Misallocation and Inequality*

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Abstract

We document how inequality in wage and salary earnings varies with GDP per capita for a large set of countries. The mean-to-median ratio and the Gini coefficient decline as we move from poorer to richer countries. Yet, this decline masks divergent patterns: while inequality at the top of the earnings distribution falls, inequality at the bottom increases. We interpret these facts within a model economy with heterogeneous workers and firms, featuring industry dynamics, search frictions, and skill accumulation of workers through on-the-job learning and training. The benchmark economy is calibrated to the UK. We then study how the earnings distribution changes with distortions that penalize high-productivity firms and frictions that reduce match formation. Distortions and frictions reduce employment, average firm size, and GDP per capita. They also affect how much firms are willing to pay workers, how well high-skill workers are matched with high-productivity firms, and how much training workers receive. The model generates the observed cross-country relation between GDP per capita and earnings inequality and a host of cross-country facts on firm size distribution, firms' training decisions, and workers' life-cycle and job tenure earnings profiles.

Keywords: earnings inequality, labor market frictions, correlated distortions, human capital, on-the-job training, productivity, firm size, life-cycle earning profiles

JEL Classification: E23, E24, J24, O11

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1 Introduction

How does the distribution of wage and salary earnings change with development? We answer this question using household surveys from around the world. As a country gets richer, the distribution of earnings shifts to the right, and the mean increases. Yet, the median increases even more, and the mean-to-median ratio falls. The Gini coefficient declines as well. However, not all inter-percentile ratios decline; while the p90-p50 ratio drops, the p50-p10 ratio increases. Hence, moving from low to high GDP per capita countries, the inequality at the bottom of the earnings distribution increases, whereas it declines at the top.

We interpret these facts through the lens of a model economy with heterogeneous workers and firms. The model economy has three key ingredients. First, different firms pay different wages to workers with similar skills (Abowd et al., 1999; Card et al., 2013; Song et al., 2019). Identical workers receive higher wages in larger and more productive firms. Second, due to labor market frictions, matching between high-skilled workers and high-productivity firms is not instantaneous (Lise et al., 2016). Finally, firms differ in how much on-the-job training they provide.

In the benchmark economy, workers who differ by their initial (or pre-market) human capital levels search for firms in a frictional labor market. Some match with firms, while others remain unemployed and keep looking for a job. Firms are heterogeneous; they differ in their productivity and training costs. Hence, a worker who matches a high-productivity firm with low training costs enjoys high earnings and high earnings growth. Workers accumulate skills with job tenure and on-the-job training, but skills depreciate during non-employment spells. Through workers' and firms' dynamics and workers' human capital accumulation, the model economy generates a host of facts that can be confronted with the data. The model's parameters are estimated using firm- and worker-level data from the UK. The model replicates the observed firm size distribution, workers' earnings profiles, and training provision across different firms. It also produces a positive and large firm-size wage premium.

We then turn to cross-country differences. We assume that countries differ along two dimensions. First, following recent literature on misallocation (Guner et al., 2008; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009), we introduce distortions, taking the form of output wedges, which are correlated with firm size. These distortions are more extensive in some countries than others. The existing literature has focused on how misallocation affects cross-country differences in firm-size distribution and aggregate productivity. We focus on how misallocation affects earnings inequality. Firms that face distortions shrink and pay lower wages. As a result, size-correlated distortions make high and low-productivity firms more similar, compressing the overall earnings distribution.

We interpret these distortions broadly as regulations and market imperfections that disproportionately affect larger firms and hinder firm growth (see Hopenhayn (2014) and Restuccia and Rogerson (2017) for reviews). They might capture existing size-dependent policies, such as labor market regulations, or result from discretionary interventions by the government in financial markets. Finally, they can reflect the lack of well-defined property rights, as in Akcigit et al. (2021).[1]

Second, we assume that countries also differ in the extent of labor market frictions. Some have more efficient labor markets, and workers and firms match easily, while in others, it takes longer to fill a vacancy or find a job. Higher frictions result in lower wage employment and higher non-employment duration. Search frictions also affect the equilibrium earnings distribution. Longer times to fill a vacancy prevent workers from accumulating human capital. It also makes workers less willing to wait for the right firms, reducing positive assortative matching between firms and workers. The link between search frictions and misallocation of labor has been recently emphasized by Martellini and Menzio (2021). Poschke (2019) shows that search frictions can account for cross-country differences in unemployment, wage employment, and self-employment. Heise and Porzio (2021) estimate a model with a frictional labor market and show that spatial frictions generate misallocation across and within regions and affect the wage distribution. Donovan et al. (2020) highlight the role of labor market frictions and endogenous separations to explain how labor market flows and wage-tenure profiles vary with development. Finally, Gulyas et al. (2018) shows that the misallocation of jobs and workers across firms due to search frictions generate significant output losses.

Distortions and frictions also affect on-the-job training provision in the model. We document that in the data the share of establishments providing training and the share of workers receiving training in a firm increases with GDP per capita. Furthermore, the probability that a firm offers on-the-job training and the share of trained workers increases with establishment size. The model is able to replicate these facts, since, in the model, distortions and frictions directly reduce gains from training in a given match, making firms less willing to incur training costs. Empirically, the importance of learning and training for life-cycle inequality has been emphasized recently, among others, by Gregory (2021) and Arellano-

[1]Beyond size-dependent distortions, financial frictions constitute another candidate for cross-country differences in firm size distribution and aggregate productivity (Buera et al. (2011), Midrigan and Xu (2014), Moll (2014), and Gopinath et al. (2017)). David and Venkateswaran (2019) try to disentangle different sources of misallocation.

Bover and Saltiel (2021). Lentz and Roys (2015) study human capital accumulation in a search model where firms can offer long-term contracts and commit to providing a certain level of expected utility to their employees. They show that increased labor market frictions reduce training in equilibrium. Flinn et al. (2017) estimate a search model of investment in general and match-specific human capital and use it to examine the impact of a minimum wage policy on training provision.

We calibrate the correlated distortions to target average firm size and the matching efficiency to target the share of wage and salary workers for different countries. Lower distortions or frictions alone would increase firm size, employment, and GDP per capita in the model economy. But to match the observed cross-country differences, we need both: while distortions help us generate observations for the poorer countries, frictions help us match observations for the richer ones.

Then we zoom into these economies and calculate inequality measures. Although not targeted directly, cross-country differences in earnings inequality that emerge from this exercise are remarkably close to what we observe in the data. The mean-to-median ratio and the Gini index decline as we move from poorer to richer countries. In the data, the p50-p10 earnings ratio increases by GDP per capita. In the model economy, higher distortions push p50-p10 down in poor countries, and lower frictions push it up in rich ones. In the data, the p90-p50 earnings ratio falls by GDP per capita. In the model, this is generated by lower matching frictions in richer countries.

The model also fits a large set of untargeted cross-country facts on firm-size distributions, life-cycle earning profiles, and training outcomes. In particular: i) Together with average firm size, the dispersion and skewness of the firm-size distribution increase with GDP per capita (Hopenhayn, 2016; Bento and Restuccia, 2017; Poschke, 2018). ii) On-the-job training provision increases with development. iii) Earnings-experience profile becomes steeper with GDP per capita (Lagakos et al., 2018). iv) On the other hand, the earnings-tenure profile becomes flatter with GDP per capita (Donovan et al., 2020).

What are the mechanisms behind these patterns? We identify three forces. First, lower distortions make the relation between firm productivity and revenue steeper, widening the entire wage distribution and increasing p50-p10 and p90-p50 in high-income countries. Second, lower frictions reduce non-employment duration, increasing human capital accumulation and wages. But the impact is more substantial for relatively lower-skilled workers, leading to lower earnings inequality. Third, lower frictions also improve sorting between firms and workers. The sorting effect increases wages for relatively high-skilled workers, who would work for a low-productivity firm in a less efficient labor market, increasing inequality. Quantitatively, the impact of second and third forces results in a higher p50-p10 and a lower p90-p50 in richer countries, as workers in the middle of the skill distribution benefit the most.

On-the-job training amplifies these patterns as it helps the workers in the middle of the skill distribution. As we move from poorer to richer countries, the training of the workers in the middle of the skill distribution increases the most. Training for low-skilled workers is too costly, while training high-skilled workers improves their outside options and makes them likely to leave. As a result, the relation between workers' skills and training decisions becomes hump-shaped when distortions and frictions are lower. We find that training accounts for up to 35% of the decline in the mean-to-median earnings ratio across countries.

Finally, following Alfonsi et al. (2020), we evaluate a fully-subsidized training program for unemployed workers in a low-income country. The program increases employment by about 12% points, reduces earnings inequality, and generates enough increase in output to cover its cost.

While our focus on the interaction between misallocation and earnings inequality is novel, the existing literature has emphasized different elements of the model. Bento and Restuccia (2017) introduce correlated distortions into a competitive model of industry dynamics to account for cross-country differences in average firm size. Guner et al. (2018) document that, for a group of high-income countries, the earnings of managers grow faster than for non-managers, and the earnings growth of managers relative to non-managers corresponds to output per worker. They interpret this finding within a span-of-control model where distortions affect the accumulation of managerial skills. Jovanovic (2014) develops a model of growth with human capital accumulation where incomplete information on workers' ability generates worker-firm mismatch. He shows that better signals lead to a more efficient worker-firm assignment which, in turn, leads to higher human capital accumulation, faster long-run growth, and more income inequality. Finally, Hsieh et al. (2019) focus on the misallocation of talent by gender and race in the US and find that the improved allocation of human capital across jobs can account for between 20% and 40% of income per capita growth in the last 50 years.

The link between labor market frictions and incentives for workers to invest in their skills has been studied by Engbom (2020). He shows that wages grow more over the life cycle in countries where job-to-job mobility is more common. He then builds a life-cycle model of on-the-job training and job-to-job transitions where a more fluid labor market allocates workers to firms more efficiently and provides larger incentives for skill accumulation. Karahan et al. (2022) estimate a job ladder model with on-the-job learning and show that differences in lifetime wage growth in the U.S. can be attributed to heterogeneity in job loss, job finding, and contact rates. Along similar lines, Ma et al. (2021) explore the role of firm-provided training in explaining why workers in richer countries have faster rates of wage growth over their lifetimes than workers in poorer countries. They find on-the-job training can explain between 10% and 15% of the income differences across countries.

2 Cross-Country Facts

2.1 Earnings Distribution

This section documents how the distribution of wage and salary earnings varies with GDP per capita across countries. The results are based on household surveys from 57 countries between 1974 and 2016, for a total of 497 country-year observations. The primary data sources are IPUMS International, European Union Survey on Income and Living Conditions (EU-SILC), and Luxembourg Income Study Database (LIS). The poorest country in our dataset is India in 1993, with a GDP per capita of 1,845 in 2011 USD, while the richest one is Luxembourg in 2007, with a GDP per capita of 97,864 in 2011 USD.[2]

We restrict the sample to all individuals between 18 and 64 who are not students and have non-missing information on their wage and salary income. For each individual, we then calculate total gross (pre-tax) wage and salary income (referred to as *earnings* below), which includes any payment received as an employee. For each country-year pair, wage and salary earners (referred to as *earners* below) consist of those with strictly positive wage and salary income. Hence, any earner in the sample has a labor relationship with an employee and receives payments from this relationship. The employees can be private or public; they can also be formal or informal. We label everyone with zero earnings as a no-earner, including those who are out of the labor force, unemployed, unpaid family workers, or self-employed.[3] We then study how the share of earners and the distribution of earnings change by GDP per capita.

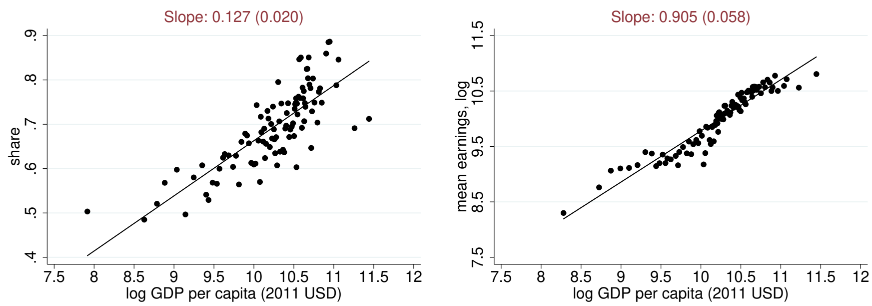
Figure 1 shows how the share of earners (panel a) and the average log earnings (panel

[2]Details on these three datasets (sample restrictions and variable definitions) are in Appendix A.1.

[3]This approach is consistent with recent evidence on labor rationing for developing countries, where a large portion of excess labor supply is disguised as self-employment (Breza et al., 2021). Herreno and Ocampo (2023) argue that in developing countries, self-employment acts as a substitute for missing unemployment insurance, rather than being a permanent career choice. Donovan et al. (2020) show that in many low- and middle-income countries, the self-employed are as likely to transition to wage employment as the non-employed.

Figure 1: Wage and salary earners and earnings across countries

(a) Earners (b) Average earnings

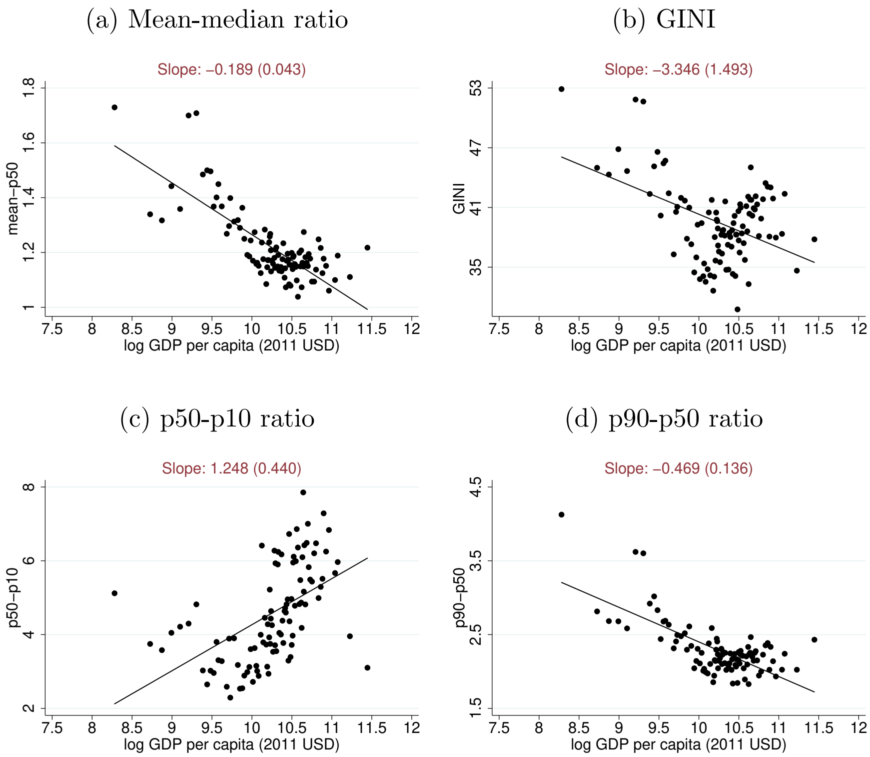


Notes: Each dot corresponds to the average outcome for countries in a given percentile of the GDP per capita distribution. Outcomes are reported as residuals (rescaled by the constant) from a regression with year-fixed effects. In red, we report the estimated slope in the regression. Standard errors (in parenthesis) are robust and clustered at the country level. Source: IPUMS, EU-SILC, LIS, and author's calculations.

b) change with (log) GDP per capita across countries. To construct Figure 1, we first regress the outcome of interest for country i and year t on a set of year dummies. Each dot corresponds to average residuals from this regression (rescaled by the constant), for countries in a specific GDP-per-capita bin. We report 100 bins corresponding to the percentiles of the GDP-per-capita distribution. As we move from poorer to richer countries, workers become significantly more likely to work as employees and report positive earnings. Since our focus is on earnings inequality, we do not include very poor countries in the sample where a majority of workers do not receive any wage and salary income. The share of earners ranges from around 50 percent for the poorest countries to almost 90 percent for the richest countries in the sample. Not surprisingly, the average log earnings increase almost one-to-one with log GDP per capita (panel b).

Figure 2 documents earnings inequality. We again regress different measures of earnings inequality for country i and year t on a set of year dummies. Each dot in Figure 2 corresponds to the average values of the residuals from this regression (dependent variable minus the year dummies) in a specific bin of GDP per capita. In each panel, we also report the estimated regression coefficient for GDP per capita, indicated as the *slope*. Panel (a) shows that the mean-to-median ratio declines significantly with GDP per capita. It drops from around 1.6 for the poorest countries in the sample to about 1.1 for the richest ones. Hence, while the average earnings increase, the median workers gain even more. The gains of the workers at the center of the earnings distribution also lower the Gini coefficient, as illustrated in panel (b). As we move from the sample's poorest to the richest country, the Gini declines by around 15 percentage points, from 50% to 35%.

Figure 2: Earnings inequality across countries



(a) Mean-median ratio (b) GINI

(c) p50-p10 ratio (d) p90-p50 ratio

Notes: Each dot corresponds to the average outcome for countries in a given percentile of the GDP per capita distribution. Outcomes are reported as residuals (rescaled by the constant) from a regression with year-fixed effects. In red, we report the estimated slope in the regression. Standard errors (in parenthesis) are robust and clustered at the country level. Source: IPUMS, EU-SILC, LIS, and author's calculations.

However, the decline in earnings inequality masks significant heterogeneity in how the earnings distribution changes with development. Panel (c) of Figure 2 shows that the lower tail of the earnings distribution does not catch up with the median, and the gap between the bottom and the median opens up: the 50-to-10 earnings ratio increases from around 3 in poor countries to about 8 in the richest ones. Moving to a country with twice the amount of GDP per capita is associated with a higher bottom inequality of about 1.3 points. Yet, the opposite happens in the upper tail, as shown in panel (d). Labor income for workers in the 90th percentile does not grow as fast as the median, and the 90-to-50 earnings ratio declines with GDP per capita, from around 3.5 in poor countries to about 2 in the richest ones. Moving to a country with twice the amount of GDP per capita is associated with a lower top inequality of about 0.5 points.

2.2 Robustness

The facts we document in Figure 2 are robust to different sample restrictions, to controlling for additional country-level observables, or using different percentiles beyond the 90-50 and 50-10 ratios. The results are also not driven by cross-country differences in hours worked.

Worker-level heterogeneity. Table 1 presents the slope coefficients from a regression of each measure of earnings inequality on log GDP per capita (controlling for year-fixed effects) under different sample restrictions. The first raw is the Full Sample, and coefficients correspond to what we report in Figure 2. We find exactly the same patterns when we restrict the sample in each country to workers employed in specific sectors (non-agriculture or manufacturing) or workers with or without a college degree. We also find the same patterns when the sample is restricted to only males, only household heads, or only prime-age workers (25 to 54 years olds).

Cross-country heterogeneity. Next, we consider the Full Sample of workers in each country but add additional controls, not just year dummies, in the cross-country regression that generates the outcomes in Figure 2. The lower block in Table 1 reports the slope coefficients obtained from regressing each measure of earnings inequality on log GDP per capita and controlling for cross-country differences in average years of schooling, women's labor force participation rates, shares of self-employment, shares of agricultural and industrial employment, the average number of hours worked per year, and values of trade over GDP.[4] Conditional on observables, the patterns of inequality over GDP p.c. become stronger: the slope coefficient for the 50-to-10 ratio increases, from 1.25 to 1.80 (column 3), while the one for the 90-to-50 ratio declines further, from -0.47 to -0.57 (column 4).

Alternative cut-offs. In Figure 19 in Appendix A.3, we use alternative measures of bottom (40-to-10 and 50-to-20 ratios), and top (80-to-50 and the 90-to-60 ratios) earnings inequality. We find that independently of the particular cut-off we use, earnings in lower and upper tails grow much slower than those in the center of the distribution.

