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Comparative Advantage and Human Capital: A Cross-country Quantitative Analysis *

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Abstract

Trade openness can affect welfare through changes in workers' skill acquisition. We develop a multisector Eaton–Kortum model, in which skill intensities and on-the-job learning opportunities are heterogeneous across sectors. Workers decide whether to become skilled before entering the labor market, and accumulate human capital on the job. Through the lens of our model, trade-induced sector reallocation changes the returns of becoming skilled and on-the-job learning opportunities. Our model allows for an analytical formula of the gains from trade. This formula is an augmented version of the ACR formula and includes gains due to changes in skill acquisition. Our calibrated model suggests that the gains from trade due to changes in skill acquisition are vastly different across countries and may be negative, with sizable gains for the United States, the United Kingdom, and India, as well as considerable losses for Germany, Brazil, and Argentina.

JEL Codes: F1; J2. Key Words: international trade; sector reallocation; gains from trade; skill acquisition; human capital; college education; on-the-job learning.

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I Introduction

Trade openness can affect welfare through changes in workers' skill acquisition. By shifting economic activities across sectors, firms, or occupations, freer trade alters returns and opportunities for schooling and on-the-job learning. For instance, [Atkin \(2016\)](#) finds that growth of manufacturing exports led to more high-school dropouts in Mexico, whereas [Ferriere, Navarro and Reyes-Heroles \(2019\)](#) show that greater exposure to the "China Trade Shock" encouraged college enrollment in the United States.¹ These studies are rich in empirical analysis, mostly focusing on specific countries, however little quantitative evidence describes how educational choice affects welfare gains from trade across a large set of countries. Moreover, the role of on-the-job learning—which is important in fostering human capital ([Manuelli and Seshadri 2014](#)) and vastly different across sectors ([Islam, Jedwab, Romer and Pereira 2018](#))—is understudied in the trade literature.

In this paper, we study how trade affects welfare by changing workers' education choices and on-the-job learning opportunities. We develop a multisector Eaton–Kortum model with heterogeneous skill intensities and on-the-job learning opportunities across sectors. On the worker side, we embed an OLG model, in which workers first choose whether to become skilled before entering the labor market and then accumulate human capital on the job. Through the lens of the model, trade-induced sector reallocation changes the demand for skills, as well as on-the-job learning opportunities for workers. This model yields the same gravity equation as in [Eaton and Kortum \(2002\)](#). Most notably, this model allows for an analytical solution to the gains from trade, measured by changes in real consumption from autarky to the observed economy. Our formula incorporates [Arkolakis, Costinot and Rodríguez-Clare \(2012\)](#) (ACR) formula, augmented by gains due to changes in skill acquisition.

We combine multiple data sources to calibrate the model to 53 countries and the Rest of the World in 2005, with 20 sectors. We show that the gains from trade due to skill acquisition are vastly different across countries and are possibly negative. The United States, the United Kingdom, and India gain the most from trade-induced shifts in skill acquisition, with a 0.5%, 0.88%, and 0.49% increase in real consumption, largely because of their comparative advantage in services that require more skills and entail faster on-the-job learning than manufacturing and agriculture. In contrast, the biggest losses from trade due to skill acquisition occur in Germany, Brazil, and Argentina, with a 0.74%, 0.68%, and 0.77%

¹Also see [Blanchard and Olney \(2016\)](#), [Li \(2018\)](#), among others.

reduction in real consumption, as they specialize in manufacturing sectors or agriculture after trade openness. Finally, quantitative results suggest that developed countries enjoy better on-the-job learning opportunities after trade openness.

We then provide supportive evidence of how exporting may alter on-the-job learning opportunities. Across broad sectors (agriculture, industry, services), poor countries tend to shift employment toward sectors with higher on-the-job learning opportunities by exporting. However, in detailed manufacturing sectors, rich countries specialize in manufacturing sectors with faster on-the-job learning by exporting, which is consistent with our quantitative findings.

With this study, we contribute by providing a tractable framework that incorporates the gains due to changes in skill acquisition to the ACR formula. Two channels are central to the skill acquisition term: the change in skill acquisition through educational choices and on-the-job learning. We are not the first to examine the relationship between trade and schooling decisions. However, we contribute to the literature by incorporating on-the-job learning as a new channel generating dynamic effects of trade, which is driven by labor reallocation between industries with different learning opportunities.

This paper relates to several strands of the literature. The first strand is the vast literature on the gains from trade. Extant studies emphasize the importance of several factors in accounting for the gains from trade, such as multiple industries, intermediate inputs, firm entry, nonlinearities, and productivity correlations (see e.g., [Costinot and Rodríguez-Clare 2014](#), [Caliendo and Parro 2015](#), [Adão, Costinot and Donaldson 2017](#), [Lind and Ramondo 2017](#), [Baqaee and Farhi 2019](#)). Complementing these earlier contributions, we explore the effect of two other factors—education choices and on-the-job learning—on the gains from trade. We show how the ACR formula is modified to account for these two factors. Moreover, workers' on-the-job learning provides an extra channel through which trade can affect wage returns, in addition to firm revenues commonly studied in the literature (e.g., [Helpman, Itskhoki, Muendler and Redding 2017](#), [Fajgelbaum 2019](#)).

