersion in Higher-Income Countries using Alternative Discretizations for Skills and Skill Requirements

(A) Discretization: Terciles (Robustness)

(B) Discretization: Quintiles (Baseline)

(C) Discretization: Deciles (Robustness)



Note: This figure plots the share of dispersion in log wages not explained by cell dummies defined as the interaction between worker skills, job skill requirements, and firm size. For robustness, panel A forms cells using skill and skill requirement terciles and a binary firm size dummy. Panel B, our baseline specification, is included for comparison and uses skill and skill requirement quintiles and a binary firm size dummy. Finally, panel C uses skill and skill requirement deciles and a binary firm size dummy. *Source:* PIAAC.

F Counterfactuals Appendix

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

F.1 Implementation of Counterfactuals

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

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

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

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

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

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

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

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

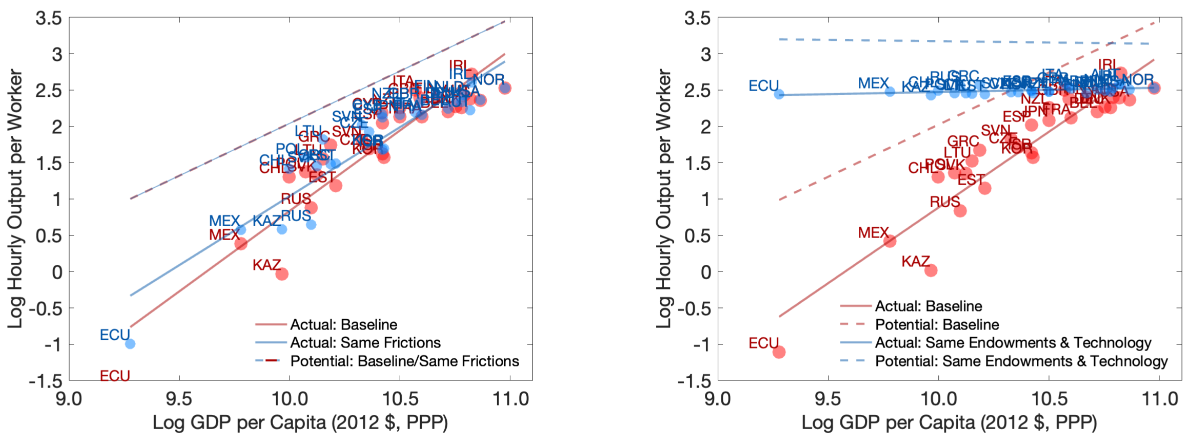
$$\Big(\sum_{x,y} \mu_c(x, y) f_c(x, y)\Big)^{\text{fixed matching}} = \Big(\sum_{x,y} \mu_c^*(x, y) f_c(x, y)\Big)^{\text{counterfactual}} \times \frac{\sum_{x,y} \mu_c(x, y) f_c(x, y)}{\sum_{x,y} \mu_c^*(x, y) f_c(x, y)}.$$

F.2 Additional Counterfactual Simulations

Figure F32: Counterfactual of Imposing Frontier Matching Frictions (A) versus Frontier Technology + Endowments (B) across Countries: The Role of Potential Output