Hours worked. Finally, a potential concern might be that the results are driven by cross-country differences in hours worked. In particular, the higher p50-p10 ratio in richer countries might be driven by larger dispersion of hours worked in richer countries. In Appendix A.4, Figure 20, we report how the distribution of hours worked changes with GDP per capita. Two messages emerge from this figure: First, the 50-to-10 ratio in hours worked increases with GDP per capita. This could explain why we get a higher p50-p10 in earnings for higher GDP per capita countries. But the 90-to-50 ratio in hours also increases. Yet, we

[4]Details are reported in Appendix A.2

Table 1: Slope Coefficients of Earnings Inequality on log GDP per capita

	Earnings inequality				
	Mean-to-median ratio	GINI	p50-p10 ratio	p90-p50 ratio	N
	(1)	(2)	(3)	(4)	(5)
Full Sample	-0.189***	-3.346***	1.248***	-0.469***	497
	(0.043)	(1.493)	(0.440)	(0.136)	
Worker-level heterogeneity.					
Non-Agriculture	-0.171***	-2.602***	1.244***	-0.379***	497
	(0.017)	(0.539)	(0.193)	(0.056)	
Manufacturing	-0.165***	-1.097	2.886***	-0.276***	497
	(0.020)	(0.674)	(0.400)	(0.055)	
Non-College	-0.122***	-2.383***	0.725***	-0.299***	497
	(0.012)	(0.456)	(0.109)	(0.032)	
College	-0.116***	-1.206*	1.444***	-0.303***	497
	(0.016)	(0.629)	(0.209)	(0.059)	
Males	-0.184***	-4.454***	1.066***	-0.465***	497
	(0.015)	(0.544)	(0.217)	(0.050)	
Household Heads	-0.220***	-5.813***	0.452**	-0.614***	497
	(0.017)	(0.537)	(0.189)	(0.060)	
25-54 y.o.	-0.202***	-5.259***	0.363**	-0.551***	497
	(0.0176)	(0.531)	(0.143)	(0.0608)	
Cross-country heterogeneity					
Full Sample	-0.229***	-4.551*	1.797***	-0.570***	420
+ Controls	(0.055)	(2.603)	(0.437)	(0.203)	

Notes: The upper block of the Table reports the slope coefficients from regressing measures of earnings inequality on log GDP per capita, controlling for year-fixed effects, separately for various categories of individuals. The lower block of the Table reports the slope coefficients obtained using the full sample and controlling for the average years of schooling (Penn-Word), women's labor force participation rate (World Bank), the share of self-employment (World Bank), shares of agricultural and industrial employment (World Bank), the average number of hours worked per year (Penn-Word), aggregate capital stock (Penn-Word), and the value of trade as a share of GDP (World Bank). N refers to the number of observations. GDP p.c. is expressed in 2011 USD. Standard errors are robust and clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1

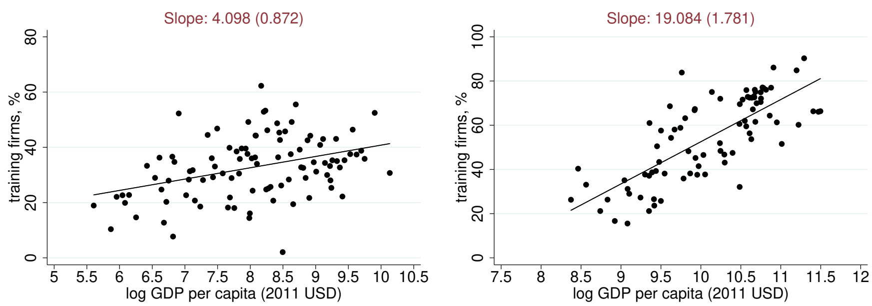
document that the p90-p10 in earnings declines with GDP per capita, so it is unlikely that hours can account for both patterns. Second, compared to the observed changes in earnings distribution (Figure 2) the magnitude of changes in hours dispersion is quite small. The 50-to-10 ratio for hours goes from 0.8 to 1.2, while the p50-p10 earnings ratio increases by about 4 points. Hence, the latter evidence is unlikely to be explained by the former one.

2.3 On-the-Job Training

This section complements the cross-country evidence on earnings inequality with facts on on-the-job training provision. To this end, we use data from the World Bank Enterprise Survey (WB-ES) and the Eurostat Continuing Vocational Training Survey (CVTS).[5]

Figure 3: Training provision across countries

(a) WB-ES (b) CVTS



Notes: Each dot corresponds to the average outcome for countries in a given percentile of the GDP per capita distribution. Outcomes are reported as residuals (rescaled by the constant) from a regression with year-fixed effects. In red, we report the estimated slope in the regression. Standard errors (in parenthesis) are robust and clustered at the country level. Source: World-Bank Enterprise Survey (WB-ES) and Eurostat Continuing Vocational Training Survey (CVTS).

Figure 3 shows how the percentage of firms offering job training to their employees varies with (log) GDP per capita across countries. Richer countries have a larger share of firms investing in job training. The correlation between the percentage of firms providing job training and log GDP per capita is equal to 0.52 in the WB-ES data (panel a). The coefficient from regressing the former on the latter implies that one log point higher GDP per capita is associated with 4 percentage points more firms providing training. The correlation in the CVTS data is even higher, 0.75. The slope coefficient suggests that one log point higher GDP per capita is associated with 19 percentage points more firms offering training (panel b). In Appendix A.5, we show that the share of workers receiving training in a given firm also increases with GDP per capita in both datasets.

Next, we show how training varies by firm size within each country. Table 2 reports the percentage of firms providing training by different firm size categories, separately for countries belonging to different regions; Latin America (LAC), Middle East and Africa (ME+AFR), and Asia in the WB-ES sample, and EU15 and non-EU15 in the CVTS sample. Training increases significantly with firm size. The share of firms investing in training more than doubles as we move from firms with less than 50 employees to more than 250 employees.

[5] Details on these two datasets are provided in Appendix A.5.

Table 2: Job training across firm size

				Training firms, %			
WB-ES	LAC	ME+AFR	ASIA	others	CVTS	EU15	non-EU15
Firm size (# employees)					Firm size (# employees)		
<20	34.84	18.42	19.32	26.35			
20-49	54.31	31.99	33.63	38.48	<49	60.27	40.71
50-249	66.94	41.31	47.02	46.47	50-249	82.37	63.94
250-449	81.13	56.86	47.32	56.65	≥250	93.68	84.17
≥500	92.12	68.45	52.28	68.88			

Notes: Each entry denotes the percent of firms that reports providing on-the-job training, separately for firms with different size (number of employees) and different groups of countries. Firm size refers to the number of employees. Source: World-Bank Enterprise Survey (WB-ES) and Eurostat Education and Training Dataset (CVTS).

This difference is robust across regions, and it is higher in countries belonging to the WB-ES sample. In Appendix A.5 we also show that conditional on investing in training, larger firms train a larger share of their workforce.

2.4 Recap

This section documented three key cross-country patterns. As we move from low to high GDP per capita countries: 1. The mean-to-median ratio and Gini coefficient for earnings decline. 2. While the p50-p10 ratio increases, the p90-p50 ratio declines. 3. On-the-job training provision (measured by the share of establishments that provide training and the share of workers receiving training within a given firm) increases.

These facts complement other recently documented cross-country patterns in the firm size distribution and life-cycle earnings growth. As we go from poorer to richer countries: 1. Average firm size increases (Bento and Restuccia, 2017). 2. Dispersion and skewness of firm size distribution increase (Poschke, 2018). 3. Age-earnings profiles become steeper (Lagakos et al., 2018). 4. Tenure-earnings profiles become flatter (Donovan et al., 2020).

In the next section, we develop a model of heterogeneous firms and workers and use it to understand these patterns.

3 Model

Consider a closed economy populated by two types of agents: a unitary measure of heterogeneous workers and an endogenous measure of heterogeneous firms. Time is discrete. Workers can live forever, but in each period, they face a constant probability of death (or retirement). Workers enter the economy with a given level of human capital (skill or ability). Each period they can be employed or non-employed. Labor market frictions are represented by a matching function that maps non-employed workers and open vacancies into potential matches. If a match between a worker and a firm is formed, workers' skills grow due to on-the-job learning and training. In contrast, non-employment lowers workers' skills. Firms differ along four dimensions: productivity, cost of training, the total number of employees, and skill distribution of their employees. Finally, firms face size-dependent output distortions (wedges) that are correlated with their productivity.

3.1 Workers

Workers maximize the expected present value of their lifetime utility

$$\mathcal{U} = \sum_{t=0}^{\infty} \left(\frac{1-\delta_w}{1+r} \right)^t c_t,$$

where c_t is consumption, $r > 0$ is a discount rate, and $\delta_w > 0$ is an exogenous probability of death (or retirement).

Workers are ex-ante heterogeneous in their initial level of human capital, denoted by $a^0 \in \mathcal{A} \subset \mathcal{R}_+$ and distributed according to a probability density function $\psi_a(a)$. Upon matching with a firm, workers improve their skills through job experience (on-the-job learning) and on-the-job training. Job experience and training cause a Δ_a-step jump in $\mathcal{A}$ with probabilities p^e and p^t, respectively. Human capital is fully portable between jobs, so when a job is destroyed, workers retain their human capital fully.[6] But, each period of non-employment induces a Δ_a-step depreciation of skill a with probability p^d.

3.2 Firms

The industry is populated by an endogenous measure of firms, each producing a homogeneous good and characterized by firm-specific productivity $z \in \mathcal{Z} \subset \mathcal{R}_+$. The productivity level z is drawn before entry from a probability density function, $\psi_z(z)$, and remains constant as long as the firm is active. Firms differ also by the cost they incur to train their workforce. Let $\xi \in \mathcal{E} \subset \mathcal{R}_+$ denote the per-period cost to train one worker, defined in units of the final output. Like productivity, the training cost is firm-specific, it is drawn before entry from a probability density function $\psi_\xi(\xi)$, and it is time-invariant.

[6] Kambourov and Manovskii (2009) and Gathmann and Schönberg (2010) document that human capital is not specific to the firm, but rather to the occupation or task that a worker performs, suggesting high portability across employers.

To produce, firms combine labor services (expressed in efficiency units) from their employees through a linear production technology. Let $\psi(i|z,\xi,\ell)$ be the measure of worker i in a firm with productivity z, training costs ξ and workforce ℓ. Then, we can write the total firm output as

$$y(z,\xi,\ell,\psi) = \int_0^\ell g(z,i)\psi(i|z,\xi,\ell)di,$$

where $g(z,i) = \kappa z a(i)$ is the amount produced by a match between a firm z and a worker i with human capital $a(i)$, and $\kappa > 0$ is the aggregate productivity. Re-arranging terms, we can write the production function as

$$y(z,\xi,\ell,\psi) = \kappa z \bar{a}(z,\xi,\ell,\psi)\ell, \tag{1}$$

with

$$\bar{a}(z,\xi,\ell,\psi) = \int_0^1 a(i)\psi(i|z,\xi,\ell)di.$$

Linearity of the aggregate production function with respect to ℓ implies that each firm, independent of their productivity z, would like to hire as many workers as possible, and, as it will become clear below, are only constrained in their hiring by matching frictions and adjustment costs. This makes the problem tractable since a firm treats each of its workers as an independent production unit. As a result, wage bargaining and training decisions take place between each worker and their employer separately. Finally, in each period firms face two types of destruction shocks. They can lose a particular worker with probability δ_s, or lose all workers and exit with probability δ_f.

3.3 Distortions

Firms are subject to output distortion. Distortions are modeled as in Bento and Restuccia (2017) and Guner et al. (2018). Each firm retains a fraction $1-\tau$ of its output, where τ depends on firm-level productivity z, given by

$$\tau(z) = 1 - z^{-\zeta}, \quad \zeta > 0. \tag{2}$$

The parameter ζ is the elasticity of a firm's distortion with respect to its productivity. This formulation implies that the net revenue function for a worker-firm pair is

$$r(z,a) = (1-\tau(z))g(z,a) = \kappa z^{1-\zeta} a. \tag{3}$$

3.4 Frictions

The labor market is subject to search and matching frictions. To hire workers, firms need to post vacancies. To find a job, workers need to search, which is random and costless. There is no on-the-job search. The number of new matches depends on the total measure of workers searching for a job, U, and the vacancies posted, v. New matches are formed according to a constant return to scale matching function, given by

$$m(U,v) = \chi \frac{Uv}{(U^\eta + v^\eta)^{\frac{1}{\eta}}}, \quad \chi > 0, \eta > 0.$$

The parameters χ and η govern the efficiency of the matching and the elasticity of new matches with respect to the pool of searchers. This matching function implies the following contact rates for workers and for firms:

$$\phi_w = \frac{\chi}{(1+\theta^{-\eta})^{\frac{1}{\eta}}} \quad \text{and} \quad \phi_f = \frac{\chi}{(1+\theta^{\eta})^{\frac{1}{\eta}}},$$

where $\theta = v/U$ is the labor market tightness. Workers matched with a firm earn a wage equal to $w(z,\xi,a)$, which results from bargaining between the workers and the firms and depends on the productivity of the firm they work for, the training costs faced, and their human capital. Workers who fail to get matched end up being non-employed, supporting themselves by means of home production, equal to b.

3.5 The Problem of the Worker

3.5.1 Value of Non-employment

The value of being not-employed at the beginning of the period for a worker with ability a is equal to

$$\begin{aligned} J^u(a) =& (1-\phi_w)[p^d J^{u,h}(a-\Delta_a) + (1-p^d)J^{u,h}(a)] \\ &+ \phi_w \int_{z\in\mathcal{Z}} \int_{\xi\in\mathcal{E}} [\mathbf{1}^h(z,\xi,a)J^{e,h}(z,\xi,a) + (1-\mathbf{1}^h(z,\xi,a))J^{u,h}(a)]\psi_v(z,\xi)d\xi dz, \end{aligned}$$

where $\mathbf{1}^h(z,\xi,a)$ is an indicator function for match formation (*hiring*). Non-employed workers fail to match with a firm with probability $(1-\phi_w)$ and remain without a job for the period. Non-employment can result in lower skills with probability p^d. The value of being non-employed at the end of the period, $J^{u,h}(a)$, is given by

$$J^{u,h}(a) = b + \frac{(1-\delta_w)}{1+r} J^u(a). \tag{4}$$

With probability ϕ_w the worker matches with a firm and takes a random draw from $\psi_v(z, \xi)$, the distribution of vacancies posted by firms with productivity z and training cost ξ, which is endogenously determined. When a worker and firm are matched and there is a positive surplus, then $\mathbf{1}^h(z, \xi, a) = 1$, and employment takes place. Otherwise, a match is not formed, and the worker stays non-employed. The function $J^{e,h}(z, \xi, a)$ is the end-of-period value of employment for a worker with skill a in a firm with productivity z and training costs ξ.

3.5.2 Value of Employment

The value of being employed at the beginning of the period in a firm with productivity z and training costs ξ for a worker with skill a is equal to:

$$J^e(z, \xi, a) = \mathbf{1}^h(z, \xi, a) J^{e,h}(z, \xi, a) + (1 - \mathbf{1}^h(z, \xi, a)) J^{u,h}(a). \tag{5}$$

If the surplus is positive, the value of employment is given by

$$\begin{aligned} J^{e,h}(z, \xi, a) &= w(z, \xi, a) + \frac{(1-\delta_w)}{1+r}(\delta_f + (1-\delta_f)\delta_s) J^{u,h}(a) \\ &+ \frac{(1-\delta_w)}{1+r}(1 - (\delta_f + (1-\delta_f)\delta_s))[p^h(z, \xi, a) J^e(z, \xi, a + \Delta_a) - (1 - p^h(z, \xi, a)) J^e(z, \xi, a)], \end{aligned}$$

Note that $p^h(z, \xi, a) = p^e + \mathbf{1}^t(z, \xi, a) p^t$ sums the probability of an improvement in a due to experience and training, where $\mathbf{1}^t(z, \xi, a)$ is an indicator function for job-training provision.

3.6 The Problem of the Firm

3.6.1 Value of an Active Match

Consider a match between a type-(z, ξ) firm and a worker with ability a. The value of this match for the firm at the beginning of the period is

$$V(z, \xi, a) = \mathbf{1}^h(z, \xi, a) V^h(z, \xi, a), \tag{6}$$

with

$$\begin{aligned} V^h(z, \xi, a) &= r(z, a) - w(z, \xi, a) \\ &+ \frac{1-\delta}{1+r}\left[-\mathbf{1}^t(z, \xi, a)\xi + p^h(z, \xi, a) V(z, \xi, a + \Delta_a) + (1 - p^h(z, \xi, a)) V(z, \xi, a)\right], \end{aligned}$$

and $\delta = \delta_w + (1-\delta_w)\delta_s + (1-\delta_w)(1-\delta_s)\delta_f$. A worker-firm match produces $r(z, a)$, as defined in equation (3), and the worker is paid $w(z, \xi, a)$, which is defined below. Next period, any active job can be destroyed due to death/retirement by the worker (δ_w), exogenous destruction of a particular job (δ_s), or exogenous destruction of the firm (δ_f). If the match is destroyed due to δ_w or δ_s, the firm keeps its remaining matches, while in case of exit, all the matches are destroyed and the firm disappears. An active job can also be destroyed endogenously if the value of the match is low enough and $\mathbf{1}^h(z, \xi, a) = 0$. Finally, if training takes place, i.e. $\mathbf{1}^t(z, \xi, a) = 1$, the firm incurs into a training cost, ξ.

3.6.2 Vacancy Posting

Firms choose the number of vacancies $v(z, \xi)$ to maximize the total value of new hires subject to convex costs, $c(v)$, given by

$$c(v) = \frac{v^{\lambda_1}}{\lambda_1}, \quad \lambda_1 > 1,$$

where λ_1 governs the degree of convexity in the cost function. In each period, the problem of a firm reads as follows:

$$\pi(z, \xi) = \max_{v(z,\xi) \geq 0} \quad v(z, \xi)\phi_f \int_{a \in \mathcal{A}} \mathbf{1}^h(z, \xi, a) V^h(z, \xi, a) \psi_a^u(a) da - c(v(z, \xi)), \tag{7}$$

where $\psi_a^u(a)$ is the endogenous probability density function of skills for unemployed workers. A firm posting $v(z, \xi)$ vacancies get in contact with $v(z, \xi)\phi_f$ unemployed workers. Each match with a positive surplus is valued as $V^h(z, \xi, a)$. The first order condition implies the following vacancy posting rule for a type-(z, ξ) firm

$$v(z, \xi) = \left(\phi_f \int_{a \in \mathcal{A}} \mathbf{1}^h(z, \xi, a) V^h(z, \xi, a) \psi_a^u(a) da \right)^{\frac{1}{\lambda_1 - 1}}.$$

The amount of new hires for a firm-(z, ξ) are then given by $v(z, \xi)\phi_f \int_{a \in \mathcal{A}} \mathbf{1}^h(z, \xi, a) \psi_a^u(a) da$.

3.6.3 Entry

In equilibrium, the measure of firms is determined by entry decisions. Each period, a fixed measure of potential entrants, N_e, draw a productivity z and a training costs ξ from two independent distributions, ψ_z, and ψ_ξ. Upon learning their type, firms decide to enter if they can cover the entry cost c^e, i.e., whenever

$$\Pi(z, \xi) \geq c^e. \tag{8}$$

The discounted sum of per-period profits is given by

$$\Pi(z, \xi) = \sum_{t=0}^{\infty} \left(\frac{1 - \delta_f}{1 + r} \right)^t \pi(z, \xi) = \frac{1 + r}{r + \delta_f} \pi(z, \xi), \tag{9}$$

where $\pi(z, \xi)$ is defined in equation (7). In an equilibrium with a positive measure of firms, there exist pairs of productivity and training costs (z^*, ξ^*) such that $\Pi(z^*, \xi^*) = c^e$. This defines a region in the space of (z, ξ) for firms that decide to enter.

3.7 The Surplus Function, Hiring, and Training

Because of search and matching frictions, each match has a potential surplus for workers and firms. The surplus, $S(z, \xi, a)$, can be written as

$$S(z, \xi, a) = \max\{0, S^h(z, \xi, a)\}, \tag{10}$$

with

$$\begin{aligned} S^h(z, \xi, a) &= r(z, a) + \frac{(1-\delta_w)}{1+r}(1-(1-\delta_f)(1-\delta_s))J^{u,h}(a) - J^{u,h}(a) \\ &+ \frac{(1-\delta)}{1+r}\left[-\mathbf{1}^t(z, \xi, a)\xi + (1-p^h(z, \xi, a))M(z, \xi, a) + p^h(z, \xi, a)M(z, \xi, a+\Delta_a)\right]. \end{aligned}$$

The function $M(z, \xi, a)$ denotes the joint match value at the beginning of the period, which is equal to the sum of the value of employment, $J^e(z, \xi, a)$, and the match value for the firm, $V(z, \xi, a)$, i.e.,

$$M(z, \xi, a) = J^e(z, \xi, a) + V(z, \xi, a) = S(z, \xi, a) + J^u(a). \tag{11}$$

We report the full derivation of these functions in Appendix B.1.