Second, we naturally relate to the literature on skill acquisition and trade. In addition to [Atkin \(2016\)](#) and [Ferriere et al. \(2019\)](#), many empirical studies also find that trade affects schooling. [Blanchard and Olney \(2016\)](#) show that growth in skill-intensive exports increases schooling using a panel of 102 countries and 45 years, and [Li \(2018\)](#) documents similar evidence for China. In the quantitative strand of the literature, some papers study the effects of trade on schooling decisions starting with [Findlay and Kierzkowski \(1983\)](#) who first incorporates education choices into the two-factor, two-good trade model. After

this early work, some work has been devoted to quantify the dynamics effects of trade on schooling decisions and, in some cases, to characterize the transition paths of wages and skill premia (e.g., [Falvey, Greenaway and Silva 2010](#), [Harris and Robertson 2013](#), [Danziger 2017](#)). These papers on trade and schooling decisions mostly study the skill premium, but they do not consider on-the-job human capital accumulation. We complement these studies by investigating the understudied relationship between on-the-job learning and trade. We also fill the gap in the literature by implementing quantitative analysis on how trade affects welfare across a large set of countries through schooling choices and on-the-job learning.

Finally, we make contact with recent papers that highlight the importance of life-cycle human capital accumulation in accounting for cross-country income differences. [Manuelli and Seshadri \(2014\)](#) finds that on-the-job training accounts for almost half of human capital differences across countries, which implies a large role of on-the-job learning in determining the gains from trade. Our results imply that trade liberalization has differential impacts on on-the-job learning in developing and developed economies and may even widen the income gap.

This paper is organized as follows. Section II develops the model. Section III provides the model calibration and quantitative results on the gains from trade. Section IV includes some model extensions and discussions. Section V documents suggestive evidence on exports and on-the-job learning. Section VI concludes.

II Model

This section develops a model to understand how trade affects welfare through changes in skill acquisition. The production side rests on a multisector Eaton–Kortum model with sector-specific skill intensities and on-the-job learning opportunities. On the worker side, we embed a two-period OLG model. Each worker decides whether to become skilled before entering the economy, then looks for jobs by random search, and works for two periods. Workers accumulate human capital on the job.

II.A Production

The world contains I countries and S industries, and we index country by i and sector by s respectively. There is a non-storable final good in each country $Q_i = \prod_s Q_{is}^{\beta_{is}}$, where β_{is}

is the expenditure share on intermediate goods from sector s with $\sum_s \beta_{is} = 1$. Denote P_i as the final-good price. Intermediate goods are produced by a unit measure of varieties $[0, 1]$ competitively:

$$Q_{is} = \left(\int_0^1 q_{is}(\omega)^{\frac{\sigma_s-1}{\sigma_s}} d\omega \right)^{\frac{\sigma_s}{\sigma_s-1}} \quad (1)$$

The intermediate-good producer sources each variety from the cheapest supplier around the world.

$$p_{is}(\omega) = \min_j p_{jis}(\omega) \quad (2)$$

where $p_{jis}(\omega)$ is the selling price from country j to i . Denote the intermediate-good price as P_{is} , which equals $P_{is}^{1-\sigma_s} = \int_0^1 p_{is}(\omega)^{1-\sigma_s} d\omega$.

Every country i has the technology to produce each variety ω of sector s , with the productivity level z drawn from a *Fréchet* distribution $F_{is}(z) = \exp(-A_{is}z^{-\vartheta_s})$. The scale parameter A_{is} governs the average productivity and thus comparative advantage of sector s in country i . The shape parameter ϑ_s governs the dispersion of productivity draws, and we require $\vartheta_s > \sigma_s - 1$ to obtain a finite integral of sales. The production function is:

$$y = z \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1 - \alpha_s) \psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}} \quad (3)$$

where l and h represent efficiency units of time for unskilled and skilled workers. The parameter α_s characterizes the skill intensity of sector s 's production. The parameter ψ_i captures skilled-biased technology in production for country i . The parameter ϕ is the elasticity of substitution between two types of labor. This production technology is freely available to a large number of potential entrants that take prices as given. Moreover, shipping one unit of goods from country i to j incurs iceberg costs $d_{ijs} \geq 1$.

II.B Workers

In country i , there is a measure N_i of workers in each generation. Workers in each generation decide whether to become skilled in the pre-period, and then work and consume for two periods. We solve the workers' choices by backward induction. After determining whether to become skilled, a young worker enters the labor market, searches for a job, and obtains utility from consuming final goods, according to the utility function $U(c) = \log(c^Y) + \frac{1}{1+\rho} \log(c^O)$. Working in sector s for one period generates a τ_{is}^h and τ_{is}^l increase in the next-period's human capital for skilled and unskilled workers, respectively.