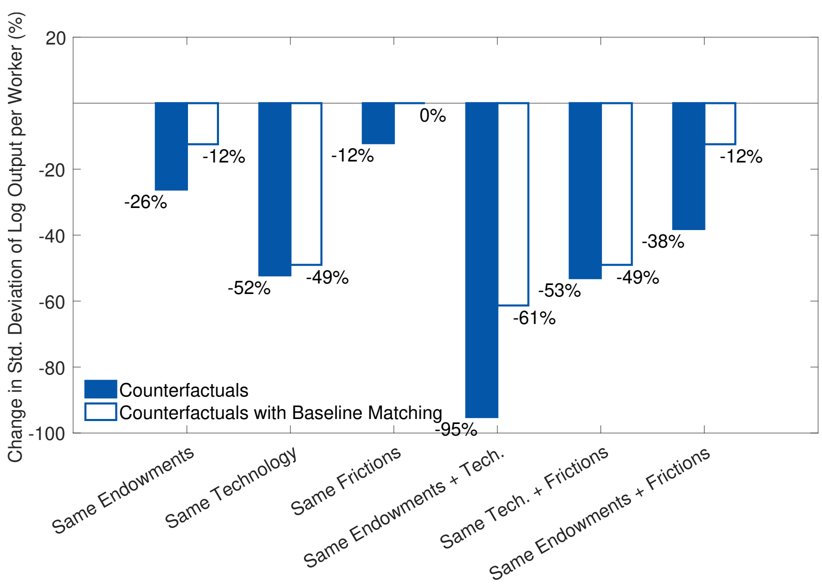
(A) Frontier Matching Frictions

(B) Frontier Technology and Endowments



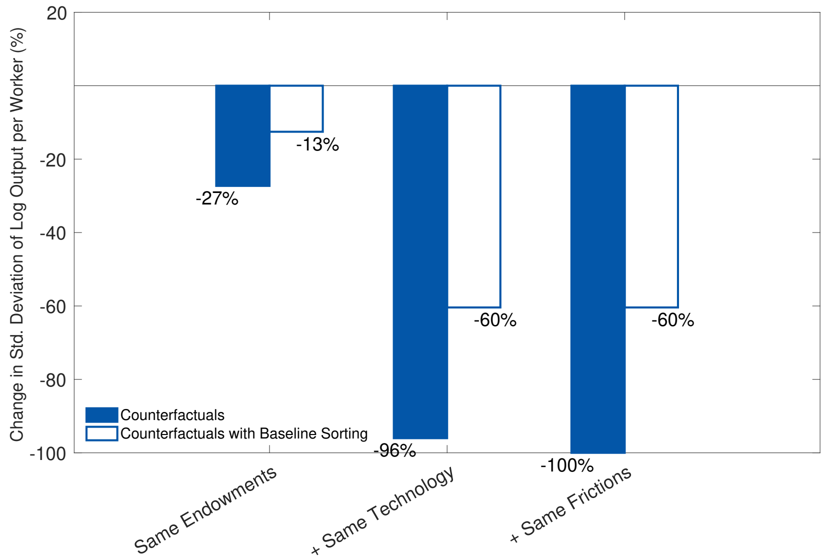
Notes: This figure shows the model-based counterfactual effects on log hourly output per worker of implementing Norway's matching frictions (panel A), and Norway's technology + endowments (panel B) in all countries. Red dots represent the baseline model estimates for each country, with red solid lines indicating the linear best fit across log GDP per capita. Blue dots represent the counterfactual results for each country, with blue solid lines indicating the linear best fit across log GDP per capita. Red (blue) dashed lines indicate the linear best fit of potential output in the baseline (counterfactual) scenario across log GDP per capita. *Source:* Model simulations.

Figure F33: Detailed Summary of Counterfactuals: Change in Standard Deviation of Log Output per Worker



Notes: This figure summarizes the results from all counterfactual simulations in terms of their effects on the standard deviation of log hourly output per worker across countries. Compared to Figure 13, we here report the interactions between all model primitives. The solid bars indicate outcomes based on the equilibrium counterfactuals. The hollow bars indicate outcomes in the counterfactual exercises while keeping each country's matching index at its baseline level. The numbers next to each counterfactual bar indicate the percentage change relative to the baseline. *Source:* Model simulations.

Figure F34: Development Accounting for Aggregate Output: Robustness



Notes: This figure provides a robustness check to panel B of Figure 13. The counterfactuals are based on alternative estimates for the frontier country Norway, where we targeted a lower residual wage dispersion of 0.2. The solid bars indicate outcomes based on the equilibrium counterfactuals. The hollow bars indicate outcomes in the counterfactual exercises while keeping each country's matching index at its baseline level. The numbers next to each counterfactual bar indicate the percentage change relative to the baseline. Note, as before, that numbers are rounded to the nearest integer. *Source:* Model simulations.