A match between a worker with skill $a \in \mathcal{A}$ and a firm with productivity $z \in \mathcal{Z}$ and training cost $\xi \in \mathcal{E}$ is formed upon contact (or kept alive if it already exists) as long as the match surplus is positive, i.e.

$$\mathbf{1}^h(z, \xi, a) = \begin{cases} 1 & \text{if} \quad S^h(z, \xi, a) > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{12}$$

where $S^h(z, \xi, a)$ is defined above.

Finally, each worker-firm pair decides to invest in training to maximize the joint value of the match, i.e.,

$$\mathbf{1}^t(z, \xi, a) = \arg\max_{\mathbf{1}^t \in \{0,1\}} \quad \mathbf{1}^t p^t[M(z, \xi, a+\Delta_a) - M(z, \xi, a)] - \mathbf{1}^t\xi, \tag{13}$$

where $M(z, \xi, a)$ is defined in equation (11), which implies that

$$\mathbf{1}^t(z, \xi, a) = \begin{cases} 1 & \text{if} \quad p^t[M(z, \xi, a+\Delta_a) - M(z, \xi, a)] > \xi \\ 0 & \text{otherwise.} \end{cases}$$

We assume firms cover the cost of training. This choice reflects the observation that firms often pay for general training, although it might not be optimal in this environment. Human capital accumulation increases the workers' future value of being employed elsewhere, and firms do not internalize this benefit. Still, in an environment with search frictions like ours, firms have incentives to provide general training - see Acemoglu and Pischke (1999) for a review of the literature and Fu (2011) for a recent model with search frictions and firm-sponsored general training.[7]

3.8 Wage Bargaining

Bargaining occurs not only at new matches but also at continuing ones, on a period-by-period basis. Employers and employees solve the following problem,

$$\max_{w(z,\xi,a)} \quad \left[J^{e,h}(z,\xi,a) - J^{u,h}(a)\right]^{\beta} V^{h}(z,\xi,a)^{1-\beta}, \tag{14}$$

where $\beta \in (0,1)$ is the workers' bargaining power. This implies wages $w(z,\xi,a)$ are chosen such the worker's surplus equals a β share of the match surplus, i.e.,

$$J^{e,h}(z,\xi,a) - J^{u,h}(a) = \beta S^{h}(z,\xi,a).$$

A definition of a recursive competitive equilibrium and the numerical algorithm to find a solution are described in Appendices B.2 and B.3.

4 Bringing the Model to the Data

We estimate the model parameters by matching a set of facts on firms and workers from the UK for the 2011-2018 period. The choice of the UK reflects two considerations: First, it is a high-income economy that we contrast with poorer economies in the counterfactuals. Second, the availability of data on firm- and worker-level job training allow us to identify parameters governing human capital accumulation due to experience and training.

We take the UK as a distortion-free economy and set ζ to zero. Moreover, we normalize the aggregate productivity shifter κ and the efficiency of the matching function χ to one.

[7] Incentives to invest in general human capital could increase if the matched pair could credibly commit to long term contracts, preventing workers from leaving the job at any moment and searching for better employers. However, this would reduce the efficiency gains obtained from workers moving to firms with higher productivity. See Flinn et al. (2017) for a discussion.

These three values should be interpreted as normalizations against which the counterfactual economies will be compared.

A few parameters are set directly to their data counterparts. The interest rate, r, is 0.0033 to match an annual return of 4%. On average, workers stay in the labor force for forty years, corresponding to ages 22 to 62, so δ_w is 0.0099. The firm destruction rate δ_f is chosen to match an annual firm exit rate of 10.5% [8] Finally, the parameter governing the elasticity of the matching function, η, is estimated externally using the generalized method of moments, by minimizing the distance between new matches formed according to the model's matching function (given data on vacancies, non-employed and self-employed workers) and the number of new hires in the data. The estimated value for η is 0.5416, with a standard error of 0.0134. Details of data, estimation, and sensitivity analysis following Andrews et al. (2017) are reported in Appendix C.

4.1 Estimated Parameters

The initial human capital of workers and productivity of firms are drawn from log-normal distributions, $a \sim \log\mathcal{N}(0, \sigma_a)$, with $\sigma_a > 0$, and $z \sim \log\mathcal{N}(0, \sigma_z)$, with $\sigma_z > 0$. The training costs come from a uniform distribution, given by $\xi \sim \mathcal{U}(\underline{\xi}, \overline{\xi})$, with $0 < \underline{\xi} < \overline{\xi}$. Given these parametric assumptions, there are 13 parameters to be estimated, collected in the following vector

$$\vartheta = \{c_e, \sigma_z, \underline{\xi}, \overline{\xi}, \lambda_1, N_e, \beta, \sigma_a, p^d, p^e, p^t, b, \delta_s\}.$$

These parameters are estimated using the method of simulated moments, with standard errors calculated following Chernozhukov and Hong (2003). Table 3 reports estimates and their standard errors.

The estimated values imply significant heterogeneity in training costs across firms; the maximum ($\overline{\xi}$) is about 15 times the minimum ($\underline{\xi}$). The average cost of training one worker equals 21% of the output produced by a worker-firm pair and 8% of the output produced by a pair undertaking training. Flinn et al. (2017) find workers spent 11% of their working time undertaking on-the-job training. Within their model, this corresponds to a comparable value for training cost, 11% of forgone worker-firm output. Large dispersion in training costs across firms is consistent with recent evidence provided by Almeida and Carneiro (2009) and Martins (2021).

[8] Data on firm exit rate come from Business Demographic Statistics of the Office for National Statistics (ONS) for 2011-2018.

Consistent with available estimates (see, among others, Merz and Yashiv (2007)), the hiring costs are highly convex, with $\lambda_1 = 2.525$. We estimate firm-productivity dispersion, σ_z, to 1.20, which implies a coefficient of variation for firm-level labor productivity of 1.38, consistent with the estimates reported by the ONS (Black et al., 2019).

We estimate workers' bargaining power to be 0.46, a value consistent with the estimates in Flinn (2006), which has a similar wage-setting mechanism for non-employed workers. Estimated values of p^e and p^d imply that for each period of employment, there is about 22% chance that workers' skills can jump by one level. In contrast, for each period of non-employment, they decline by one level with 43% probability. Using a similar process for human capital, Jarosch (2021) estimates a monthly probability of skill depreciation equal to 0.24 for the U.S., corresponding to a quarterly value of 55%. The training jumps skills by one level with a small probability, about 3%. Finally, the value of non-employment, b is about 22.5% of average earnings in the economy, while the entry costs, c_e is 19.9% of the per-capita income in the economy.

Table 3: Estimated parameters

Parameters	Description	Estimate	St.Error
c_e	Entry cost	39.26	3.665
σ_z	Firm-productivity dispersion	1.204	0.106
$\underline{\xi}$	Training cost (lower bound)	1.735	0.157
$\overline{\xi}$	Training cost (upper bound)	26.69	2.304
λ_1	Hiring costs, convexity	2.525	0.166
N_e	Measure of potential entrants	0.013	0.044
β	Workers' bargaining power	0.457	0.042
σ_a	Initial human capital dispersion	1.195	0.111
p^e	Experience jump	0.223	0.019
p^t	Training jump	0.028	0.003
p^d	Depreciation jump	0.432	0.040
b	Home production	20.94	1.824
δ_s	Match separation, %	1.235	0.120

Notes: The entries show the parameters estimated by the method of simulated moments. The standard errors are computed following Chernozhukov and Hong (2003).

4.2 Model Fit and Identification

The estimation uses 40 moments, reported in Table 4 and Figures 4 and 5. Overall, the model does remarkably well in fitting the data with an average log deviation of 0.086. The first column of Table 4 pertains to firm-level targets: i) average firm size, ii) mean and standard deviation of log employment, iii) fraction of firms that offer training by firm size, and iv) fraction of employees receiving training. The average firm in the data has about 16.4 employees, and the standard deviation of log employment is about 1.2. About 65% of firms offer training. The share increases sharply by firm size, 85% of firms with more than 250 employees offer training to their workers. Across all establishments, about 46% of employees receive training. The model matches all these targets and also generates a firm size distribution that is in line with the data (Figure 4).

Table 4: Selected Targeted Moments

	Data	Model		Data	Model
Firm-level employment			*Worker earnings distribution*		
Average firm size, $\mathrm{E}(\ell_t)$	16.42	16.19	Average earnings at entry, $\mathrm{E}[\log(w_1/\bar{w})]$	-0.518	-0.505
Average log-firm size, $\mathrm{E}(\log \ell_t)$	1.739	1.700	Average earnings after 20 y.o., $\mathrm{E}[\log(w_{20}/\bar{w})]$	0.107	0.109
Dispersion log-firm size, $\mathrm{std}(\log \ell_t)$	1.220	1.392	Average earnings at re-emp, $\mathrm{E}[\log(w_R/\bar{w})]$	-0.301	-0.170
			Earnings dispersion at entry, $\mathrm{sd}[\log w_1]$	0.582	0.675
Firm training provision			Earnings dispersion after 20 y.o., $\mathrm{sd}[\log w_{20}]$	0.796	0.795
$E\left(\frac{\#\textit{training firms}}{\#\textit{firms}}\right)$			Earnings dispersion at re-emp, $\mathrm{sd}[\log w_R]$	0.834	0.833
All firms	0.646	0.650			
Firms with 1-49 employees	0.611	0.644	*Worker-level training return*		
Firms with 20-249 employees	0.776	0.714	$\log w_{it} = \beta_1 \mathbf{1}^t_{it-1} + \epsilon_{it}$	0.199	0.208
Firms with 250+ employees	0.855	0.888			
			Aggregate moments		
$E\left(\frac{\#\textit{trained employees}}{\#\textit{employees}}\right)$			Job duration (years)	6.700	6.185
All firms	0.436	0.482	Employment rate	0.776	0.788

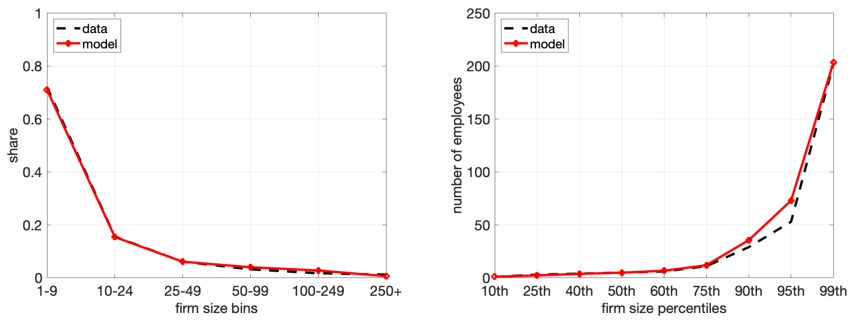
Notes: This table reports a set of firm-level and worker-level empirical moments used in the estimation, together with their model counterparts.

While the estimation does not provide with a one-to-one map between parameters and targets, specific targets have more impact on specific parameters in ϑ. In particular, the entry cost c_e determines the average firm size, while firm-productivity dispersion, σ_z, maps into dispersion in firm size. The convexity of the hiring costs, λ_1, is identified by the different percentiles of firm size distribution. Finally, the boundaries in the support of training costs, $\underline{\xi}$ and $\overline{\xi}$, are identified by the share of firms providing training and the number of workers trained within the firm for different firm sizes.

The second column of Table 4 presents a set of worker-level moments: i) earnings level and dispersion, conditional on labor market experience, and at re-employment after an unemployment spell, ii) returns to training, iii) returns to tenure, and iv) average job duration and the employment rate (the share of wage and salary earners in the population). The model does a great job matching the worker-level moments. Workers enter the labor market

Figure 4: Firm size distribution

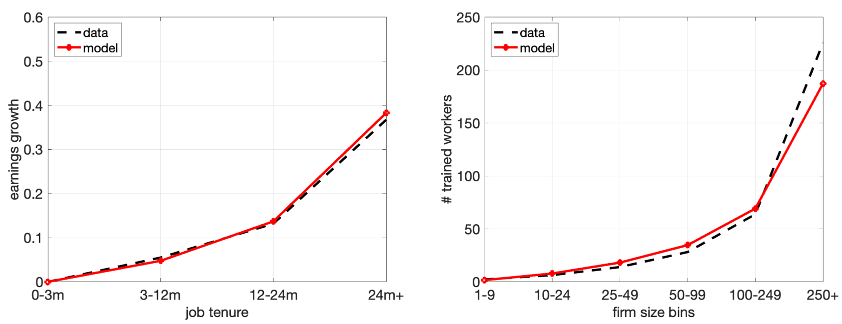
(a) Firm size distribution (b) Firm size percentiles



Notes: Panel (a) shows the share of firms in different firm-size bins. Panel (b) shows the average number of employees across different firm size percentiles.

Figure 5: Earnings profile and training provision

(a) Job tenure-earnings profiles (b) Trained workers over firm size



Notes: Panel (a) shows the average earnings for workers with different job tenures. Panel (b) shows the number of workers receiving training in firms of different sizes.

with earnings that are on average 50% below the mean, and after 20 years in the labor market, their earnings grow to 10% above the mean. After a non-employment spell, re-employed workers' earnings are lower than the mean, both in the data and in the model (although the model underestimates the decline). The dispersion of earnings is relatively small when workers enter the labor market, but as their labor market histories diverge, it increases by 20 log points higher after 20 years in the labor market. The returns to past training, calculated with a simple Mincerian regression in the data and the model, are large, about 20%. So are the returns to job tenure; workers with more than two years of job tenure earn almost 40% more than the entrants (panel (a) in Figure 5).

As far as the identification of different parameters is concerned, the exogenous separation rate, δ_s, determines the average job duration, about 6.7 years. Moreover, the measure of potential entrants N_e maps, given all other parameters, into a value wage and salary employment of about 78% of the population, through its effect on the aggregate vacancies posted and job finding probability, ϕ_w. The parameters governing how skills change during employment and non-employment, p^e and p^d, are disciplined by the earnings profile of workers, while the probability of skill accumulation due to training, p^t is identified by the earnings premium of training workers.[9] Finally, the distribution of the initial human capital, σ_a, and bargaining power for workers, β are identified, given all other parameters, by the dispersion of earnings at entry and along workers' life cycle.

Table 5: Non-targeted Moments

	Data	Model		Data	Model
Earnings-size regression			*Earnings inequality*		
<10 employees	0	0	Log-earnings dispersion, sd[log w_{it}]	0.779	0.852
$\in [10, 25)$ employees	0.151	0.183	Mean-median earnings ratio, E[w_{it}]/p^{50}[w_{it}]	1.276	1.207
$\in [25, 50)$ employees	0.244	0.342	90-50 pct. earnings ratio, p^{90}[w_{it}]/p^{50}[w_{it}]	2.410	2.551
$\in [50, 250)$ employees	0.407	0.680	50-10 pct. earnings ratio, p^{50}[w_{it}]/p^{10}[w_{it}]	2.938	5.262
≥250 employees	0.586	1.039			

Notes: The entries show a set of empirical moments not included in the estimation, together with their model counterparts.

4.2.1 Non-targeted Moments

Table 5 reports two sets of non-targeted moments: the relation between firm size and earnings and different moments of the earnings distribution. Standard search and matching models with large firms and concave production functions fail to generate a positive and large earnings-size premium - see Elsby and Michaels (2013) for a discussion. In contrast, the linearity in the production function allows the estimated model to deliver an earnings-size premium close to the one observed in the data.

The model also replicates well the observed earnings inequality in the UK. Two-sided heterogeneity, workers and firms, and human capital accumulation allow the model to match dispersion in log earnings and the mean to median earnings, even though we abstract from

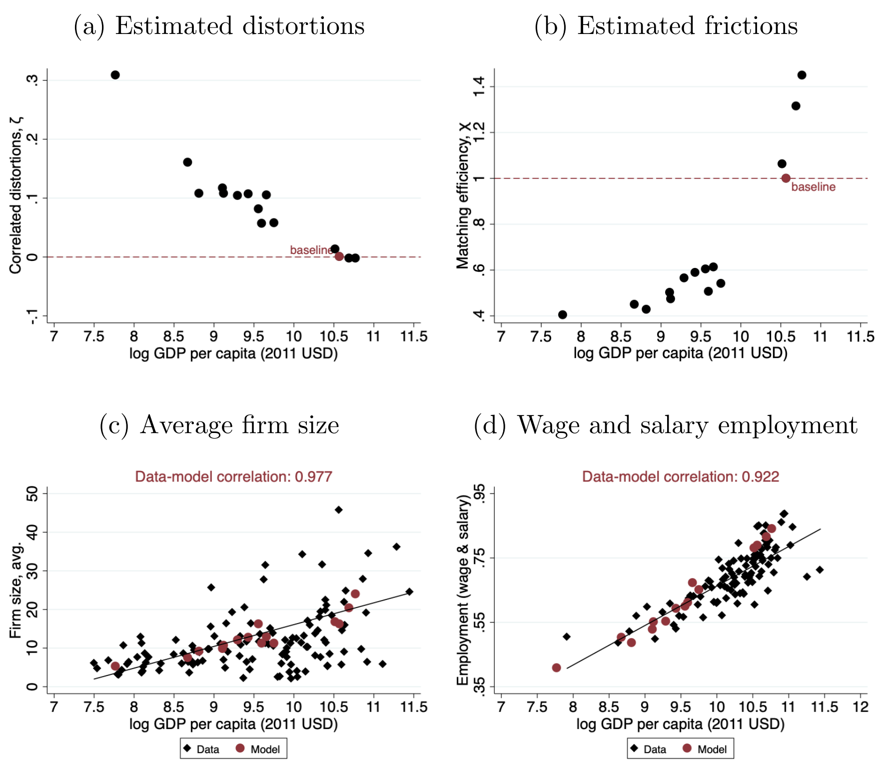
[9] There are 60 equally-spaced grid points for workers' human capital. Following Flinn et al. (2017) we set minimum and maximum human capital to -4 and 4 respectively so that given σ_a, the grid covers 99.9% of the estimated distribution. This makes the parameters p^e, p^t, and p^d interpretable as the probability of having an 8.5% increase (or decrease) in human capital.

the on-the-job search - see Hornstein et al. (2011) for a discussion.[10] On the other hand, while the model captures the magnitude of the dispersion in the upper tail of the earnings distribution very well, it generates a more left-skewed earnings distribution.

5 Cross-Country Facts, Revisited

We are now ready to interpret the cross-country facts documented in Section 2 through the lens of the model. To this end, we construct counterfactual economies that differ from the benchmark along two key features: size-dependent distortions, captured by the parameter ζ, and matching frictions captured by the parameter, χ. In Appendix D, we discuss how the data allows us to identify ζ and χ separately.

Figure 6: Distortions and matching frictions across countries



Notes: Panels (a) and (b) report the estimated counterfactual parameters, correlated distortions ζ, and matching efficiency, χ, for every targeted country. Panels (c) and (d) report cross-country moments targeted in the estimation of the counterfactual parameters, average firm size, and wage and salary employment, respectively.

[10] In absence of on-the-job search, on-the-job human capital accumulation operates similarly, as it provides a way for workers' earnings to grow on the job as in Burdett and Mortensen (1998) and Postel-Vinay and Robin (2002).

In the benchmark economy, ζ was set to zero, i.e., there were no size-dependent distortions, while the efficiency of the matching function χ was normalized to one. Keeping all other parameters fixed at their benchmark values, we search for values of ζ and χ that generate the average firm size and wage and salary employment observed in other countries. As a result, the counterfactual economies are replicas of the UK, except for differences in two key parameters that we focus on. We consider eight countries: Brazil, Georgia, Indonesia, Mexico, Peru, Poland, Serbia, and South Africa. We complement these eight countries with six representative economies to span the range of GDP per capita levels observed in the data. The representative economies have the average firm size and wage employment rate of countries with log GDP per capita in the following brackets: [8,9), [9,9.5), [9.5,10), [10,10.5), [10,5,11), [11,12). For each counterfactual economy, we adjust the value of home production b, so that it is about 22.5% of the average earnings, the value estimated in the baseline economy.

Figure 6 shows values of ζ and χ for each counterfactual economy, together with the targeted moments, average firm size, and wage employment. The range of calibrated values is quite wide, which is necessary to match the data. While ζ is zero for the UK, it is as high as 0.3 for the poorest counterfactual economy (Indonesia). As panel (a) in Figure 6 shows, ζ increases quickly for poorer countries. In particular, they increase substantially for countries with a log GDP per capita lower than 8.5 (about 3000 USD). Similarly, χ is as low as 0.4 in the poorest countries and increases sharply for countries that have larger wage and salary employment than the UK (panel b).