The budget constraint for a young worker who finds a job in sector s is:

$$w_i^m + \frac{(1 + \tau_{is}^m)w_i^m}{1 + r_i} = c^Y + \frac{c^O}{1 + r_i}, \quad m \in \{h, l\} \quad (4)$$

where r_i is the interest rate, and m denotes workers' type (skilled or unskilled). w_i^m is the type-specific and country-specific wage rate per efficiency unit of labor. We will describe job searching and the wage determination in the next two subsections.

Denote $\mathbb{E}U(\mathbf{c}_i^l)$ ($\mathbb{E}U(\mathbf{c}_i^h)$) as the expected utility from consumption *before* entering the labor market, for unskilled (skilled) workers. In the pre-period, each worker chooses to become skilled or unskilled by maximizing:

$$U_i = \begin{cases} \mathbb{E}U(\mathbf{c}_i^l) + \log(\epsilon^l) & \text{if choosing to be unskilled} \\ \mathbb{E}U(\mathbf{c}_i^h) + \log(\epsilon^h) + \log(1 - e_i) & \text{if choosing to be skilled} \end{cases}$$

where $\{\epsilon^h, \epsilon^l\}$ are idiosyncratic preferences on becoming a skilled or unskilled worker respectively, which are i.i.d. and drawn from a *Fréchet* distribution $G(\epsilon) = \exp(-\epsilon^{-\kappa})$. For example, $\log(\epsilon^h) < 0$ may capture that for some workers, learning requires more efforts and generates higher disutility. The parameter e_i characterizes the time spent for becoming skilled in the pre-period, following [Hsieh, Hurst, Jones and Klenow \(2019\)](#).

Thus, in [Appendix A.1](#), we show that the share of workers who decide to become skilled in country i is:

$$\Lambda_i^h = \frac{\exp(\kappa \mathbb{E}U(\mathbf{c}_i^h))(1 - e_i)^\kappa}{\exp(\kappa \mathbb{E}U(\mathbf{c}_i^h))(1 - e_i)^\kappa + \exp(\kappa \mathbb{E}U(\mathbf{c}_i^l))} \quad (5)$$

Define $H_i = \Lambda_i^h N_i$ and $L_i = \Lambda_i^l N_i$ as the efficiency units of skilled and unskilled young workers, respectively. The parameter κ determines the magnitude of the response of education choices to changes in wage returns, which will be disciplined by reduced-form evidence in the next section.

Recent theory papers by [Monge-Naranjo \(2016\)](#) and [Buera and Oberfield \(2020\)](#) suggest that trade openness can change learning opportunities $\{\tau_{is}^l, \tau_{is}^h\}$ through cross-country knowledge diffusion. However, there is still limited empirical evidence on their mechanisms. Therefore, we focus on the role of trade-induced sector reallocation in shaping on-the-job learning opportunities and assume that sector-specific learning opportunities $\{\tau_{is}^l, \tau_{is}^h\}$ are unaffected by trade openness. In [Appendix B.1](#), we show that in a Ben-Porath model in which on-the-job learning requires time and the available knowledge remains constant, sector-specific on-the-job learning is unaffected by trade because marginal re-

turns and marginal costs of learning change by the same proportion after trade openness.

II.C Labor Market

Following [Mortensen and Pissarides \(1994\)](#) and [Pissarides \(2000\)](#), we assume that workers meet firms by random search. Skilled and unskilled workers search in separate markets. Firms post vacancies to hire unskilled and skilled workers, which cost f^l and f^h units of final goods respectively.

We make several simplifying assumptions on labor market dynamics to ease aggregation, and we relax these assumptions in our robustness check in Section [IV](#). There is one national labor market for each type of worker. The amount of vacancies for each type of worker is aggregated across all firms and sectors. We abstract from job destruction, and therefore all searchers are young workers. We also abstract from unemployment by assuming that the matching function is $M(U, V) = \min\{U, V\}$, and that vacancy posting costs (f^l and f^h) are small enough such that there is full employment. Denote by $\theta_i^h = \frac{V_i^h}{H_i}$ and $\theta_i^l = \frac{V_i^l}{L_i}$ the market tightness for skilled and unskilled workers, where V_i^h and V_i^l are the total number of vacancies for recruiting skilled and unskilled workers, respectively.

After searching and matching, workers and firms engage in wage bargaining as in [Stole and Zwiebel \(1996\)](#),² and workers capture a portion $0 < \beta < 1$ of the marginal output.

II.D Trade Shares

Taking market prices as given, a firm producing variety ω chooses vacancies v_i^h and v_i^l to maximize profits for different markets. Under perfect competition, foreign prices are proportional to domestic prices $p_{ijs}(\omega) = d_{ijs}p_{iis}(\omega)$ by the same proportion as losses in output due to iceberg costs. For analytical tractability, we assume that firms are myopic in the sense that they only maximize one period profits when posting vacancies and therefore ignore future profits from hiring young workers (when they turn old). This assumption will be relaxed in Section [IV](#). We can write a firm's profit maximization problem as:

$$\begin{aligned} \max_{\{v_i^h, v_i^l\}} & (1 - \beta)p_{iis}(\omega)z_{is}(\omega) \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1 - \alpha_s)\psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}} - v_i^l f^l P_i - v_i^h f^h P_i \\ \text{s.t. } & l = \frac{v_i^l}{\theta_i^l} + (1 + \tau_{is}^l)l^O, \quad h = \frac{v_i^h}{\theta_i^h} + (1 + \tau_{is}^h)h^O \end{aligned}$$

²This way of modelling the wage bargaining is widely used (see e.g., [Helpman et al. 2017](#)).

where $(1 + \tau_{is}^l)l^O$ and $(1 + \tau_{is}^h)h^O$ denote the efficiency units of unskilled and skilled old workers that were hired in the last period.³ Moreover, $\frac{v_i^h}{\theta_i^h}$ and $\frac{v_i^l}{\theta_i^l}$ specify the amount of new hires from posted vacancies for skilled and unskilled workers, respectively. Firms spend profits from hiring the remaining old workers on final goods.

In the equilibrium, free entry of vacancies implies that:

$$\begin{aligned} f^l \theta_i^l P_i &= (1 - \beta) z_{is}(\omega) p_{iis}(\omega) \alpha_s \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1 - \alpha_s) \psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{1}{\phi-1}} l^{\frac{-1}{\phi}} \\ f^h \theta_i^h P_i &= (1 - \beta) z_{is}(\omega) p_{iis}(\omega) (1 - \alpha_s) \psi_i \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1 - \alpha_s) \psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{1}{\phi-1}} h^{\frac{-1}{\phi}} \end{aligned} \quad (6)$$

The left-hand side is the average vacancy costs to hire one unit of labor, whereas the right-hand side is the one period profit from hiring that worker. By using the assumption that workers capture a portion $0 < \beta < 1$ of the marginal output and equation (6), we obtain wages for unskilled and skilled workers:

$$\begin{aligned} w_i^l &= \beta z_{is}(\omega) p_{iis}(\omega) \alpha_s \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1 - \alpha_s) \psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{1}{\phi-1}} l^{\frac{-1}{\phi}} = \frac{\beta f^l \theta_i^l P_i}{1 - \beta}, \\ w_i^h &= \beta z_{is}(\omega) p_{iis}(\omega) (1 - \alpha_s) \psi_i \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1 - \alpha_s) \psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{1}{\phi-1}} h^{\frac{-1}{\phi}} = \frac{\beta f^h \theta_i^h P_i}{1 - \beta} \end{aligned} \quad (7)$$

Wages are constant across firms within a country due to free entry. Define w_{is} as labor costs per unit of goods in sector s when $z = 1$:

$$w_{is} = \left(\alpha_s^\phi (w_i^l)^{1-\phi} + (1 - \alpha_s)^\phi \psi_i^\phi (w_i^h)^{1-\phi} \right)^{1/(1-\phi)} \quad (8)$$

By equation (7), we obtain:

$$p_{iis}(\omega) = \frac{w_{is}}{\beta z_{is}(\omega)} \quad (9)$$

We solve for the share of country j 's expenses in sector s that source from country i (shown in [Appendix A.2](#)) which derives as:

$$\Pi_{ijs} = \frac{A_{is} (d_{ijs} w_{is})^{-\vartheta_s}}{\sum_k A_{ks} (d_{kjs} w_{ks})^{-\vartheta_s}} \quad (10)$$

Therefore, the model predicts identical trade shares as in multisector Eaton–Kortum models (e.g., [Burstein and Vogel 2017](#)). Production costs are sector-specific, because different sectors have different skill intensities in production.

³The next-period old workers' efficiency units are decided by this period's hires: $l^{O'} = \frac{v_i^l}{\theta_i^l}$ and $h^{O'} = \frac{v_i^h}{\theta_i^h}$.

II.E Equilibrium

We assume that trade is balanced at the national level for each period. Also, we denote Λ_{is}^h (Λ_{is}^l) as the ratio of employment of skilled (unskilled) workers in sector s to total employment of skilled (unskilled) workers: $\sum_s \Lambda_{is}^h = \sum_s \Lambda_{is}^l = 1$. The labor-market clearing conditions imply:

$$H_i \Lambda_{is}^h (2 + \tau_{is}^h) = \frac{(1 - \alpha_s)^\phi \psi_i^\phi (w_i^h)^{-\phi}}{(w_{is})^{1-\phi}} \sum_j \Pi_{ijs} \beta_{js} \left(w_j^h H_j \sum_s \Lambda_{js}^h (2 + \tau_{js}^h) + w_j^l L_j \sum_s \Lambda_{js}^l (2 + \tau_{js}^l) \right) \quad (11)$$