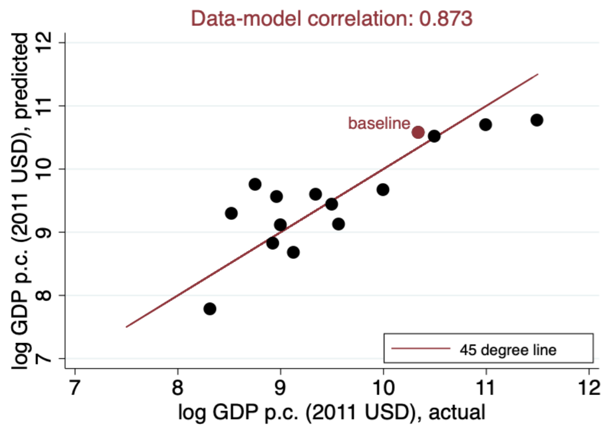
We do not directly target the GDP per capita in counterfactual economies. Yet, as illustrated in Figure 7, the model endogenously generates the levels of GDP per capita that are almost perfectly aligned with the data. This is achieved without exogenous productivity differences in aggregate productivity, which is normalized to one for all countries.

5.1 Workers and Firms around the World

We now have several economies that differ in average firm size, employment rate, and GDP per capita. Each of these economies also provides us with measures of earnings inequality that we can compare with the data. However, as a validation exercise, we first show that the counterfactual economies, differing in only ζ and χ, display several cross-country patterns that are remarkably consistent with the available evidence.

We start by looking at how earnings change along the life cycle. Panel (a) in Figure 8 shows earnings growth. The data, from Lagakos et al. (2018), is the earnings growth between

Figure 7: GDP p.c. across countries: Model vs. Data

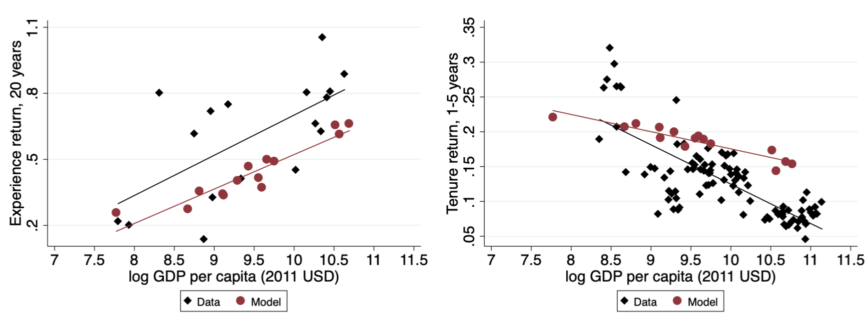


Notes: Each dot compares the observed GDP per capita for a targeted country against the value predicted by the model.

ages 22 (labor market entry) and 42. The model counterpart is the average earnings growth during the first 20 years of working life. In the data, age-earnings trajectories are much steeper in richer countries. In the model, frictions and distortions depress wage and salary employment, preventing workers from accumulating human capital and depressing wage growth as much as in the data.

Figure 8: Earnings profile across countries

(a) Life cycle earnings growth (b) Tenure return

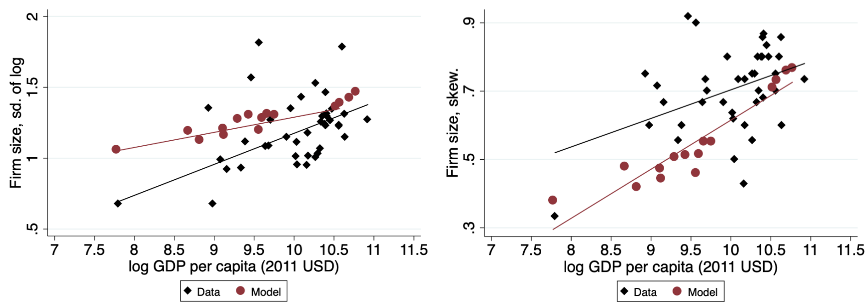


Notes: Panel (a) shows the earnings growth during the first 20 years of a worker's life cycle for countries with different log GDP per capita. Panel (b) shows the earnings growth during the first 5 years of job tenure. The black diamonds represent the data and the red dots the model.

Earnings grow much faster, however, during the initial years of job tenure in poorer countries. This is documented in panel (b) of Figure 8. The data, from Donovan et al. (2020), shows the average earnings for those between 1 and 5 years of tenure relative to those with less than 6 months of tenure. We calculate the same statistics in the model economy

Figure 9: Firm distribution across countries

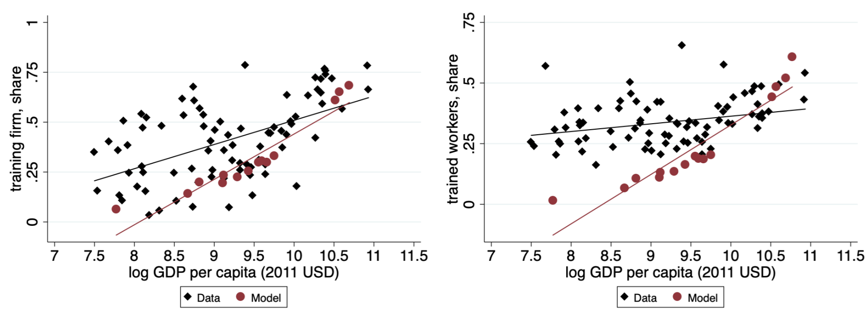
(a) Firm size dispersion (b) Firm size skewness



Notes: Panels (a) and (b) show how the dispersion (measured as the standard deviation of log size) and the skewness of firm-size distribution change with log GDP per capita. The black diamonds represent the data and the red dots the model.

Figure 10: Training provision across countries

(a) Share of training firms (b) Share of trained workers



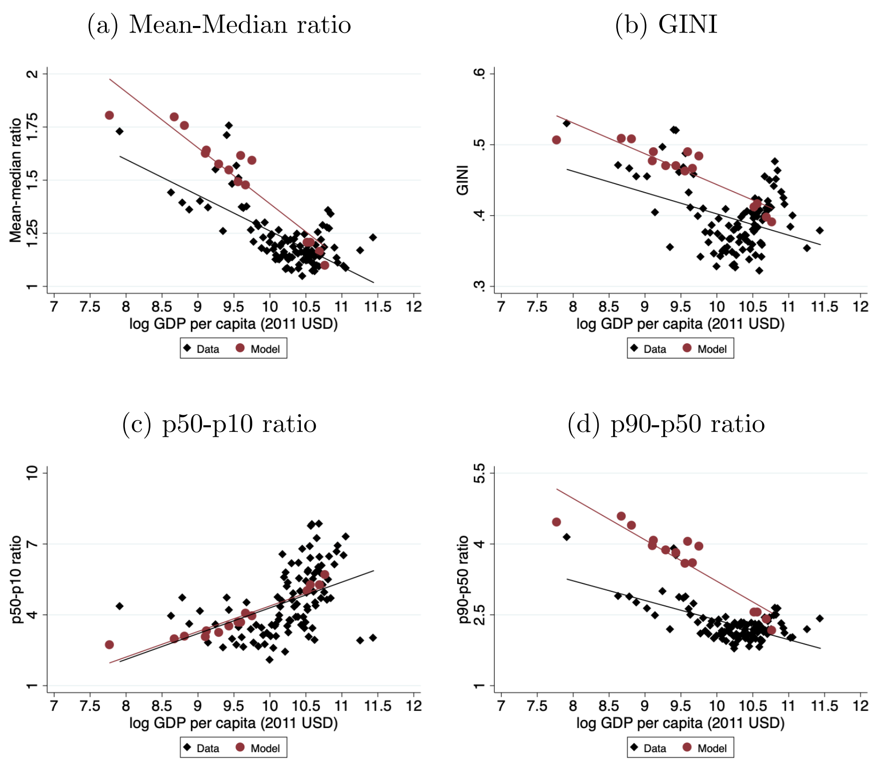
Notes: Panels (a) and (b) show how the share of firms that provide on-the-job training and the share of workers who received on-the-job training change with log GDP per capita. The black diamonds represent the data and the red dots the model.

and again the model predictions are in line with the data. Earnings increase sharply with tenure and do so more in poorer countries, where the share of wage and salary earners is significantly lower, and only the high-ability workers are able to find wage and salary jobs. On the other hand, workers in poorer countries spend longer time non-employed, and as a result, these gains do not translate into lifetime earnings growth. In contrast, workers are less likely to stay non-employed in richer countries, and despite their returns to tenure being lower, they experience higher earnings growth along the life cycle.

Figure 9 shows that dispersion and skewness of the firm size distribution are significantly higher in richer countries. The data, from Poschke (2018), shows the standard deviation of log firm size (panel a) and the 90/10 percentile skewness (panel b). The model is again in line with the data. In the model, distortions and frictions prevent firms from growing, squeezing the size distribution towards the left of the support, cutting the distribution's right tail, and reducing size dispersion. Moreover, distortions and frictions reduce the gains from training, which leads to a lower number of firms that offer training and to a lower share of trained workers within each firm, as documented in Section 2. Figure 10 shows that the model can also account for these cross-country patterns.

Finally, we look at how earnings inequality changes with economic development (Figure 11). As in the data, the mean-to-median ratio and the Gini index declines with GDP per capita. But while the p50-p10 ratio increases sharply, the p90-p50 ratio declines. The workers at the bottom of the earnings distribution are not able to catch up with the median workers, but the median workers are getting closer to those at the top. Hence, just by re-calibrating two parameters (χ and ζ), the model does a great job replicating how earnings inequality changes with higher GDP per capita.

Figure 11: Earnings inequality across countries: Model vs. Data



Notes: Each panel shows how a particular measure of earnings inequality changes with log GDP per capita across countries. The black diamonds represent the data and the red dots the model.

5.2 Results in Perspective

Our strategy to generate the observed cross-country patterns of inequality, firm size distribution, and life-cycle earnings profiles relies only on cross-country differences in correlated distortions and matching efficiency, χ and ζ. Differences in correlated distortions and lower matching efficiencies generate GDP per capita differences, even if we keep the aggregate productivity parameter κ at its baseline (UK) level. The results in the previous section show that this strategy is very successful. As discussed in the next section, it is also transparent and allows us to highlight the mechanisms in the model that generate cross-country patterns in earnings inequality.

In this section, we consider alternative strategies that can generate cross-country differences in employment, the average firm size, and GDP per capita. We show that they fail quantitatively along several dimensions. We also show that allowing more parameters, not just χ and ζ, to differ across countries so as to match a broader set of moments does not add much to the quantitative analysis. To keep the discussion compact, we only compare the benchmark economy (UK) with Indonesia, which has one-tenth of the UK's GDP per capita (4,095 USD vs. 39,000 USD). The results are presented in Tables 15 and 16 in Appendix E.

Uncorrelated distortions. We first consider distortions that are uncorrelated with firm productivity. Suppose each firm retains a fraction $(1-\bar{\tau})z^{-\zeta}$ of its output, where $\bar{\tau}$ is the same across producers. In the baseline economy (reproduced as column (1) in Table 15), we assume that both $\bar{\tau}$ and ζ are zero. Then, we allow ζ to vary across countries (column 2). In column (3) of Table 15, we fix $\zeta = 0$ and choose $\bar{\tau}$ to match the GDP per capita of Indonesia (χ is chosen to match the wage and salary employment and b is adjusted to be 22.5% of the average earning). The estimated distortion amounts to $\bar{\tau} = 53.4\%$. This experiment delivers the observed patterns in inequality, i.e., changes in the 90-50 and the 50-10 ratios align with what we obtain in the baseline results. However, the average firm size generated for Indonesia is more than twice what we observe in the data (8.9 vs. 4.2 employees). Furthermore, the share of firms providing training is much higher (40.1% vs. 6.2%).

Aggregate productivity. Next, we focus on the role of aggregate productivity. We calibrate the productivity shifter κ to match the GDP per capita of Indonesia (recall that this parameter is set to one in the benchmark). Then we multiply home production b, training costs, $\underline{\xi}$ and $\overline{\xi}$, and entry costs c_e by the same factor. All the other parameters are kept at their UK level, so there are no distortions, and the matching is as efficient in Indonesia as it is in the UK. The results are in column (4) of Table 15. Changes in aggregate productivity alone can't generate the observed decline in average firm size, wage employment, training provision, and life-cycle earnings growth. Furthermore, changes in inequality are much more muted than what we observe in the data.

Labor Market Frictions - Worker separation. Can our results be generated by other frictions in the labor market (other than matching efficiency)? Donovan et al. (2020) document that worker separation rates decline with GDP per capita. To study this potential channel, we conduct an alternative experiment where we calibrate δ_s to match the average job tenure of 3.3 years in Indonesia (Marinescu and Triyana (2016), Table 1). As in the baseline case, we re-calibrate ζ to match the average firm size. Recall that in the benchmark (UK), δ_s was estimated to be 1.235% per month, and the average job tenure was 6.2 years. All the other parameters are kept at their UK level, except for home production b, which is adjusted to be the same fraction of the average wage. The outcomes are in column (5) of Table 15. With a higher separation rate, the employment rate and GDP per capita decline significantly, as they do in our baseline results. However, while an increase in separation rate can qualitatively account for inequality patterns observed over development, quantitatively, changes in the mean-to-median ratio, the GINI, and the 90-50 ratio are much smaller compared to the baseline results. Moreover, this strategy fails to generate the observed decline in life-cycle earnings growth (from 80.1% to 61.4% rather than 21.6%).

Distortions - Firm turnover. Next, we focus on differences in firm exit rate, δ_f, as an alternative force that might generate smaller firms in poorer countries. Bartelsman et al. (2009) show that firms' turnover declines with GDP per capita. We study this channel by calibrating δ_f so that the yearly firms' exit rate in Indonesia is equal to 13.66% (Hallward-Driemeier and Rijkers (2013), Table 1, for 2001). We re-calibrate χ to match the wage and salary employment rate in Indonesia (and b is again adjusted). The firm exit rate in the UK is 10.5% per year. This approach successfully generates the observed patterns of inequality in Indonesia. However, it cannot capture the very small firm size or the fraction of firms offering training observed in the data.

Recalibrating More Paramaters. Finally, in Table 16, we present an alternative counterfactual where many more parameters are re-calibrated to match different targets for Indonesia. In particular, together with matching efficiency, χ, and correlated distortion, ζ, we re-estimate the aggregate productivity shifter, κ to match the GDP per capita, the experience probability jump, p^e to match the life-cycle wage growth after 20 years, and the training probability jump, p^t to match the share of firms providing training. Moreover, we adjust the values of home production, b, the boundaries for training costs, $\underline{\xi}$ and $\bar{\xi}$, and the entry cost c_e such that they are equal to the value estimated in the baseline economy, as

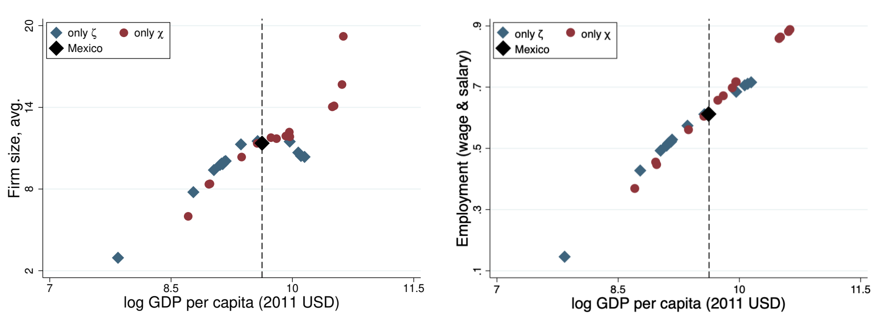
% of average earnings. Two messages emerge. First, despite allowing multiple parameters to change, the estimated matching efficiency in Indonesia, χ, is still significantly lower than in the U.K. (0.382 vs. 1) while the correlation in distortions, ζ, is positive and large (0.252 vs. 0). Second, changes in earnings inequality in the main counterfactual (column 2), with differences in only χ and ζ, are very close to what we obtain from this alternative counterfactual.

6 Frictions vs Distortions

How does the model generate these cross-country patterns? We answer this question by first discussing the relative importance of correlated distortions and matching frictions. To this end, we consider a country in the middle of the GDP per capita distribution, Mexico (the GDP per capita of Mexico is 11,400 USD vs. 39,000 USD of the UK). Then, for each counterfactual economy in Section 5, we either impose the calibrated values of distortions, ζ, or frictions, χ, from Figure 6. If we impose the calibrated value of ζ for a country, we keep the value of non-employment, b, and χ at their calibrated values for Mexico. If instead, the calibrated value of χ is imposed, b and ζ are kept at their values for Mexico. As a result, starting from Mexico, we increase or decrease the GDP per capita due to changes in ζ or χ alone.

Figure 12: Firm size and employment across countries: distortions vs. frictions

(a) Average firm size (b) Wage and salary employment

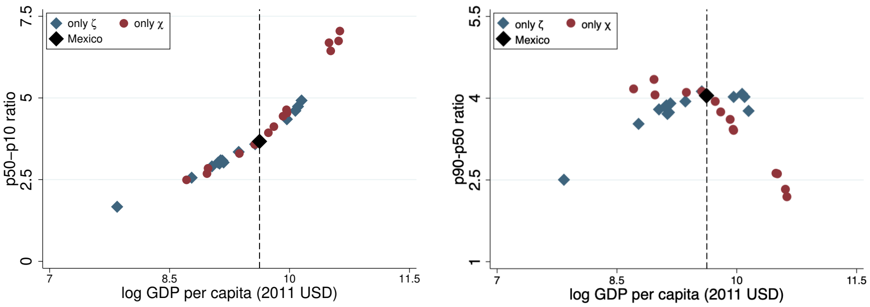


Notes: Panel (a) and (b) shows the average firm size and the share of wage and salary workers across countries when only χ (red dots) or ζ (blue diamonds) are allowed to change, while the other parameters are fixed at Mexico's value.

Figure 12 shows the average firm size (panel a) and wage and salary employment (panel b) when either correlated distortions (blue diamonds) or search frictions (red dots) are allowed to change across countries. Either correlated distortions, ζ, or matching frictions, χ, alone

Figure 13: Earnings inequality across countries: distortions vs. frictions

(a) p50-p10 ratio (b) p90-p50 ratio



Notes: Panel (a) and (b) shows the p50-10 and p90-p50 earnings ratios when only χ (red dots) or ζ (blue diamonds) are allowed to change, while the other parameter is fixed at Mexico's value.

can generate a positive correlation between GDP per capita and both average firm size and wage and salary employment. Yet, their impact differs markedly depending on whether we look at poorer or richer countries than Mexico.

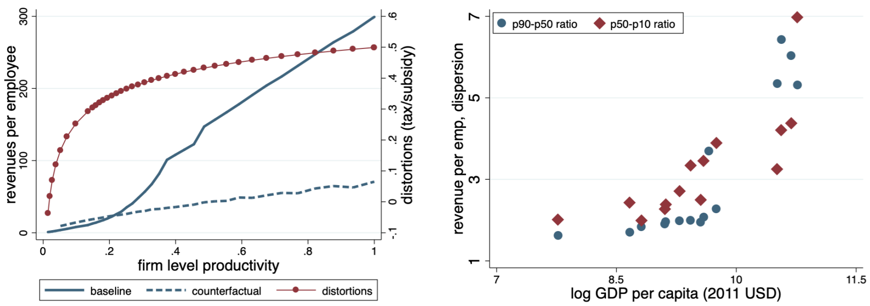
While search frictions are quantitatively more important in richer countries, correlated distortions are necessary to generate observed patterns in poorer ones. Consider, for example, panel (a) of Figure 12. A reduction in correlated distortions alone can only account for changes in firm size for countries poorer than Mexico. Indeed, there is very little change in the average firm size as we move to countries with a lower ζ. In contrast, lower search frictions generate a larger average firm size in richer countries, but they cannot quantitatively account for changes in firm size observed in very low-income countries. Both search frictions and correlated distortions are necessary to generate variation in firm size and employment across the entire spectrum of GDP per capita. The same argument applies to changes in employment rate, reported in Figure 12, panel (b).[11]

What about earnings inequality? Start with the role of correlated distortions. Changes in ζ alone generate a positive relationship between GDP per capita and inequality at both ends of the earnings distribution. Both the p50-p10 and p90-p50 ratios increase with GDP per capita (blue diamonds in Figure 13). Search frictions instead affect the distribution of earnings asymmetrically. As matching in the labor market becomes more efficient, GDP per capita increases. But while earnings become more dispersed at the bottom and the p50-p10

[11]Note that for high levels of GDP per capita, the relation between GDP per capita and firm size becomes flat or can even be slightly negative. This is due to general equilibrium effects. A low ζ encourages entry and, because of matching frictions, the probability of filling a vacancy reduces and firm growth can slow down.