$$L_i \Lambda_{is}^l (2 + \tau_{is}^l) = \frac{\alpha_s^\phi (w_i^l)^{-\phi}}{(w_{is})^{1-\phi}} \sum_j \Pi_{ijs} \beta_{js} \left(w_j^h H_j \sum_s \Lambda_{js}^h (2 + \tau_{js}^h) + w_j^l L_j \sum_s \Lambda_{js}^l (2 + \tau_{js}^l) \right) \quad (12)$$

where the left-hand side is the supply of each type of worker to each sector, and the right-hand side is the demand for each type of worker, aggregated over destinations. Note that by equation (10), Π_{ijs} is also a function of $\{w_i^h, w_i^l\}_i$. Therefore, combining equations (5), (11), and (12) as well as $\sum_s \Lambda_{is}^l = 1$ and $\sum_s \Lambda_{is}^h = 1$, we can solve for each country's wages $\{w_i^h, w_i^l\}_i$, share of workers in each sector $\{\Lambda_{is}^l, \Lambda_{is}^h\}$ and the share of skilled workers $\Lambda_i^h = 1 - \Lambda_i^l$. With wages and the measure of workers, we can solve all other endogenous variables $\{\theta_i^l, \theta_i^h, P_{is}, P_i, p_{ijs}(\omega), \Pi_{ijs}\}$. The interest rate r_i is determined such that the aggregate saving is zero for each country in each period.

II.F Gains from Trade

We follow [Costinot and Rodríguez-Clare \(2014\)](#) to measure welfare by workers' real consumption. For country i , denote GT_i as the ratio of real consumption in the observed economy to that in the autarkic economy in which bilateral trade costs are infinite $d_{ijs} \rightarrow \infty \forall i \neq j$. We use superscript o for variables in the autarkic economy.

Proposition 1 (Gains from Trade). *Assume that trade is balanced at the national level. The gains from trade are:*

$$GT_i = \underbrace{\prod_s (\Pi_{iis})^{-\frac{\beta_{is}}{\theta_s}}}_{ACR \text{ formula}} \times \underbrace{\frac{\lambda_i^l L_i \sum_s \Lambda_{is}^l (1 + \tau_{is}^l/2) + \lambda_i^h H_i \sum_s \Lambda_{is}^h (1 + \tau_{is}^h/2)}{\lambda_i^{l,o} L_i^o \sum_s \Lambda_{is}^{l,o} (1 + \tau_{is}^l/2) + \lambda_i^{h,o} H_i^o \sum_s \Lambda_{is}^{h,o} (1 + \tau_{is}^h/2)}}_{\text{Gains due to skill acquisition}} \quad (13)$$

where $\lambda_i^m = \prod_s \left(\frac{w_i^m}{w_{is}} \right)^{\beta_{is}}$, $m \in \{h, l\}$ measures the effect of relative wages on the aggregate price.

Proof: See [Appendix A.3](#).

The first term on the right-hand side is exactly the multisector version of the formula in ACR, which reflects gains due to changes in wages and prices after trade openness.

The key contribution of this paper is the second term that captures gains from trade due to changes in skill acquisition and involves three forces. First, trade openness alters the skill premium, which affects the relative ratio of wages to prices faced by different workers, as shown by $\lambda_i^m, m \in \{h, l\}$. Second, trade openness changes the measure of unskilled and skilled workers through education choices in equation (5). This force is reflected by changes in the number of skilled and unskilled workers H_i and L_i . Third, trade openness also affects on-the-job learning, by shifting employment (Λ_{is}^l and Λ_{is}^h) across sectors with different learning opportunities (τ_{is}^l and τ_{is}^h) for each type of worker.

If there is only one type of worker, i.e. $\alpha_s = 1 \forall s$ or $\alpha_s = 0 \forall s$, then the formula in equation (13) can be further simplified as (omit the superscript for workers' types):

$$GT_i = \underbrace{\prod_s (\Pi_{iis})^{-\frac{\beta_{is}}{\vartheta_s}}}_{\text{ACR formula}} \times \underbrace{\frac{\sum_s \Lambda_{is}(1 + \tau_{is}/2)}{\sum_s \Lambda_{is}^o(1 + \tau_{is}/2)}}_{\text{Gains due to on-the-job learning}} \quad (14)$$

This simplified formula is intuitive: it captures changes in employment-weighted on-the-job human capital accumulation. As a result, shifting employment to a sector with more learning opportunities (higher τ_{is}) can lead to larger gains from trade.

For analytical tractability, we abstracted from job turnover and workers' and firms' internalization of benefits from on-the-job learning. In Section IV, we study a realistic extension of our model with rich labor market dynamics, in which workers search for jobs and firms post vacancies by considering sector-specific learning opportunities. We will show that this extended model leads to similar quantitative results as our baseline model.

III Quantitative Analysis

We first show how we calibrate the model to the data. After that, we present quantitative results on how changes in workers' skill acquisition after trade openness shape the gains from trade.