Figure 14: Firm-level revenues per employee

(a) UK versus Indonesia (b) Cross-country



Notes: The red dots in Panel (a) shows the correlated distortions in Indonesia (left axis). The solid and dashed-blue lines show revenue per worker in the benchmark (UK) and counterfactual (Indonesia), respectively. Panel (b) shows p90-p50 (blue dots) and p50-p10 (red diamonds) ratios for the revenue-per-worker distribution.

ratio rises, they become less dispersed at the top, and the p90-p50 ratio drops (red dots in Figure 13).

6.1 Mechanisms

Why is this happening? We shed light on this by focusing on three key determinants of earnings inequality in the model: i) how revenues are distributed across firms with different productivity levels, ii) how long it takes for workers to match with a firm (non-employment duration), and iii) sorting between workers and firms. We do that by comparing again the UK with Indonesia. The calibrated values of ζ and χ for Indonesia are 0.312 (versus 0 in the UK) and 0.403 (versus 1 in the UK).

Distribution of firm-level revenues. The first channel operates through changes in the distribution of firm-level revenues. Panel (a) in Figure 14 shows the average distortions, τ, faced by firms of different productivity levels z in Indonesia (red dots). Recall that the implicit tax rate, τ, is zero in the baseline economy. In Indonesia, implicit taxes on firms' output increase sharply with firm productivity. The employment-weighted average tax rate is around 51% in Indonesia and the tax rate increases from 30% for firms with less than 10 workers to 50% for those with more than 25 employees.

Panel (a) of Figure 14 also reports the average revenues per employee in the UK and Indonesia (blue lines). A higher value of ζ implies more progressive output taxes, which reduce the difference between productive and unproductive firms, making them more similar as potential employees to workers in Indonesia. Notice that in the UK, a firm in the top 10% of the productivity distribution has about 7 times higher revenues per employee than the median firm. A firm with median productivity, in turn, has about 5 times higher revenue per worker than a firm at the bottom 10%. As we move to poorer countries, these differences shrink significantly. Panel (b) in Figure 14 compares revenue per worker for firms at different points of the revenue-per-worker distribution. Both p50-p10 (red diamonds) and p90-p10 (blue circles) increase with the GDP per capita. The earnings distribution mirrors the distribution of revenue per employee. As a result, both p50-p10 and p90-p50 earnings ratios also increase as we move from countries with higher to lower distortions (blue diamonds in Figure 13).

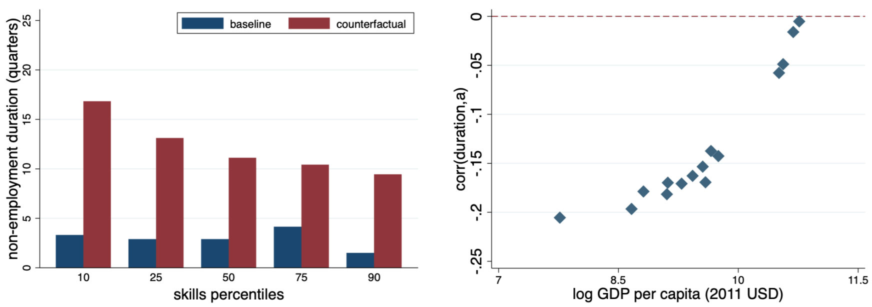
Non-employment duration. Let's now turn to the second channel, which operates through changes in non-employment duration across workers. Panel (a) in Figure 15 shows the average non-employment duration for workers of different skills at the time of re-employment in the benchmark (UK) and the counterfactual (Indonesia). In the UK, re-employed workers have spent on average 3 quarters before transiting from non-employment to employment. Moreover, duration is only slightly lower for workers with higher skills. Non-employment spells are much longer in Indonesia, about 11 quarters for the average re-employed worker. Furthermore, the average spells decline significantly by workers' skills. Hence, as a country gets richer, non-employment duration shrinks and becomes more uniform across re-employed workers with different skills. The decline is most significant for workers with low skills: higher labor market efficiency prevents skill depreciation during non-employment and this effect is stronger for low-ability workers because it allows them to stay attached to the labor market.

Panel (b) in Figure 15 shows the correlation between the skills of the re-employed workers and their non-employment duration across countries. The correlation is always negative: more skilled workers get out of non-employment faster. But the correlation is stronger in the poorest countries, it increases monotonically with GDP per capita, and it is almost zero in the richest countries. In the model, non-employment duration decreases as frictions in the labor market are removed, and the decline is stronger for low-skilled workers. This effect implies more employment opportunities and higher human capital accumulation for the low-skilled, resulting in compression in the distribution of skills and lower earnings inequality.

Worker-firm sorting. Finally, Figure 16 describes the sorting between firms and workers. In panel (a), the horizontal axis ranks workers again by their skills while the vertical axis shows the average productivity of firms that employ these workers. Workers at the bottom

Figure 15: Non-employment duration

(a) UK versus Indonesia (b) Cross-country

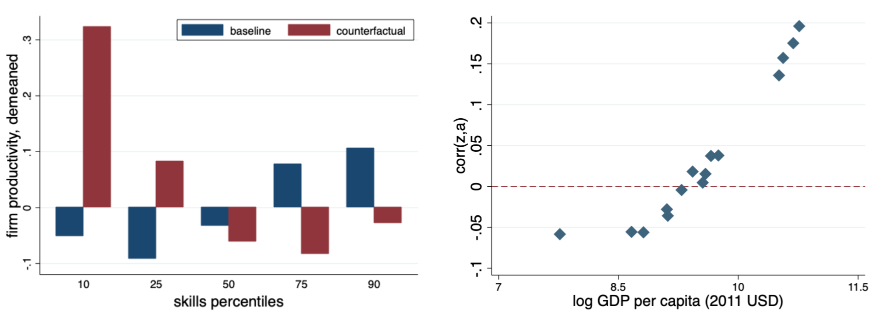


Notes: Panel (a) shows non-employment duration in the benchmark (UK) and counterfactual (Indonesia) for workers in different percentiles of the skill distribution. Panel (b) shows the correlation between GDP per capita and non-employment duration across countries in the model.

of the skill distribution in the benchmark economy are employed by firms with about 10% lower productivity than the average firm in the economy (blue bars in panel a). As workers become more productive, so do their employers, generating positive assortative matching. This is not the case in the counterfactual (red bars in panel a). Low-skill workers are matched to high-productivity firms, and a high-productivity firm does not necessarily have a more skilled workforce, resulting in negative assortative matching.

Figure 16: Sorting

(a) UK versus Indonesia (b) Cross-country



Notes: Panel (a) shows the level of firm productivity, measured as log deviations from the overall mean, for workers in different percentiles of the skill distribution for the benchmark (UK) and counterfactual (Indonesia). Panel (b) shows the correlation between firm productivity (z) and their workers' skills (a) across countries in the model.

Stronger labor market frictions make it costly for high-ability workers to wait for better employers, and they end up accepting any job they can find. It takes about 3.5 quarters for a vacancy to encounter a potential hire in the UK. In Indonesia, a firm has to wait on average 5.6 quarters. Panel (b) in Figure 16 shows the correlation between workers' skills, a, and the productivity of their employers, z, for each counterfactual economy. The correlation is negative for the poorest countries, increases monotonically with GDP per capita, and eventually becomes positive as frictions and distortions vanish. This effect on sorting increases earning inequality.

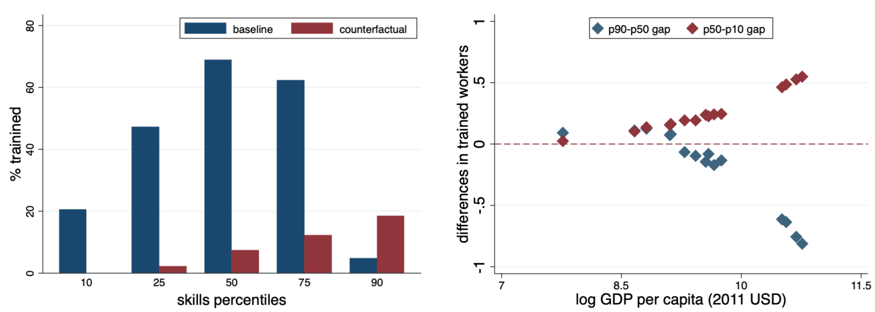
A more fluid labor market increases firm-worker sorting and reduces non-employment spells. The former favors workers who are more skilled, and who reap the benefits from matching with high-productivity firms. The latter is relatively stronger for less skilled workers, who progressively populate employment and accumulate human capital as GDP per capita increases. In the simulations, the net effect is a distribution of skills with a much larger mass in the middle, generating an increase in the p50-p10 earnings ratio and a reduction in the p90-p50 earnings ratio along with development (red dots in Figure 13).

6.2 Role of Training

What is the role of OTJ training in the model? Panel (a) in Figure 17 shows the fraction of workers who receive training in the model economy, conditional on their skills.

Figure 17: Training

(a) UK versus Indonesia (b) Cross-country



Notes: Panel (a) shows the fraction of workers receiving on-the-job training in the benchmark (UK) and counterfactual (Indonesia) for workers in different percentiles of the skill distribution. Panel (b) shows the differences between the shares receiving training for workers who are at the 90th versus the 50th percentile (blue diamonds) and the 50th versus the 10th percentile (red diamonds) of the skill distribution.

In the benchmark (UK), workers in the middle of skill distribution are more likely to receive training than those at the bottom or the top. Firms do not have strong incentives to train low-skilled workers since productivity gains can't always cover the cost of training. On the other hand, training improves the matching opportunities of all workers; in particular, of the high-skilled ones. As a result, their outside options significantly improve, reducing gains from training these workers.

In a poor country, training provision shrinks dramatically. Training reduction mainly affects workers in the middle of the skill distribution. On the other hand, the intensity of training is now increasing in workers' skills. Low-skilled workers receive less training since it is even harder for the firm to cover its cost. But with stronger labor market frictions, workers have no incentives to leave the firm. As a result, firms have now larger incentives to invest heavily in their skilled workers.

Panel (b) in Figure 17 illustrates how the share of workers who receive training varies with GDP per capita. We compare the share of workers with median skills with those at the bottom (p10) and the top (p90). Relative to the lower-skilled ones, the share of trained workers with median skills increases with GDP per capita: median-skilled workers are more likely to get training than low-skilled workers. In contrast, the share of high-skilled workers who receive training relative to the median-skilled ones declines. These cross-country differences in training are reflected in how the p50-p10 and p90-p50 earnings ratios change with development.

How much does OTJ training account for the cross-country patterns of inequality? To quantify it, we re-calibrate the baseline economy (UK) without training, i.e., we set $p^t = 0$ so that no one receives training. The re-calibration uses the same targets in Tables 4, except the ones on training. The moments and parameter estimates are reported in Appendix F. Columns (1) and (3) in Table 6 show the baseline economy with and without training. We then move to Indonesia, i.e., impose $\chi = 0.403$ and $\zeta = 0.308$. Columns (2) and (4) in Table 6 report the counterfactual results with and without training.

A comparison between Columns (1) and (2) versus (3) and (4) shows that changes in inequality are more muted. When we allow for OTJ training, the mean-median earnings ratio declines from 1.81 in Indonesia to 1.21 in the UK. Without training, the decline is from 1.67 to 1.28. Hence, training accounts for about 35% of the total change. Similarly, the difference in the Gini coefficient is also smaller. The Gini declined by 9 percentage points for the benchmark calibration, while without on-the-job training, the decline is about 7 percentage points. Training also magnifies changes in p90-p50 and p50-p10 ratios.

In Appendix G, we also report outcomes from an alternative experiment where we exogenously impose training decisions from the counterfactual economy (Indonesia) on UK firms. With this experiment, we find that endogenous training decisions account for about 11% of changes in the mean-to-median ratio and the Gini coefficient.

Table 6: A World without OJT Training

	Baseline	Counterfactual	Baseline	Counterfactual	Explained
	with OTJ training		w/o OTJ training		
	(1)	(2)	(3)	(4)	
Matching friction: χ	1	0.403	1	0.403	-
Distortion correlation: ζ	0	0.308	0	0.308	-
Home production: b	20.94	3.505	20.94	3.505	-
		Aggregates			
Employment rate	0.788	0.407	0.797	0.561	38.05%
Average earnings	1	0.124	1	0.140	1.84%
Income per capita	1	0.061	1	0.086	2.69%
		Earnings profile over experience/tenure			
Earnings growth, $\mathrm{E}[\log(w_{25}/\bar{w}_1)]$	0.801	0.280	0.731	0.363	29.45%
		Earnings inequality			
Mean-median ratio, $\mathrm{E}[w_{it}]/\mathrm{p}^{50}[w_{it}]$	1.207	1.805	1.280	1.667	35.13%
GINI	0.416	0.506	0.416	0.487	20.99%
90-50 pct. ratio, $\mathrm{p}^{90}[w_{it}]/\mathrm{p}^{50}[w_{it}]$	2.551	4.462	2.815	3.990	33.87%
50-10 pct. ratio, $\mathrm{p}^{50}[w_{it}]/\mathrm{p}^{10}[w_{it}]$	5.262	2.729	4.118	2.854	58.51%

Notes: The entries in columns (1) and (2) show the benchmark (UK) and the counterfactual (Indonesia). The entries in columns (3) and (4) show the benchmark (UK) and the counterfactual (Indonesia) when there is no on-the-job training. The last column shows the ratio of differences between (3) and (4) compared with (1) and (2).

7 A Re-training Program

We next assess the value of a re-training program for unemployed workers. Until recently, the accepted view on the active labor programs, e.g., vocational training, wage subsidies, or job search assistance, was that they had little impact on employment or earnings (see reviews by McKenzie (2017) and Card et al. (2018)). Alfonsi et al. (2020) show, however, that an intensive intervention in Uganda aimed at providing unemployed young workers with vocational or firm-sponsored training increased both employment and wages significantly.[12] The vocational training arm of their randomized control trial (RCT) provides unemployed young workers, between ages 18 and 25, with a six-month, fully-subsidized, sector-specific training. Motivated by their design, we introduce a fully subsidized re-training program available for all non-employed workers in the model, scaling up their program to the entire economy.

[12] Attanasio et al. (2011) evaluate a program that combines vocational and firm-provided training in Colombia and find significant effects on employment and earnings for women, but not for men.

We assume that non-employed workers have the option of either searching for a job or participating in a re-training program and postponing their search. Compared to those who choose to search for jobs, re-trained workers do not face any skill depreciation. Instead, because of re-training, their skills can increase with probability p^t. The other features of the model are kept the same. We report details in Appendix H.

Table 7 compares benchmark (the UK, column 1) and counterfactual outcomes. Column (2) is Indonesia without a re-training program, while column (3) shows the outcomes for Indonesia with the re-training program. We calibrate the cost of re-training following Alfonsi et al. (2020). They report a training cost of 470 USD per participant in a six-month-long training session in Uganda. Using their costs as a fraction of GDP per capita, training a worker for a model period of a quarter should cost 1024 USD in Indonesia. The program is fully subsidized and financed by a lump sum tax on everyone (employed and non-employed).

Table 7: Re-training program

	UK	Indonesia	
	Baseline	Counterfactual	
	(1)	(2)	(3)
Re-training under non-employment	no	no	yes
Cost per re-trained individual:	-	-	1024 USD
Re-trained workers			
$\text{E}\left(\frac{\#\text{re-trained workers}}{\#\text{non-employed workers}}\right)$, %	0	0	43.07
Aggregates			
Employment rate	0.788	0.407	0.529
Average earnings	1	0.124	0.140
Income per capita	1	0.061	0.095
Income per capita (net of re-training costs)	1	0.061	0.070
Earnings profile over experience			
Earnings growth, $\text{E}[\log(w_{25}/\bar{w}_1)]$	0.801	0.280	0.329
Earnings inequality			
Mean-median ratio, $\text{E}[w_{it}]/\text{p}^{50}[w_{it}]$	1.207	1.805	1.787
GINI	0.416	0.506	0.500

Notes: The entries in columns (1) and (2) show the benchmark (UK) and the counterfactual (Indonesia). The entries in column (3) show the counterfactual economy with a re-training program.

Not every non-employed workers choose to receive training, even if it is fully subsidized. But the re-training is popular; more than 40% of non-employed workers participate in the program.[13] Figure 23 in Appendix H reports the probability of choosing to re-train by non-employment duration (panel a) and pre-non-employment earnings (panel b). Workers who have just lost their jobs prefer to search since their human capital remains relatively intact.

As the unemployment duration increases and workers' human capital depreciates, they are more likely to re-train instead of looking for a job. On the other hand, workers with low pre-non-employment earnings, hence low human capital, are more likely to opt for a re-training program, while those with high pre non–employment earnings are more likely to look for jobs. These patterns endogenously replicate the sample selection implemented in the RCT of Alfonsi et al. (2020). Compared to labor-market active workers, the targeted sample in their RCT is worse off in terms of labor-market outcomes at baseline. The selected workers were less likely to have any wage employment in the week prior and had on average lower total earnings from wage employment in the previous month (see Table A.II in their Appendix). This suggests that the incentives provided by this program within our model are able to scale up the sample restriction in the RCT to the entire economy.

How valuable is the re-training program? It increases employment opportunities significantly since there are substantial gains in human capital accumulation for the participants; recall that p^t, the probability of a one-step jump in a with training is about 2.8% per month while p^d, the likelihood of a one-step decline in a is more than 40%. As a result, re-training opportunities increase employment from 41% to 53% (excluding re-trained workers). With better employment opportunities, average earnings, and income per capita increase significantly. After considering the program's cost, income per capita is around 15% higher (0.061 vs. 0.070). Not surprisingly, the re-training program also implies a 5 percentage point steeper age-earnings profile for workers (and a lower mean-to-median earnings ratio).

8 Conclusion

A growing literature in macroeconomics has been emphasizing how the misallocation of resources at the micro-level can generate aggregate income and productivity differences. This literature has been built around the idea of distortions, either modeled as explicit policies or implicit taxes on firms' production decisions. If correlated with firms' productivity, distortions result in smaller firms on average and lower incomes. However, this literature has been silent on how misallocation might affect earnings distribution since distortions often are

[13] Alfonsi et al. (2020) report that 68% of workers assigned to vocational training starts the program. It is reassuring that our take-up rate is lower since their program targets disadvantaged youth.

embedded within competitive labor markets. Yet, there is growing evidence that firm-level drivers are fundamental to understanding earnings inequality.

Search and matching models provide a natural framework for studying firm-level earnings inequality drivers. In these models, labor market frictions determine how workers are matched with firms and affect firms' and workers' incentives to invest in their skills. Yet, search and matching models often focus on workers with one-firm abstraction and do not necessarily speak to cross-country differences in firm dynamics.

We combine these two approaches to study how misallocation affects earnings inequality. The benchmark economy speaks to a large set of facts on firms (size distribution, size-earnings profiles, and size-training decisions) and workers (age-earning and tenure-earnings profiles, and training provision). The model also delivers a natural framework to study how the distribution of earnings changes with economic development. In the data, the dispersion of earnings at the bottom increases with development, and it declines at the top. We show that the model replicates this pattern when poorer countries are characterized by higher correlated distortions and labor market frictions.

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Online Appendix

A Data

A.1 Earnings inequality

We use data from three different sources: the IPUMS-International, the EU Statistics on Income and Living Conditions (EU-SILC), and the Luxembourg Income Study Database (LIS) datasets. In all three sources, the sample is restricted to individuals between 18 and 64 who are not students. Table 8 provides a list of countries, years, and sources.

IPUMS-International. IPUMS provides harmonized census microdata for a large set of countries. Details on sampling and stratification design and harmonization of variables across countries can be in https://international.ipums.org/international/. The surveys identify whether or not a respondent was working over a specified period of time (variable "EMPSTAT"). When this is missing, we use the information on the average number of hours worked per week, in total (variable "HRSWORK1") or in the main job (variable "HRSMAIN"), and define a person as employed if she reports a positive number of hours worked in at least one of these variables. To distinguish between employees and self-employed workers, we use the variable "INCWAGE", which records the respondent's weekly, monthly, or annual wage and salary income. We annualize weekly or monthly wage and salary income estimates by multiplying them by 52 or 12 respectively. The final sample includes all individuals with non-missing information on employment and wage and salary income. We consider anyone with strictly positive wage and salary income as an employee.