III.A Calibration

We extend the model to incorporate intermediate inputs because input–output linkages are important in understanding the gains from trade (e.g., [Costinot and Rodríguez-Clare 2014](#), [Baqee and Farhi 2019](#)). With this extension, firms’ production function becomes $y_{is} = z \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1 - \alpha_s) \psi_i h^{\frac{\phi-1}{\phi}} \right)^{\gamma_{is}^l \frac{\phi}{\phi-1}} \prod_{s'} (m_{s'})^{\gamma_{is}^{s'}}$, where $m_{s'}$ represents expenses on intermediate inputs from sector s' . The parameter $\gamma_{is}^{s'}$ represents the share of production costs in industry s that are spent on materials from sector s' , and the parameter γ_{is}^l is the share of costs spent on labor. In [Appendix A.4](#), we extend the formula for the gains from trade in [Proposition 1](#) to account for the input–output linkages.

We calibrate our model to 53 countries and the Rest of the World in 2005.⁴ We consider 20 sectors—agriculture, mining, 16 manufacturing sectors, low-skill services, and high-skill services. [Appendix C](#) provides the details of countries and sector decomposition.

We require values for $\{\rho, \beta, \phi, f^h, f^l, \vartheta_s, N_i, d_{ijs}, \gamma_{is}^l, \gamma_{is}^{s'}, \beta_{is}, \tau_{is}^h, \tau_{is}^l, \alpha_s, \psi_i, e_i, A_{is}, \kappa\}$ to solve the model, and we present those values in [Table 1](#). We set $\rho = (1 + 0.04)^{20} - 1$, as we consider 20 years to be one period with an annualized discount rate of 4%. We set the labor share to be $\beta = 2/3$ according to estimates in [Gollin \(2002\)](#), and the elasticity of substitution between skilled and unskilled labor to be $\phi = 1.5$, as commonly found in the labor literature (e.g., [Katz and Murphy 1992](#)). In the equilibrium, $P_i f^m \theta_i^m = \frac{(1-\beta)w_i^m}{\beta}$ $m \in \{l, h\}$, and vacancy costs f^m cannot be separated from market tightness θ_i^m without information on each country’s labor market tightness. Because the separation of f^m from θ_i^m does not affect equilibrium production and trade flows, we normalize $f^m = 0.1$ $m \in \{l, h\}$.⁵

We use sector-specific trade elasticities ϑ_s from [Caliendo and Parro \(2015\)](#).⁶ We obtain employment N_i for each country in 2005 from the World Bank. We follow [Head and Ries \(2001\)](#) to assume symmetric trade costs $d_{ijs} = d_{jis}$ and infer them from actual trade

⁴We consider the following 53 countries in the calibration: Argentina, Australia, Austria, Bulgaria, Belgium-Luxembourg, Brazil, Canada, Switzerland, Chile, China, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, the United Kingdom, Greece, Croatia, Hungary, Indonesia, India, Ireland, Iceland, Israel, Italy, Japan, Cambodia, Korea, Lithuania, Latvia, Mexico, Malaysia, Netherlands, Norway, New Zealand, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, Slovak Republic, Slovenia, Sweden, Thailand, Turkey, Taiwan, the United States, Viet Nam, and South Africa.

⁵Note that we need labor market tightness $\theta_i^m \geq 1$ to ensure full employment. If $\theta_i^m \geq 1$ is violated, we normalize f^m to a much lower value to restore full employment.

⁶Because trade elasticity ϑ_s is not available for service sectors, we use aggregate trade elasticity ($\vartheta_s = 4.5$) in [Caliendo and Parro \(2015\)](#) for service sectors. $\vartheta_s = 4.5$ is also a common trade elasticity used in the trade literature ([Simonovska and Waugh 2014](#)).

Table 1: Parameter Values and Sources

Parameters			Moments
Notation	Value	Description	Description
ρ	1.19	Discount rate (20 years)	Annualized discount rate of 4%
β	2/3	Labor share	Estimates in Gollin (2002)
ϕ	1.5	Elasticity of substitution btw skilled/unskilled	Katz and Murphy (1992)
f^m	0.1	Vacancy costs by skill types	Normalization
ϑ_s	8.07 (10.86)	Sector-specific trade elasticity	Estimates in Caliendo and Parro (2015)
N_i	0.37 (1.01)	Country-specific employment ($N_{US} = 1$)	World Bank
d_{ijs}	23.85 (81.99)	Origin-destination-sector-specific trade costs	Trade shares between j and i
γ_{is}^l	0.36 (0.14)	Country-sector-specific value added share	World I/O Table 2005
$\gamma_{is}^{s'}$	0.03 (0.07)	Country-sector-specific input–output linkages	World I/O Table 2005
β_{is}	0.05 (0.10)	Country-sector-specific consumption shares	World I/O Table 2005
τ_s^m	0.73 (0.22)	On-the-job human capital accumulation by sectors/skill types	RTE by sectors/skill types in the U.S.
τ_i	1.25 (0.41)	Country-specific on-the-job learning returns	Relation between RTE and GDPPC in Lagakos et al. (2018)
α_s	0.39 (0.08)	Parameters governing sector-specific skill intensities	Sector-specific college employment share in the U.S. ACS 2005
ψ_i	0.36 (0.16)	Country-specific relative productivity of college workers ($\psi_{US} = 1$)	Country-specific college premium
e_i	0.69 (0.16)	Time costs of becoming skilled	Country-specific college population share in Barro and Lee (2013)
A_{is}	1.29 (1.05)	Country-sector-specific productivity ($A_{US,s} = 1$)	Country-sector-specific output in 2005
κ	4	Shape parameter of <i>Fréchet</i> distribution for idiosyncratic education preferences	Reduced-form estimate in Column (1) of Table 3