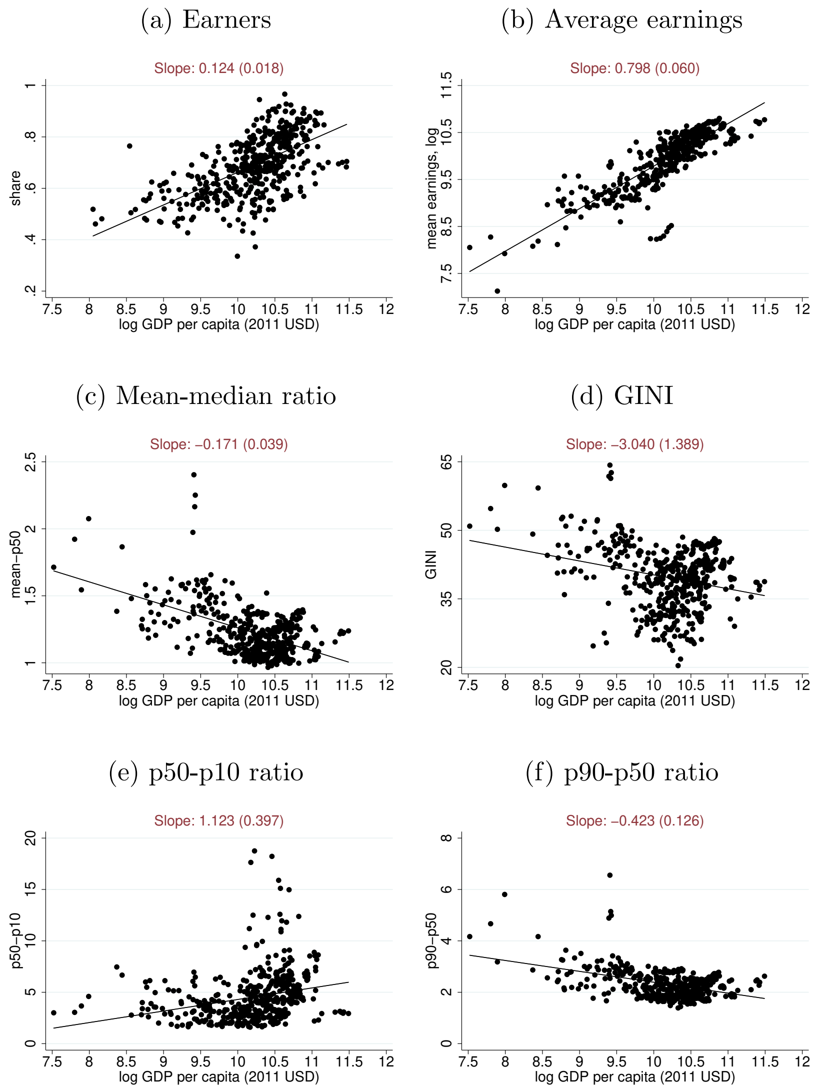
The EU Statistics on Income and Living Conditions (EU-SILC) database. EU-SILC collects comparable cross-sectional microdata on income and other living conditions of households in European Union countries. Details are provided in https://ec.europa.eu/eurostat/web/microdata/statistics-on-income-and-living-conditions. For each household member, the survey collects information on several demographic characteristics - age, gender, marital status, citizenship and head of households - education attainment, and labor market outcomes. The survey uses self-declared current labor market status to distinguish working and non-working individuals (variable PL040). Employee income is defined as the total cash remuneration payable by an employer to an employee in return for work done by the latter during the income reference period, typically the calendar year prior to the survey date (variable PY010G). The sample includes all individuals with non-missing information on employment status and employee income and defines earners as anyone with a strictly positive employee income. The self-declared main activity status is determined on the basis of whether the interviewed performs any work for pay or profit during the reference week or if he/she was not working but had a job or business from which he/she was absent during the reference week. Employees are defined as persons who work for a public or private employer and who receive compensation in the form of wages, salaries, fees, gratuities, payment by results, or payment in kind; non-conscripted members of the armed forces are also included. Apprentices or trainees receiving remuneration are considered employees. Self-employed persons are defined as persons who work in their own business, professional practice, or farm for the purpose of earning a profit, while family workers are persons who help another member of the family-run an agricultural holding or other business, provided they are not considered as employees.

We do not consider any non-monetary salary income components. The income reference period for most of the countries is the calendar year previous to the survey year with two exceptions. In Ireland, the income reference period is the last twelve months, whereas in the United Kingdom, the current income is annualized and aims to refer to the current calendar year, i.e. weekly estimates are multiplied by 52, monthly by 12. Reimbursements for work-related expenses, severance and termination pay, and employers' social insurance contributions are excluded from employee income.

The Luxembourg Income Study Database (LIS). LIS collects and harmonizes household and person-level micro-data for about 50 countries in Europe, North America, Latin America, Africa, Asia, and Australia, spanning five decades. Besides basic demographics, this dataset provides information on employment, labor and capital income, social benefits, private transfers, taxes, and social security contributions. More information about sample and stratification is reported at www.lisdatacenter.org/our-data/lis-database. The dataset identifies the labor market status (employed, unemployed or inactive) of the surveyed individual (variable "lfs": labour force status). If this information is missing, we use the information on the average number of hours worked per week (variable "hourstot": total weekly hours worked), or the number of weeks worked per year (variable "weeks": annual weeks worked), and define a person as employed if she reports a positive number of hours or weeks worked. Conditional on being employed, we distinguish whether the surveyed individual is employed as a salaried worker or not in his main job using the variable "status1" (status in employment, main job). For these individuals, we compute a measure of annual wage and salary earnings using the variable ”pi11” (Wage income, annual), which includes any monetary payments received from regular and irregular dependent employment, i.e., cash wage and salary income (gross of social security contributions and income taxes) and monetary supplements to the basic wage, such as overtime pay, employer bonuses, 13th-month bonus, profit-share, tips.

Summary statistics. In Figure 18 we report the raw shares of earners, raw average earnings, and raw measures of earnings inequality for each country-year pair.

Figure 18: Earners and earnings across countries, raw data



Notes: Each dot corresponds to country-year data points. In red we report the estimated slope in the regression. Standard errors (in parenthesis) are robust and clustered at country level. Source: IPUMS, EU-SILC, LIS, and author’s calculations.

Table 8: Data source

Country	Year	Source
Australia	1981, 1985, 1989, 1995, 2001, 2003, 2004, 2008, 2010, 2014	LIS
Austria	1994, 1997, 2000, 2004, 2005, 2007, 2010, 2013, 2016	EU-SILC, LIS
Belgium	1995, 1997, 2000, 2003-216	EU-SILC, LIS
Bulgaria	2007, 2009	EU-SILC
Brazil	2006, 2009, 2011, 2013, 2016	LIS
Canada	1981, 1987, 1991, 1994, 1997, 1998, 2004, 2007, 2010, 2012-2016	LIS
Chile	1990, 1992, 1994, 1996, 1998, 2000, 2003, 2006, 2009, 2011, 2013, 2015	LIS
China	2002, 2013	LIS
Colombia	2004, 2007, 2010, 2013, 2016	LIS
Croatia	2010	EU-SILC
Cyprus	2005, 2010	EU-SILC
Czech republic	1992, 1996, 2002, 2004, 2006, 2007, 2009, 2010, 2013, 2016	EU-SILC, LIS
Denmark	1987, 1992, 1995, 2000, 2004, 2005, 2007, 2009, 2010, 2013, 2016	EU-SILC, LIS
Dominican Republic	1981, 2007	IPUMS, LIS
Egypt	2012	LIS
Estonia	2004, 2005, 2007, 2010, 2013, 2016	EU-SILC, LIS
Finland	1987, 1991, 1995, 2000, 2004, 2005, 2007, 2009, 2010, 2013, 2016	EU-SILC, LIS
France	1978, 1984, 1989, 1994, 2000, 2005, 2010	EU-SILC, LIS
Germany	1973, 1978, 1981, 1983, 1984, 1987, 1989, 1991, 1994, 1995, 1998, 2000-2016	EU-SILC, LIS
Georgia	2010, 2013, 2016	LIS
Greece	1995, 2000, 2004, 2005, 2007, 2009, 2010, 2013, 2016	EU-SILC, LIS
Guatemala	2006, 2011, 2014	LIS
Hungary	1991, 1994, 1999, 2005-2007, 2009, 2010, 2012, 2015	EU-SILC, LIS
Iceland	2004, 2005, 2007, 2010	EU-SILC , LIS
Israel	1979, 1986, 1992, 1995, 1997, 2001-2016	IPUMS, LIS
Italy	1986, 1987, 1989, 1991, 1993, 1995, 1998, 2000, 2004, 2005, 2008-2010, 2014	EU-SILC, LIS
India	1993, 1999, 2004, 2011	IPUMS, LIS
Indonesia	1976, 1995	IPUMS
Ireland	1994-1996, 2000, 2002-2013	EU-SILC, LIS
Jamaica	1981, 1991, 2001	IPUMS
Japan	2008, 2010, 2013	LIS
Latvia	2006, 2010	EU-SILC
Lithuania	2006, 2009-2016	EU-SILC, LIS
Luxembourg	1985, 1991, 1994, 1997, 2000, 2004, 2005, 2007, 2010, 2013	EU-SILC, LIS
Malta	2007, 2010	EU-SILC
Mexico	1984, 1989, 1992, 1994, 1996, 1998, 2000, 2002, 2004, 2008, 2010, 2012, 2014, 2016	LIS
Netherlands	1983, 1987, 1990, 1993, 1999, 2004, 2006, 2007, 2010, 2013	EU-SILC, LIS
Norway	1979, 1986, 1991, 1995, 2000, 2004, 2005, 2007, 2010, 2013, 2016	EU-SILC, LIS
Panama	2007, 2010, 2013, 2016	IPUMS, LIS
Peru	2004, 2007, 2010, 2013, 2016	LIS
Poland	1986, 1992, 1995, 2004, 2005, 2007, 2009, 2010, 2013, 2016	EU-SILC, LIS
Portugal	2005, 2010	EU-SILC
Puerto Rico	1990, 2000, 2005	IPUMS
Paraguay	2000, 2004, 2007, 2010, 2013, 2016	LIS
Romania	2007, 2009	EU-SILC
Russia	2000, 2004, 2007, 2010, 2011, 2013-2016	LIS
Serbia	2006, 2010, 2013, 2016	LIS
Slovakia	1992, 2004, 2006, 2007, 2009, 2010, 2013, 2014-2016	EU-SILC, LIS
Slovenia	1997, 1999, 2004, 2006, 2007, 2009, 2010, 2012, 2015	EU-SILC, LIS
Spain	1980, 1990, 1995, 2000, 2004, 2005, 2007, 2009, 2010, 2013, 2016	EU-SILC, LIS
Sweden	1975, 1981, 1987, 1992, 1995, 2000, 2005, 2009	EU-SILC, LIS
Switzerland	1982, 1992, 2006-2016	EU-SILC, LIS
Trinidad and Tobago	2000	IPUMS
USA	1974, 1979, 1980, 1986, 1990-2016	IPUMS, LIS
Uruguay	2004, 2006, 2007, 2010, 2013, 2016	IPUMS, LIS
United Kingdom	1974, 1979, 1986, 1991, 1994-2016	EU-SILC, LIS
South Africa	2008, 2010, 2012, 2015	LIS

A.2 Cross-country heterogeneity

In Table 9 we report the outcomes of the following regression:

$$y_{it} = \alpha + \mu_t + \beta \log \text{GDP p.c.}_{it} + \gamma X_{it} + \epsilon_{it}$$

where y_{it} are various measures of earnings inequality for country i at time t, μ_t are time fixed-effects and X_{it} are various controls, including average years of schooling, women's labor force participation rate, the share of self-employment, shares of agricultural and industrial employment, the average number of hours worked per year, aggregate capital stock and the value of trade as a share of GDP.

Table 9: Earnings inequality across countries

	Mean-median ratio			GINI		
	(1)	(2)	(3)	(1)	(2)	(3)
log GDP p.c.	-0.171***	-0.189***	-0.229***	-3.040**	-3.346**	-4.551*
	(0.0386)	(0.0429)	(0.0549)	(1.389)	(1.493)	(2.603)
Observations	497	497	420	497	497	420
R-squared	0.286	0.420	0.690	0.067	0.194	0.499
Time FE		✓	✓		✓	✓
Controls			✓			✓

	p50-p10 ratio			p90-p50 ratio		
	(1)	(2)	(3)	(1)	(2)	(3)
log GDP p.c.	1.123***	1.248***	1.797***	-0.423***	-0.469***	-0.570***
	(0.397)	(0.440)	(0.437)	(0.126)	(0.136)	(0.203)
Observations	497	497	420	497	497	420
R-squared	0.069	0.136	0.308	0.201	0.323	0.557
Time FE		✓	✓		✓	✓
Controls			✓			✓

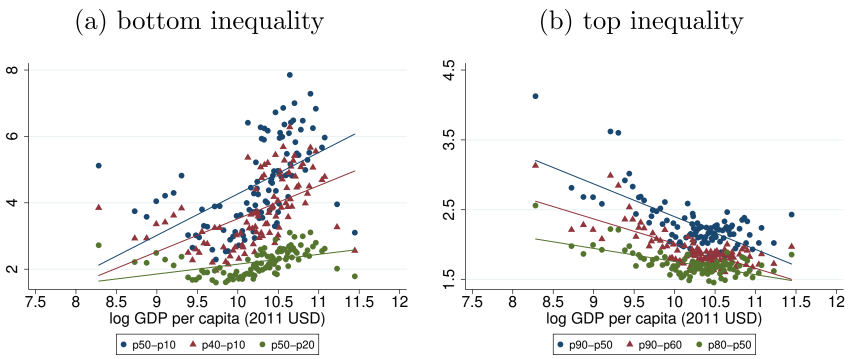
Notes: GDP p.c. is expressed in 2011 USD. Controls include the average years of schooling (Penn-Word), women's labor force participation rate (World Bank), the share of self-employment (World Bank), shares of agricultural and industrial employment (World Bank), the average number of hours worked per year (Penn-Word), aggregate capital stock (Penn-Word), and the value of trade as a share of GDP (World Bank). Standard errors are robust and clustered at country level. *** p<0.01, ** p<0.05, * p<0.1

Conditional on time-fixed effects and a full set of controls, moving to a country with twice GDP p.c. is associated with a lower mean-to-median earnings ratio (-0.23 points) and a lower GINI (-4.55 points), with a higher bottom earnings inequality (+1.80 points) and a lower top earnings inequality (-0.57 points).

A.3 Alternative cut-offs.

In Figure 19 we report alternative measures of the bottom (the p40-p10 and p50-p20 earnings ratios) and the top (the p90-p60 and p80-p50) earnings ratios.

Figure 19: Earnings inequality across countries



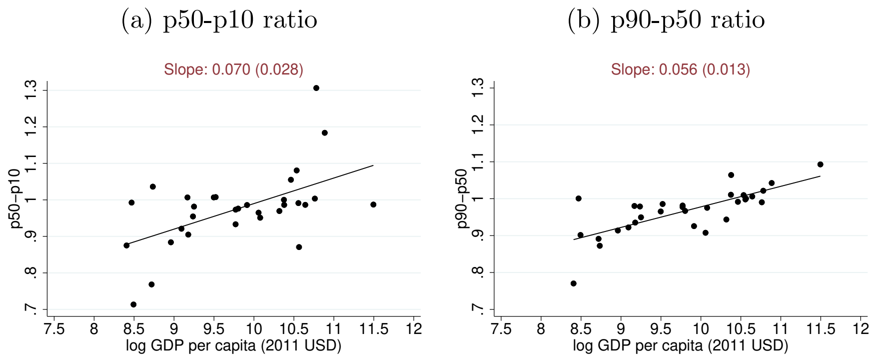
Notes: Each dot corresponds to the average outcome for countries in a given percentile of the GDP per capita distribution. Outcomes are reported as residuals (rescaled by the constant) from a regression with year-fixed effects. Source: IPUMS, EU-SILC, LIS, and author's calculations.

Regardless of the cut-offs chosen, earnings inequality at the bottom always increases with GDP per capita while earnings inequality at the top declines (though with different magnitudes).

A.4 Hours worked across countries.

In Figure 20 we report how the distribution of hours worked changes with GDP per capita. The data is taken from Bick et al. (2018) and it refers to weekly hours worked by wage and salary employees. Panel a in Figure 20 scatters the 50-to-10 ratio, whereas panel b reports the 90-to-50 ratio in weekly hours worked. Both ratios increase with GDP per capita. As we move from low to high GDP per capita countries, wage and salary workers at the top of the distribution increase their hours by about 20% relative to those in the middle, and by about 40% relative to those who are at the bottom. However, compared to the observed changes in earnings distribution (see Figure 2 in the main text) the magnitude of changes in hours dispersion is significantly smaller. Moreover, we document that the 90-to-50 ratio in earnings declines with GDP per capita, so it is unlikely that hours can account for both bottom and top earnings inequality.

Figure 20: Hours worked across countries



Notes: Each dot corresponds to the average outcome for countries in a given percentile of the GDP per capita distribution. Outcomes are reported as residuals (rescaled by the constant) from a regression with year-fixed effects. In red we report the estimated slope in the regression. Standard errors (in parenthesis) are robust and clustered at country level. Source: Bick et al. (2018) and author's calculations.

A.5 On-the-job Training

The World-Bank Enterprise Survey (WB-ES) is a firm-level survey of a representative sample of an economy's private sector. It is a cross-sectional survey and targets formal (registered) companies with 5 or more employees, operating in the manufacturing and services sectors. For more details about the sampling methodology, see https://www.enterprisesurveys.org/en/methodology. For each firm, the dataset records demographic information (age, region of operation, ownership status), number of employees, annual sales, and annual wage bills (firm-level average wage is constructed using wage bill divided by the number of employees). The survey also provides different measures of training provision: 1) whether a firm has provided training to all or some of its workforce, and 2) the share of the workforce who received training in a given year. To construct our main empirical evidence, we use the March-04-2019 survey release. This version of the survey covers firms in 139 countries surveyed during the period 2006-2018. We remove countries lacking information on firm-level training or countries where the firm-level number of employees or wage bills are either missing or inconsistent with the aggregate indicators reported by the World Bank. We remove also Sweden (which is instead included in the Eurostat CVTS dataset). This leaves us with 122 countries: Afghanistan, Albania, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, Bahamas, Bangladesh, Barbados, Belarus, Belize, Bhutan, Bolivia, Bosnia-Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Cape-Verde, Central African Republic, Chad, Chile, China, Colombia, Congo, Costa Rica, Cote d'Ivoire, Croatia, Czech Republic, D.R.C., Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Eritrea, Estonia, Eswatini, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana ,Grenada, Guatemala, Guinea, Guinea Bissau, Guyana, Honduras, Hungary, India, Indonesia, Iraq, Israel, Jamaica, Jordan, Kazakhstan, Kenya, Kosovo, Kyrgyzistan, Lao P.D.R., Latvia, Lebanon, Liberia, Lithuania, Macedonia, Madagascar, Malaysia, Mali, Mauritius, Mexico, Micronesia, Moldova, Mongolia, Montenegro, Morocco, Myanmar, Namibia, Nicaragua, Nigeria, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Romania, Russia, Samoa, Serbia, Sierra Leone, Slovakia, Slovenia, Solomon Islands, South Africa, South Sudan, Sri Lanka, St.Kitts and Nevis, St.Lucia, St,Vincent and Grenadines,, Tanzania, Tonga, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, Uruguay, Uzbekistan, Vanuatu, Vietnam, West-Bank, Yemen, Zambia and Zimbabwe.

The Continuing Vocational Training Survey (CVTS) is a firm-level survey that covers a representative sample of formal enterprises with 10 or more employees in 27 EU countries plus Norway, North Macedonia, and the United Kingdom, for the years 2005, 2010 and 2015. Besides demographic information, the survey includes information about the firm-level provision of on-the-job vocational training and the share of employees participating in vocational training for each firm. To construct our main empirical evidence, we use the aggregate statistics reported by the Eurostat, available here. Statistics are constructed for the overall sample and broken by firm size categories.

We merge the WB-ES and the CVTS with information on GDP per capita and population from the World Bank Indicators. GDP per capita is expressed in constant 2011 USD. Finally, we use the World Bank PPP deflator to convert firm-level average wages from local currency units to current international dollars.

A.5.1 Further empirical evidence on job training

Using the WB-ES, we can measure the share of trained workers in firm i as

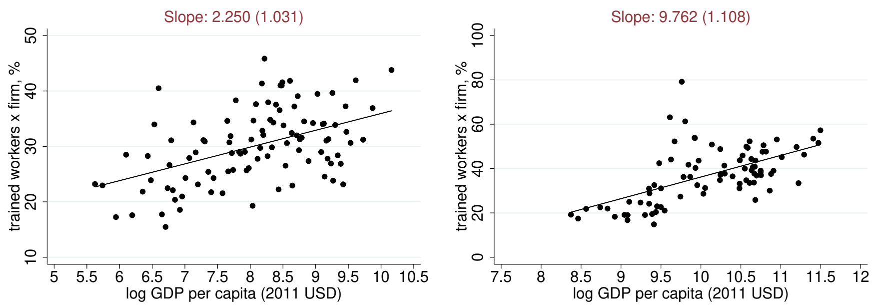
$$\text{trained-workers}_{it} = \mathbf{1}_{it}^{\text{training}} \frac{\%\text{permanent full-time workers trained}_{it}}{100}$$

The Eurostat reports this variable constructed using data from the CVTS. Figures 21 (a) and (b) show the average share of workers within each firm receiving formal job training. In both figures, the measure of training provision is scattered over the country-average real GDP per capita. The correlation between the share of workers trained and the country's log GDP per capita is between 0.49 for more developed countries and 0.57 for developing countries. The slope coefficient from a regression of the average share of workers trained

Figure 21: Training provision across countries

(a) World Bank Enterprise Survey

(b) Continuing Vocational Training Survey



Notes: Each dot corresponds to the average outcome for countries in a given percentile of the GDP per capita distribution. Outcomes are reported as residuals (rescaled by the constant) from a regression with year-fixed effects. In red we report the estimated slope in the regression. Robust standard errors are in parenthesis. Source: World-Bank Enterprise Survey and Eurostat Education and Training Dataset.

within each country and log GDP per capita is around 0.11 for developing countries, and 0.08 for more developed countries, and is statistically significant at the five percent level in both cases. These coefficients imply that one log point higher GDP per capita is associated with about 10% percent more workers receiving training. Table 10 reports the share of trained workers by firm size. In both data sets, larger firms provide training to a larger set of their workforce.

Table 10: Job training across firm size

	Trained workers within firms, %						
	WB-ES					CVTS	
	LAC	ME+AFR	ASIA	others		EU15	non-EU15
Firm size (# employees)					Firm size (# employees)		
<20	34.36	21.01	27.95	29.63			
20-49	40.06	25.56	29.72	30.18	<50	29.31	21.96
50-249	44.35	26.68	35.51	30.36	50-249	37.92	30.13
250-449	52.51	30.30	32.22	28.86	≥250	49.71	46.25
≥500	50.73	32.37	34.34	28.98			

Notes: Each entry denotes the average share of workers (in percent) receiving training within firms reporting to provide training, separately for firms with different sizes (number of employees), and different groups of countries. Source: World-Bank Enterprise Survey (WB-ES) and Eurostat Education and Training Dataset (CVTS).

B Model

B.1 The Surplus function, Hiring and Training decisions

Each match has a potential surplus, $S(z, \xi, a)$, given by

$$S(z, \xi, a) = M(z, \xi, a) - J^{u,h}(a), \tag{15}$$

where $M(z, \xi, a)$ denotes the joint match value at the beginning of the period, equal to the sum of the value of employment $J^e(z, \xi, a)$ and the match value for the firm $V(z, \xi, a)$,

$$\begin{aligned} M(z, \xi, a) &= J^e(z, \xi, a) + V(z, \xi, a) \\ &= \mathbf{1}^h(z, \xi, a)[J^{e,h}(z, \xi, a) + V^h(z, \xi, a)] + (1 - \mathbf{1}^h(z, \xi, a))J^{u,h}(a). \end{aligned}$$

Using equations (5) and (6), $M(z, \xi, a)$ can be express using the following recursive formulation

$$M(z, \xi, a) = \mathbf{1}^h(z, \xi, a)M^h(z, \xi, a) + (1 - \mathbf{1}^h(z, \xi, a))J^{u,h}(a) \tag{16}$$

where $M^h(z, \xi, a)$ is the match value at the end of the period, defined as

$$M^h(z, \xi, a) = r(z, a) + \frac{(1 - \delta_w)}{1 + r}(1 - (1 - \delta_f)(1 - \delta_s))J^{u,h}(a) +$$
$$\frac{(1 - \delta_w)}{1 + r}(1 - \delta_f)(1 - \delta_s)\left[-\mathbf{1}^t(z, \xi, a)\xi + (1 - p^h(z, \xi, a))M(z, \xi, a) + p^h(z, \xi, a)M(z, \xi, a + \Delta_a)\right]$$

Combining equations (17) and (4), we can write the surplus function as

$$S(z, \xi, a) = \max\{0, S^h(z, \xi, a)\} \tag{17}$$

where $S^h(z, \xi, a)$ is the difference between the value of an active match and the value of being non-employed, i.e.

$$S^h(z, \xi, a) = M^h(z, \xi, a) - J^{u,h}(a). \tag{18}$$

or equivalently

$$S^h(z, \xi, a) = r(z, a) + \frac{(1 - \delta_w)}{1 + r}(1 - (1 - \delta_f)(1 - \delta_s))J^{u,h}(a) - J^{u,h}(a) +$$
$$\frac{(1 - \delta_w)}{1 + r}(1 - \delta_f)(1 - \delta_s)\left[-\mathbf{1}^t(z, \xi, a)\xi + (1 - p^h(z, \xi, a))M(z, \xi, a) + p^h(z, \xi, a)M(z, \xi, a + \Delta_a)\right].$$

A match between a worker with skill $a \in \mathcal{A}$ and a firm with productivity $z \in \mathcal{Z}$ and training cost $\xi \in \mathcal{E}$ is formed upon contact (or kept alive if it already exists) as long as the match surplus is positive, i.e.

$$\mathbf{1}^t(z, \xi, a) = \arg\max_{\mathbf{1}^t \in \{0,1\}} \quad \mathbf{1}^t p^t[M(z, \xi, a + \Delta_a) - M(z, \xi, a)] - \mathbf{1}^t \xi,$$

where $M(z, \xi, a)$ is defined in equation (16), which implies the following indicator function for training provision:

$$\mathbf{1}^t(z, \xi, a) = \begin{cases} 1 & \text{if} \quad p^t[M(z, \xi, a + \Delta_a) - M(z, \xi, a)] > \xi \\ 0 & \text{otherwise.} \end{cases}$$

B.2 Equilibrium

A stationary recursive competitive equilibrium for this economy consists of workers' value functions for employment and unemployment, firms' value functions for active jobs, policy functions for job creation, training, entry and vacancies posted, wage schedule, job contact probabilities for workers and firms, unemployment rate, distribution of employed and unemployed workers across states, distribution of open vacancies and firms across states, such that:

1. *optimality*: the value functions attain their maximum;
2. *bargaining*: the wage schedule is the solution of the problem (14);
3. *training*: training decision is the solution of the problem (13);
4. *market clearing*: goods and labor market are cleared;
5. *measure of entrants*: for all Borel sets $\mathcal{Z} \times \mathcal{E} \subset \mathcal{R}^+ \times \mathcal{R}^+$ it must be that

   $$N(\mathcal{Z} \times \mathcal{E}) = N_e \int_{z \in \mathcal{Z}} \int_{\xi \in \mathcal{E}} \mathbf{1}^e(z, \xi) \psi_z(z) \psi_\xi(\xi) dz d\xi$$

   where $\mathbf{1}^e(z, \xi)$ is the solution to the problem of potential entrant (8).

6. *measure of incumbent*: for all Borel sets $\mathcal{Z} \times \mathcal{E} \subset \mathcal{R}^+ \times \mathcal{R}^+$ it must be that

   $$N^*(\mathcal{Z} \times \mathcal{E}) = \frac{1}{\delta_f} N(\mathcal{Z} \times \mathcal{E})$$

7. *aggregate consistency*: workers′ and vacancies′ distributions replicate themselves through workers′ and firms′ policy functions.

B.3 Solution algorithm

To compute the value functions, we discretize the state space using 50 equally-spaced grid points for firm productivity, 20 equally-spaced grid points for firm-specific training costs, and

60 equally-spaced grid points for workers' human capital. While we directly estimate the boundaries for training costs, we fix minimum and maximum (log) productivity and (log) human capital to -4 and 4 respectively, covering 99.9% of both calibrated distributions.[14]

To find an equilibrium, we employ the following algorithm:

1. Formulate a guess for the labor market tightness, θ^0. Use the definition of the matching function to compute the workers' job contact rate, $\phi_w^0 = \chi(1 + (\theta^0)^{-\eta})^{-\frac{1}{\eta}}$, and job contact rate for firms, $\phi_f^0 = \chi(1 + (\theta^0)^{\eta})^{-\frac{1}{\eta}}$.

2. Formulate a guess for the distribution of vacancies, $\psi_v^0(z, \xi)$

   2.1. Given ϕ_w^0 and $\psi_v^0(z, \xi)$, solve for the surplus function, $S^h(z, \xi, a)$.

   2.2. Obtain the policy functions for job creation, $\mathbf{1}^h(z, \xi, a)$ and on-the-job training $\mathbf{1}^t(z, \xi, a)$

   2.3. Use ϕ_w^0, $\psi_v^0(z, \xi)$, $\mathbf{1}^h(z, \xi, a)$ and $\mathbf{1}^t(z, \xi, a)$ to simulate a large panel of workers and construct a distribution of non-employed workers over human capital, $\psi_a^u(a)$, and the aggregate measure of workers who are non-employed, U.

   2.4. Given ϕ_f^0, $\mathbf{1}^h(z, \xi, a)$, $\psi_a^u(a)$, and the bargaining splitting rule, solve the vacancy posting problem of the firm, $v(z, \xi)$.

   2.5. Compute the value at entry, $\Pi(z, \xi)$, and obtain a solution to the entry decision, $\mathbf{1}^e(z, \xi)$

   2.6. Given $v(z, \xi)$ and $\mathbf{1}^e(z, \xi)$, construct a new guess for the distribution of vacancy, $\psi_v^1(z, \xi)$

   2.7. Check for convergence:

      - if $\psi_v^1(z, \xi)$ and $\psi_v^0(z, \xi)$ are close enough, store $\psi_v^*(z, \xi) = \psi_v^1(z, \xi)$ and go ahead.
      - if not, set if $\psi_v^0(z, \xi) = \psi_v^1(z, \xi)$ and go back to step 2

   2.8. Iterate till convergence

3. Compute the measure of entrant firms

$$N = N_e \int_{z \in \mathcal{Z}} \int_{\xi \in \mathcal{E}} \mathbf{1}^e(z, \xi) \psi_z(z) \psi_\xi(\xi) dz d\xi \tag{19}$$

[14] This makes the parameters p^e, p^t and p^d interpretable as the probability of having an 8.5% change in human capital.

and use stationarity condition to compute the total number of incumbent firms

$$N^* = \frac{N}{\delta_f} \tag{20}$$

4. Construct the aggregate measure of vacancy posted as $v = N\bar{v}$, with the average number of vacancy posted given by

$$\bar{v} = \int_{z \in \mathcal{Z}} \int_{\xi \in \mathcal{E}} \mathbf{1}^e(z,\xi) v(z,\xi) \psi_z(z) \psi_\xi(\xi) dz d\xi \tag{21}$$

5. Use U, v and the definition of the matching function to obtain a new guess for the job contact rate of workers, θ^1

6. Check for convergence:

   - if θ^1 and θ^0 are close enough, store $\theta^* = \theta^1$ and go ahead.
   - if not, set if $\theta^0 = \theta^1$ and go back to step 1

7. Iterate till convergence

Use ϕ_w^*, ϕ_f^*, $\psi_v^*(z,\xi)$, and relevant policy functions to simulate a large panel of firms and workers and construct firm-level and worker-level statistics

To solve the model, we discretize the state space using 50 equally-spaced grid points for firms' (log) productivity, 20 equally-spaced grid points for firm-specific training costs, and 60 equally-spaced grid points for workers' (log) human capital.

C Estimation

C.1 Estimation of matching elasticity

We estimate the matching elasticity outside of the main algorithm. To compute quarterly new hires, we use employment gross inflows from the ONS Labor Force Survey Flows Estimates (dataset X02, available here). From the same source, we also obtain data on aggregate open vacancies (dataset AP2Y, available here), stock of non-employed workers (dataset ANZ6, available here), and the stock of self-employed (variable DYXN, available here). The GMM estimator minimizes the distance between new matches formed according to the model's matching function (given data on vacancies, non-employed and self-employed workers) and the number of new hires in the data:

$$\hat{x} = \arg\max_{\{\eta\}} \left[\left(\frac{1}{T} \sum_{t=1}^{T} Z_t' \epsilon_t(x) \right)' W_T \left(\frac{1}{T} \sum_{t=1}^{T} Z_t' \epsilon_t(x) \right) \right],$$

where $\epsilon_t(x)$ denotes the moment conditions, given by

$$\epsilon_t(x) = \left[h_t - \frac{u_t v_t}{(u_t^\eta + v_t^\eta)^{\frac{1}{\eta}}} \right],$$

where h_t is the number of new hires at time t, v_t the number of open vacancies, and u_t the number of searchers, equal to non-employed workers plus the self-employed.

Table 11: Matching function estimation

Parameters	Description	Estimates	St.Error
η	Elasticity	0.5416	0.013

The vector of instruments, $Z_t' = [u_t, v_t, u_{t-1}, v_{t-1}, u_{t-2}, v_{t-2}, u_{t-3}, v_{t-3}, u_{t-4}, v_{t-4}]$ includes the first four lags for the stock of searchers and active vacancies, while W_T is a weighting matrix. Hence, an estimate for η is obtained by simply minimizing the distance between new hires implied by the matching function and the data. For the estimation, we use data from the first quarter of 2002 till the fourth quarter of 2019. This makes the total number of observations equal to 68. Table 11 reports estimates and standard errors obtained using the robust GMM weighting matrix in the second step.

C.2 Model estimation

C.2.1 Data

Table 12 reports descriptive statistics for the sample of households in the Five-Quarter Longitudinal LFS. The sample is restricted to individuals between 22 and 62 who report being currently employed at the time of the interview.

The statistics used in the calibration are computed using the sample of employed workers with non-missing information on hourly pay, on-the-job training, and tenure on the job. The ultimate sample is made of 85,524 observations. About 78% of the individuals report being full-time employed, and working on average 37 hours a week. Around 25% of the respondents who are employed report having received on-the-job training in the current quarter. The LFS reports information for tenure on the job using indicators for whether an individual has been employed in the same firm for < 3 months, for a period $\in [3, 12)$ months, $\in [12, 24)$ months, and for ≥ 24 months.

The LFS also records the average hourly pay in the current quarter for individuals who are employed. We remove all the observations reporting negative hourly pay or hourly pay

Table 12: Descriptive Statistics

	Mean	SD	Min	Max	N
Employed workers					
Age	41.63	11.64	22	62	85,524
Female	0.506	0.500	0	1	85,524
Full-time	0.756	0.423	0	1	85,524
Hours worked	37.04	12.10	1	97	85,524
Log Hourly pay	2.385	0.599	0.025	7.248	85,524
Log Quarterly Earnings	8.457	0.824	3.956	13.39	85,524
Training	0.244	0.430	0	1	85,524
Tenure<3 months	0.038	0.191	0	1	85,524
Tenure∈[3,12) months	0.039	0.192	0	1	85,524
Tenure∈[12,24) months	0.109	0.311	0	1	85,524
Tenure≥24 months	0.815	0.388	0	1	85,524

lower the 40% the statutory minimum wage in that year. Therefore we deflated it using a first-stage regression where we control for year and quarters fixed effects, i.e.

$$w_{it}^h = \delta_{y(t)} + \delta_{q(t)} + \epsilon_{it}$$

where w_{it}^h denotes the hourly pay of individual i at time t while $\delta_{y(t)}$ and $\delta_{q(t)}$ are respectively year and quarter dummies for each time t. Hourly pay is then expressed in 2010-q1 LCU. This variable - together with weekly hours - allows us to construct average weekly earnings in the current quarter. Finally, we construct average quarterly earnings by multiplying average weekly earnings by 12.6, which accounts for the average number of weeks in a quarter.

C.2.2 Parameter Estimates

The model is solved at a quarterly frequency, and the population is normalized to one. A few parameters are determined based on available evidence or set to their data counterparts a priori, without solving the model. These parameters are reported in Table 13.

The remaining parameters are estimated by the method of simulated moments to minimize the sum of squared deviations between the model-implied values and the data for a set of worker- and firm-level targets. Let $\overline{m}$ be a vector of data targets and $m(\vartheta)$ their model counterparts. Let $\overline{d}(\vartheta)$ be a vector of $g \geq \dim[\vartheta]$ moment conditions (deviations between model and the data), $\overline{d}(\vartheta) = m(\vartheta) - \overline{m}$. The vector of parameter values, $\hat{\vartheta}$, is given by

$$\hat{\vartheta} = arg \min_{\vartheta \in \Theta} \mathcal{L}(\vartheta). \tag{22}$$

Table 13: Parameters directly calibrated

Parameters	Description	Value	Sources/Targets
Δ_a/a	Step-size change in skills	0.085	Discretization
ζ	Correlated distortion	0	Assumption
κ	Productivity shifter	1	Normalization
χ	Matching efficiency	1	Normalization
r	Interest rate	0.0033	Annual return of 4%
δ_w	Workers retirement	0.0099	Life-span of 40 years, ages 22-62
δ_f	Firm exit	0.0253	Annual exit rate of 10.50% (ONS)
η	Matching function	0.5416	Estimated using GMM (Appendix C.1)

Notes: The entries show the parameters set a priori without simulating the model, and their sources and/or targets.

where $\mathcal{L}(\vartheta) = \overline{d}(\vartheta)'W\overline{d}(\vartheta)$, and W is a positive semi-definite matrix. To improve the stability of our estimator while maintaining consistency, we opted for the identity matrix instead of the optimal weighting matrix. See also Lise et al. (2016) for a similar approach.

C.2.3 Algorithm

In the estimation algorithm, we exploit the definition of matching function, i.e.

$$m(U, v) = \chi \frac{Uv}{(U^\eta + v^\eta)^{\frac{1}{\eta}}}$$

to treat the equilibrium market tightness, θ as a parameter to be estimated, and let the measure of potential entrants, N_e, be an equilibrium object, equal to the solution of the following equilibrium equation:

$$\theta = \frac{U}{\bar{v}\frac{N}{\delta_f}} \tag{23}$$

where N is the measure of entrant firms and is defined in equation (19) as a function of potential entrants. To estimate the parameters, we follow this algorithm:

1. Guess the following set of parameters:

$$\vartheta^0 = \{c_e^0, \sigma_z^0, \underline{\xi}^0, \overline{\xi}^0, \lambda_1^0, \theta^0, \beta^0, \sigma_a^0, p^{d0}, p^{e0}, p^{t0}, b^0, \delta_s^0\}$$

   Let $J = \dim[\vartheta^0]$.

2. Given θ^0, compute job contact rate for workers, ϕ_w^0, and firms, ϕ_f^0 as follows

$$\phi_w^0 = \chi(1 + (\theta^0)^{-\eta})^{-\frac{1}{\eta}} \quad \text{and} \quad \phi_f^0 = \chi(1 + (\theta^0)^{\eta})^{-\frac{1}{\eta}}.$$

3. Proceed as in the solution algorithm, step 2 and obtain the equilibrium measure of potential entrants N_e using equations (19) and (23).

4. Use the parameter guesses together with N_e, $\psi_v^*(z,\xi)$, and the relevant policy functions to simulate a large panel of firms and workers.

5. Compute relevant moment condition using simulated data, i.e.

$$\bar{d}(\vartheta^0) = m(\vartheta^0) - \bar{m}$$

Let $g = \dim[\bar{d}(\vartheta^0)] \geq \dim[\vartheta]$.

6. Evaluate the distance function:

$$\mathcal{L}(\vartheta^0) = \bar{d}(\vartheta^0)' W \bar{d}(\vartheta^0)$$

7. Update guesses and iterate to minimize the distance function.

We follow a genetic algorithm to update the vector of guesses. At the obtained minimum, the log deviation between empirical and simulated moments is 0.086.