Notes: Parameter values for $\{\vartheta_s, N_i, d_{ijs}, \gamma_{is}^l, \gamma_{is}^{s'}, \beta_{is}, \tau_s^m, \tau_i, \alpha_s, \psi_i, e_i, A_{is}\}$ refer to averages across all the pairs with specific values. Standard deviations are in parenthesis.

shares $d_{ijs} = \left(\frac{\Pi_{ijs}\Pi_{jis}}{\Pi_{iis}\Pi_{jjs}} \right)^{-1/2\vartheta_s}$.⁷ We calibrate input–output linkages $\{\gamma_{is}^l, \gamma_{is}^{s'}\}$ for each country according to OECD Input–Output Tables. We calibrate consumption share $\beta_{is} = \frac{Y_{is} + IM_{is} - EX_{is} - INT_{is}}{\sum_s Y_{is} + IM_{is} - EX_{is} - INT_{is}}$, where Y_{is} , EX_{is} , IM_{is} , and INT_{is} represent sector-specific output, exports, imports, and usage as raw materials in production in the data.

Due to data availability, we assume that on-the-job learning parameters can be decomposed into $\tau_{is}^m = \tau_i \tau_s^m$, $m \in \{l, h\}$. We measure τ_s^m by estimating RTE of 40 years of experience separately for 20 sectors and two education groups using the U.S. Census and ACS in the years 1980–2017, as discussed in [Appendix C.4](#). The parameter τ_i captures country-specific learning opportunities and matters for the life-cycle wage growth. To calibrate τ_i , we can match the overall average wage relative to the average wage of the

⁷We compute actual trade shares in 2005 by combining OECD Bilateral Trade Database for Goods and Services with OECD Input–Output Tables.

young cohort in the model and in the data:

$$\underbrace{\frac{L_i w_i^l \sum_s \Lambda_{is}^l (1 + \tau_i \tau_s^l / 2) + H_i w_i^h \sum_s \Lambda_{is}^h (1 + \tau_i \tau_s^h / 2)}{L_i w_i^l + H_i w_i^h}}_{\text{model: average wage relative to average wage of young cohort}} = \underbrace{\sum_{x \in X} \Lambda_{x,i} \left(1 + \frac{\phi_{x,i}}{\phi_{20-24,i}} \times \phi_{20-24,i} \right)}_{\text{data: average wage relative to average wage of entering cohort}} \quad (15)$$

where the left-hand side represents the overall average wage relative to the average wage of the young cohort in the model. The right-hand side specifies the data counterpart, where $\phi_{x,i}$ and $\Lambda_{x,i}$ denote the RTE and the employment share for experience group $x \in X = \{0-4, \dots, 35-39\}$, with the youngest cohort's RTE $\phi_{0-4,i} = 0$. Due to the lack of data for many countries, we use the relationship between RTE and GDP per capita for 20–24 years of experience in [Lagakos et al. \(2018\)](#): $\phi_{20-24} = 0.89 + 0.26 \log(\text{GDPPC}_i / \text{GDPPC}_{US})$. We set the relative RTE across different experience groups to be the same as in the United States: $\frac{\phi_{x,i}}{\phi_{20-24,i}} = \frac{\phi_{x,US}}{\phi_{20-24,US}}$. We use country-specific populations of different age groups from [Barro and Lee \(2013\)](#) to obtain $\Lambda_{x,i}$.

The model moment in equation (15) relies on employment shares across sectors in equilibrium. Therefore, given a specific value of parameter κ (which we will calibrate in the next subsection), we jointly calibrate the parameter τ_i together with country-sector-specific aggregate productivity A_{is} , sector-specific skill intensities α_s , country-specific productivity of college workers ψ_i , and country-specific education costs e_i . We target the following moments in the data: 1) for each country, the overall average wage relative to the average wage of the young cohort, as mentioned earlier; 2) the country-sector-specific output, drawn from OECD Input–Output Tables in 2005;⁸ 3) the share of college workers in employment for each sector in the U.S., computed from the ACS data in 2005; 4) the country-specific college premium, collected from multiple data sources summarized in [Appendix C](#); and 5) the country-specific share of college graduates in 2005 from [Barro and Lee \(2013\)](#). In all simulations, we consider balanced trade at the national level and normalize the wage rate of the unskilled worker in the United States to be 1.