C.2.4 Standard errors

To obtain estimates of standard errors, we follow Chernozhukov and Hong (2003) methodology. This procedure consists of simulating a chain of parameters that has a quasi-posterior density equal to

$$f(\vartheta) = \frac{e^{\mathcal{L}(\vartheta)} p(\vartheta)}{\int e^{\mathcal{L}(\vartheta)} p(\vartheta) d\vartheta}$$

where $\mathcal{L}(\vartheta)$ is the objective function while $p(\vartheta)$ denotes a prior distribution. Standard errors are computed as the standard deviation of the sequence of elements in the converged MCMC chain. To simulate a chain that converges to the quasi posterior, we use the Metropolis–Hastings algorithm. This algorithm generates a chain of parameters $\vartheta^0, \vartheta^1, \vartheta^2, ...$ as follows. First, we choose a starting value ϑ^j. Next, we impose the proposal density to be uniform and we extract a new guess ϑ^p from it. Finally, we update from ϑ^{j+1} from ϑ^j for $j = 1, 2, ...$, using the following rule:

$$\vartheta^{j+1} = \begin{cases} \vartheta^p & \text{with probability} \quad \min\{1, \frac{e^{\mathcal{L}(\vartheta^p)}}{e^{\mathcal{L}(\vartheta^j)}}\} \\ \vartheta^j & \text{with probability} \quad 1 - \min\{1, \frac{e^{\mathcal{L}(\vartheta^p)}}{e^{\mathcal{L}(\vartheta^j)}}\} \end{cases}$$

where we use a uniform also as our prior distribution. The quasi-posterior density is obtained using a chain of 3000 model evaluations after discarding the first 10000. As in Lise et al. (2016), standard errors are computed as the standard deviation of the MC chains.

C.2.5 Identification sensitivity

Table 14: Estimate sensitivity to matching elasticity

Parameters	Description	Elasticity to changes in η
c_e	Entry cost	0.016
σ_z	Firm-productivity dispersion	0.060
$\underline{\xi}$	Training cost (lower bound)	0.061
$\overline{\xi}$	Training cost (upper bound)	-0.010
λ_1	Hiring costs, convexity	0.195
N_e	Measure of potential entrants	0.186
β	Bargaining power	-0.225
σ_a	Initial human capital dispersion	0.004
p^e	Experience jump	0.778
p^t	Training jump	-4.916
p^d	Depreciation jump	-1.391
b	Home production	0.004
δ_s	Match separation	-40.45

In this section, we explore how sensitive are parameters estimates to changes in the value of η, which is calibrated outside the model. To do this, we use the sensitivity measure proposed by Jorgensen (2020), defined as follows:

$$\mathbf{S} = \Lambda \mathbf{D}$$

where $\mathbf{D}$ is the Jacobian of the moment condition w.r.t. to η, whose (i)th entry is equal to

$$\mathbf{D}_{(i)} = \frac{\partial \bar{d}_{(i)}(\vartheta)}{\partial \eta}\Big|_{\eta=\hat{\eta}}$$

while Λ is the measure of parameters' sensitivity to moment conditions constructed by Andrews et al. (2017):

$$\Lambda = -(\mathbf{J}'\Sigma\mathbf{J})^{-1}\mathbf{J}'\Sigma$$

where Σ is a $g \times g$ weighting matrix used to construct the distance function (in our case the identity matrix), while the matrix $\mathbf{J}$ is a $g \times J$ Jacobian of the moment conditions w.r.t. the estimated parameters, whose (i,j)th entry is equal to:

$$\mathbf{J}_{(i,j)} = \frac{\partial \bar{d}_{(i)}(\vartheta)}{\partial \vartheta_{(j)}}\Big|_{\vartheta_{(j)}=\hat{\vartheta}_{(j)}}$$

Table 14 reports the elasticity of each estimated parameter j to the value of η, which is equal to

$$\mathbf{S}_{(j)} \frac{\hat{\eta}}{\vartheta_{(j)}}$$

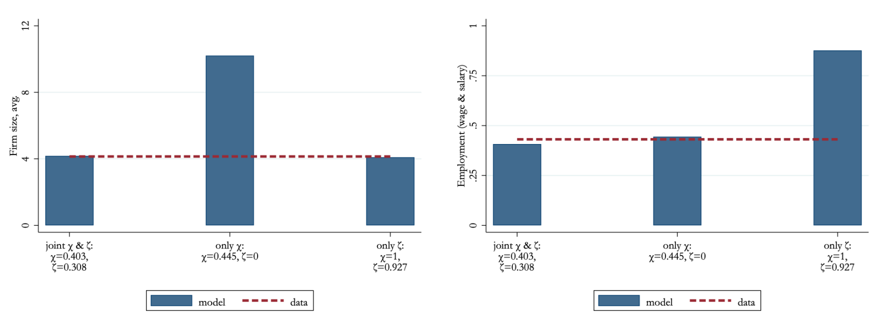
This final measure can be interpreted as the percent bias in parameter j estimate for a one percent perturbation of η. The match separation rate δ_s and the probability of human capital jump due to on-the-job training, p^t, are particularly sensitive to changes in η. This is the case because η directly affects matching elasticity, hence the rate at which jobs are formed. Changes in match formation are key determinants of job length and wage dynamics.

D Identification of ζ and χ

To illustrate how we identify ζ and χ, consider Indonesia, a country with one-tenth of the UK's GDP per capita (4,095 USD vs. 39,000 USD). The average firm size in Indonesia is just 4.14 employees, roughly 12 employees less than the average firm in the UK.[15] The share of wage and salary earners, based on our calculation from Section 2, is 43.11%, around 35 percentage points lower than the UK. To match the Indonesian firm size and the wage employment, the model requires a value of ζ around 0.308 (in contrast to 0 for the UK), while χ is about 0.403 (in contrast to 1 for the UK).

Figure 22: Identification of counterfactual parameters

(a) Average firm size (b) Wage and salary employment



Notes: Blue bars in the left and right panels refer to the simulated average firm size and wage and salary employment for different calibration strategies of the counterfactual parameters ζ and χ. The red lines refer to the empirical targets.

The identification of ζ and χ relies on the differential effect these two parameters have on average firm size and employment. Compare our approach with two alternative calibration

[15] Data for average firm size across countries is from Bento and Restuccia (2017).

strategies where these parameters are pinned down one at a time to match only one target, the average firm size for ζ, and the employment rate for χ, while still re-calibrating b. The calibrated values of ζ and χ would be 0.927 and 0.445, respectively. Targeted and non-targeted moments for these three approaches are shown in Figure 22. Panel (a) reports the average firm size, and panel (b) reports wage and salary employment. The dashed lines refer to data. The bars refer to the moments generated by the model in each calibration strategy.

Consider only finding a value for χ. Relative to joint calibration, for the same drop in employment rate, from 77.58 to 44.44% (second bar in panel b), higher labor market frictions alone generate a much smaller drop in average firm size, from 16.4 to 10.2 employees (second bar in panel a). Suppose, instead, we only look for ζ. Now, for the same drop in average firm size from 16.1 to 4.1 employees (third bar in panel a), an increase in correlated distortions alone would increase wage and salary employment to 87.67%, instead of reducing it from 77.58 to 40.75% (third bar in panel b). Correlated distortions generate many small firms that would hire workers if the matching process in Indonesia was as efficient as it is in the UK.

E Alternative counterfactual experiments

To explore the effects of alternative factors that affect the decisions of the firms and the workers in the model, Table 15 reports the outcomes of several alternative counterfactual experiments. In particular, we explore the role of uncorrelated distortions (column 3), and aggregate productivity (column 4), we target cross-country differences in worker separation rates (column 5), and firm exit rates (column 6). Again, we take the UK as a benchmark economy and compare it against Indonesia.

Table 16 reports the outcomes of an alternative counterfactual exercise where we re-estimate a larger set of parameters to match empirical targets for Indonesia. In particular, together with matching efficiency, χ, and correlated distortion, ζ, we re-estimate: i) the aggregate productivity shifter, κ to match the GDP per capita; ii) the experience probability jump, p^e to match the life-cycle wage growth after 20 years; iii) the training probability jump, p^t to match the share of firms providing training. Moreover, we adjust the values of home production, b, boundaries for training costs, $\underline{\xi}$ and $\bar{\xi}$, and entry cost c_e such that they are equal to the value estimated in the baseline economy, as % of average earnings.

Table 15: Alternative mechanisms

	UK Baseline	Indonesia Counterfactual					Indonesia Data
		Joint (χ, ζ)	Joint $(\chi, \bar{\tau})$	Only κ	Joint (δ_s, ζ)	Joint (χ, δ_f)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Matching frictions: χ	1	0.403	0.487	1	1	0.501	-
Distortion correlation: ζ	0	0.308	0	0	0.659	0	-
Uncorrelated distortions $\bar{\tau}$	0	0	0.534	0	0	0	
Aggregate productivity, κ	1	1	1	0.192	1	1	-
Separation rate: δ_s, %	1.235	1.235	1.235	1.235	5.179	1.235	-
Firm exit rate: δ_f, %	2.526	2.526	2.526	2.526	2.526	3.253	-
Home production: b	20.94	3.505	4.623	4.021	1.400	11.84	-
Training costs (lower bound): $\underline{\xi}$	1.735	1.735	1.735	0.333	1.735	1.735	-
Training costs (upper bound): $\overline{\xi}$	26.69	26.69	26.69	5.120	26.69	26.69	-
Entry cost: c_e	39.26	39.26	39.26	7.538	39.26	39.26	-
Average firm size, $\mathrm{E}[\ell_t]$	16.19	4.177	8.871	15.59	4.421	10.11	4.141
Employment rate	0.788	0.408	0.446	0.587	0.666	0.452	0.431
Income per capita	1	0.061	0.093	0.098	0.051	0.232	0.099
Training provision, overall %	65.02	6.210	9.009	40.94	0	27.59	6.291
Earnings growth, $\mathrm{E}[\log(w_{25}/w_1)]$	0.801	0.280	0.226	0.458	0.614	0.327	0.216
Mean-median ratio, $\mathrm{E}[w_{it}]/\mathrm{p}^{50}[w_{it}]$	1.207	1.805	1.875	1.464	1.327	1.835	1.687
GINI	0.416	0.506	0.526	0.447	0.427	0.513	0.502
90-50 pct. ratio, $\mathrm{p}^{90}[w_{it}]/\mathrm{p}^{50}[w_{it}]$	2.551	4.462	4.713	3.532	3.434	4.575	4.701
50-10 pct. ratio, $\mathrm{p}^{50}[w_{it}]/\mathrm{p}^{10}[w_{it}]$	5.262	2.729	2.902	3.292	2.570	2.754	2.615

Notes: The entries in column (1) show the outcomes for the benchmark (UK). The entries in columns (2) to (4) show the outcome for the counterfactual (Indonesia) across different experiments: changes in matching efficiency and correlated distortions together (column 2), changes in worker separation and correlated distortions (column 3), changes in firm exit rate and matching efficiency (column 4), changes in matching efficiency and uncorrelated distortions (column 5), changes in aggregate productivity (column 6). The entries in column (7) refer to the empirical outcomes for Indonesia.

F Baseline estimation without OTJ training

To study the role of OTJ training along with development, we re-estimate a version of the model without OTJ training. In this version of the model, human capital accumulation when employed only happens through on-the-job learning. The outcomes of this experiment are discussed in Section 6.2. Without the parameters and targets pertaining to OJT, 10 parameters are estimated to match 30 moments. Estimates are reported in Table 17. Targeted moments are reported in Tables 18.

Table 16: Alternative counterfactual

	UK Baseline	Indonesia Counterfactual Joint (χ, ζ)	Indonesia Counterfactual Full	Indonesia Data
	(1)	(2)	(3)	(4)
Matching frictions: χ	1	0.403	0.382	-
Distortion correlation: ζ	0	0.308	0.252	-
Home production: b	20.94	3.505	4.020	-
Training costs (lower bound): $\underline{\xi}$	1.735	1.735	0.232	-
Training costs (upper bound): $\overline{\xi}$	26.69	26.69	2.212	-
Entry cost: c_e	39.26	39.26	3.161	-
Aggregate productivity shifter: κ	1	1	0.938	-
Experience jump: p^e	0.223	0.223	0.205	-
Training jump: p^t	0.028	0.028	0.003	-
Average firm size, $\mathrm{E}[\ell_t]$	16.19	4.177	3.681	4.141
Employment rate	0.788	0.408	0.461	0.431
Income per capita	1	0.061	0.087	0.099
Training provision, overall %	65.02	6.210	7.006	6.291
Earnings growth, $\mathrm{E}[\log(w_{25}/w_1)]$	0.801	0.280	0.222	0.216
Mean-median ratio, $\mathrm{E}[w_{it}]/\mathrm{p}^{50}[w_{it}]$	1.207	1.805	1.772	1.687
GINI	0.416	0.506	0.503	0.502
90-50 pct. ratio, $\mathrm{p}^{90}[w_{it}]/\mathrm{p}^{50}[w_{it}]$	2.551	4.462	4.364	4.701
50-10 pct. ratio, $\mathrm{p}^{50}[w_{it}]/\mathrm{p}^{10}[w_{it}]$	5.262	2.729	2.774	2.615

Notes: The entries in column (1) show the outcomes for the benchmark (UK). The entries in columns (2) and (3) show the outcome for the counterfactual (Indonesia) after changing in matching efficiency and correlated distortions together (column 2). and after changing in a larger set of parameters, including matching efficiency, correlated distortions, aggregate productivity shifter, learning probability, training probability, training costs and entry cost (column 3).

G The role of OTJ training

In this section, we present an alternative experiment that illustrates the role of training. We impose training decisions from the counterfactual economy (Indonesia) on UK firms. If a match between a type-a worker and type-(z, ξ) implies training (or no training) in the counterfactual economy, the pair behaves the same way in the baseline economy, even if such behavior is not optimal for the match.

Given these imposed decision rules, firms still make hiring decisions to maximize their profits facing the benchmark values of ζ and χ. Hence, this experiment isolates the impact of correlated distortions and higher labor market frictions on training decisions. Column (1) in Table 19 shows the results for the benchmark economy, and column (3) shows the outcomes

Table 17: Parameters estimates (without OTJ training)

Parameters	Description	Value
c_e	Entry cost	44.75
σ_z	Firm-productivity dispersion	1.221
λ_1	Hiring costs, convexity	2.532
N_e	Measure of potential entrants	0.031
β	Bargaining power	0.427
σ_a	Initial human capital dispersion	1.035
p^e	Experience jump	0.209
p^d	Depreciation jump	0.430
b	Home production	22.26
δ_s	Match separation, %	1.226

Table 18: Targeted Moments (without OTJ training)

	Data	Model		Data	Model
Firm-level moments			*Earnings distribution*		
Average firm size, E(ℓ_t)	16.42	16.18	Average earnings at entry, E[log($w_1/\bar{w}$)]	-0.518	-0.479
Average log-firm size, E(log ℓ_t)	1.739	1.789	Average earnings after 20 y.o., E[log($w_{20}/\bar{w}$)]	0.107	0.108
Dispersion log-firm size, std(log ℓ_t)	1.220	1.371	Average earnings at re-emp, E[log($w_R/\bar{w}$)]	-0.301	-0.163
			Earnings dispersion at entry, sd[log w_1]	0.582	0.571
Firm size distribution			Earnings dispersion after 20 y.o., sd[log w_{20}]	0.796	0.738
1-9 employees	72.12	69.11	Earnings dispersion at re-emp, sd[log w_R]	0.834	0.735
10-24 employees	15.95	15.68			
25-49 employees	6.12	7.310	*Job tenure return*		
50-99 employees	3.21	4.621	tenure<3 months	1	1
100-249 employees	1.73	3.080	tenure∈[3,12) months	1.055	1.053
250+ employees	0.88	0.210	tenure∈[12,24) months	1.132	1.136
			tenure≥24 months	1.368	1.369
Firm size percentiles					
10th percentile	1	1.181	*Aggregate moments*		
25th percentile	3	2.689	Job duration	6.700	6.217
40th percentile	4	3.984	Employment rate	0.776	0.764
50th percentile	5	5.098			
60th percentile	6	7.111			
75th percentile	11	13.60			
90th percentile	29	39.89			
95th percentile	53	72.54			
99th percentile	202	175.4			

Notes: The entries show the full set of firm-level and worker-level empirical moments used in the estimation of the model without OTJ training, together with their simulated counterparts.

for Indonesia. Column (2) reports the results for the UK under Indonesia's training decisions.

The income per capita and average earnings are lower by about 10% with the training

Table 19: The Benchmark with Counterfactual Training Policies

	Baseline with baseline training (1)	Baseline with counterfactual training (2)	Counterfactual (3)	Explained (4)
Matching frictions: χ	1	0.403	0.403	-
Distortion correlation: ζ	0	0	0.308	-
Home production: b	20.94	20.94	3.505	-
Aggregates				
Employment rate	0.788	0.764	0.408	6.312%
Average earnings	1	0.932	0.124	7.729%
Income per capita	1	0.903	0.061	10.33%
Earnings profile over experience/tenure				
Earnings growth, $\mathrm{E}[\log(w_{25}/\bar{w}_1)]$	0.801	0.760	0.280	7.994%
Earnings inequality				
Mean-median ratio, $\mathrm{E}[w_{it}]/\mathrm{p}^{50}[w_{it}]$	1.207	1.269	1.805	10.37%
GINI	0.416	0.426	0.506	11.11%
90-50 pct. ratio, $\mathrm{p}^{90}[w_{it}]/\mathrm{p}^{50}[w_{it}]$	2.551	2.876	4.462	17.06%
50-10 pct. ratio, $\mathrm{p}^{50}[w_{it}]/\mathrm{p}^{10}[w_{it}]$	5.262	4.610	2.729	25.74%

Notes: The entries in columns (1) and (3) show the outcomes for the benchmark (UK) and the counterfactual (Indonesia). The entries in column (2) show outcomes when on-the-job training decisions from the counterfactual economy are imposed on the benchmark. The last column shows the ratio of differences between (1) and (2) compared with (1) and (3).

decision rules fixed at the counterfactual economy. Workers now receive much less training, which lowers human capital accumulation. With fixed training policies, changes in earnings inequality induced by correlated distortions and search frictions are muted. Although firms in the UK are forced to take constrained training decisions, they do not face size-dependent distortions or higher search frictions as the firms do in Indonesia. A comparison between columns 1 (UK) and 3 (Indonesia) versus columns 1 (UK) and 2 (UK with Indonesia's training decisions) suggests that the endogenous training decisions account for about 11% of changes in the mean-to-median ratio and the Gini coefficient, 17% of the change in p90-p50 earnings ratio and around 25% of the change in p50-p10 earnings ratio.

H A Re-training program

We model re-training by assuming non-employed workers have the option of either searching for jobs or participating in a re-training program which increases human capital with probability p^t. The value of being non-employed at the beginning of the period for a worker with ability a is equal to

$$J^u(a) = \max\{J^r(a), J^s(a)\},$$

where $J^r(a)$ is the value of re-training during non-employment, given by

$$J^r(a) = p^t J^{u,h}(a + \Delta_a) + (1 - p^t) J^{u,h}(a),$$

while $J^s(a)$ is the value of searching for a job, which is unchanged and given by

$$J^s(a) = (1 - \phi_w)[p^d J^{u,h}(a - \Delta_a) + (1 - p^d) J^{u,h}(a)] \\ + \phi_w \int_{z \in \mathcal{Z}} \int_{\xi \in \mathcal{E}} [\mathbf{1}^h(z, \xi, a) J^{e,h}(z, \xi, a) + (1 - \mathbf{1}^h(z, \xi, a)) J^{u,h}(a)] \psi_v(z, \xi) d\xi dz.$$

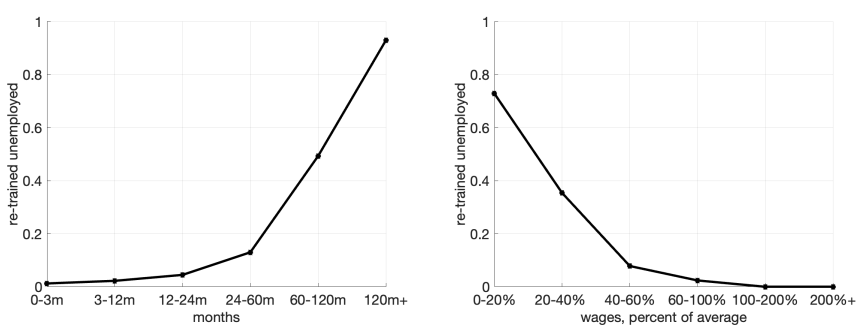
A solution to this problem is an indicator function for re-training, $\mathbf{1}^r(a)$ defined as:

$$\mathbf{1}^r(a) = \begin{cases} 1 & \text{if} \quad J^r(a) \geq J^s(a) \\ 0 & \text{otherwise} \end{cases}$$

All the other features of the model are kept the same as in the benchmark.

Figure 23: Selection into re-training

(a) by non-employment duration (b) by pre non-employment earnings



Notes: Panel (a) and (b) show the fraction of non-employed workers who choose to participate in the re-training program by non-employment duration and pre-non-employment earnings.

Figure 23 reports the probability of re-training take-up for workers with different non-employment duration (panel a) and with different pre non-employment wages (panel b).

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