In [Table 2](#), we compare the targeted moments in the baseline and in the data. In general, we find that our model matches the targeted data moments very well. In [appendix Figure 4](#), we further compare the country-sector output (targeted using A_{is}) and the origin-

⁸We draw actual data on country-sector-specific output from OECD Input–Output Tables in 2005. When we compare output between the model and the data, we normalize each country's sectoral output by the U.S.'s sectoral output in the model and in the data. We normalize productivity A_{is} for the United States to be 1, because only relative productivities matter in the model.

destination-sector trade shares (untargeted though the trade costs are inferred from actual trade shares) in the model and in the data. We find that our model does a pretty good job with the regression coefficient of the data moments on the model moments being almost unity.

Table 2: Targeted Moments in the Model vs Data

Moments	Data	Model
1. Country-specific ratio of average wage to average wages of young cohort	1.51 (0.18)	1.51 (0.18)
2. Country-sector-specific output (relative to US)	0.11 (0.24)	0.11 (0.24)
3. Sector-specific college employment share in the U.S.	0.43 (0.14)	0.42 (0.14)
4. Country-specific college premium	2.06 (0.73)	2.09 (0.74)
5. Country-specific college employment share	0.21 (0.12)	0.21 (0.12)

Notes: When we compare output between the model and the data, we normalize each country’s sectoral output by the U.S.’s sectoral output in the model and in the data. The moments refer to averages across all the pairs with specific values. Standard deviations are in parenthesis.

III.B Using Reduced-form Estimates to Discipline Parameter κ

We use reduced-form estimates to discipline parameter κ , which governs the density of population that is on the verge of switching their education choices. We first estimate how changes in the skill composition of exports affect education choices. Although several studies (e.g., [Blanchard and Olney 2016](#), [Li 2018](#)) documented similar evidence about trade and schooling, we use our reduced-form evidence mainly to discipline the structural parameter in the calibration.

We identify this parameter in the data through the effect of a change in skill composition of exports in the share of college graduates in the population which we assume are skill workers in the data. To do this we classify workers with at least some college education as skilled workers, and workers with a high-school education or lower as unskilled workers. We estimate the following regression,

$$\text{Col}_{i,t+h} = \beta_0 + \beta_1 \ln(\text{Unskill_Ex}_{i,t}) + \beta_2 \ln(\text{Skill_Ex}_{i,t}) + \beta_3 X_{i,t} + \gamma_i + v_t + \epsilon_{i,t}, \quad (16)$$

where $\text{Col}_{i,t+h}$ is the share of college graduates in the population in the year $t+h$. We allow education choices to respond sluggishly by estimating the effects of h years ahead. The control variables X_{it} include a logarithm of GDP and imports in the year t . γ_i and v_t refer to country and year fixed effects respectively. The independent variables $\text{Unskill_Ex}_{i,t}$

Table 3: The Impact of Exports on Education Choices

	(1)	(2)	(3)	(4)
	OLS★	2SLS	OLS	2SLS
Years ahead	10	10	15	15
log(unskilled exports)	-0.040*** (0.011)	-0.123* (0.076)	-0.030** (0.013)	-0.145* (0.088)
log(skilled exports)	0.046*** (0.011)	0.126 (0.085)	0.040*** (0.013)	0.144 (0.097)
Controls	Yes	Yes	Yes	Yes
Obs	831	831	732	732
R-squared	0.909	0.916	0.914	0.920

Notes: The dependent variable is the share of college graduates in the population in the year $t + h$, where h is the amount of years ahead. Columns 1 and 2 show the results for $h = 10$, and Columns 3 and 4 show the results for $h = 15$. We truncate the upper and lower 1% percentile of log(unskilled exports) and log(skilled exports) to avoid extreme values. The controls are: (1) country fixed effects; (2) year fixed effects; and (3) log GDP and log import in year t . Robust standard errors are in parenthesis: * 10%, ** 5%, *** 1%. Finally, ★ represents the targeted moment in the indirect inference.

and $\text{Skill_Ex}_{i,t}$ are the amount of unskilled and skilled exports, constructed as follows,

$$\begin{aligned}\text{Unskill_Ex}_{i,t} &= \sum_s (1 - \text{Col}_{US,s,2005}) \text{Ex}_{i,s,t}, \\ \text{Skill_Ex}_{i,t} &= \sum_s \text{Col}_{US,s,2005} \text{Ex}_{i,s,t}.\end{aligned}$$

We proxy sector-specific skill intensity using the share of college workers in each sector for the United States in 2005, which is the baseline year of our calibration. Therefore, $\text{Unskill_Ex}_{i,t}$ is the sum of exports weighted by the U.S. sector-specific share of noncollege workers in employment, which measures the export exposure of unskilled workers. Similarly, $\text{Skill_Ex}_{i,t}$ is the sum of exports weighted by the U.S. sector-specific share of college workers in employment, representing the export exposure of skilled workers. We draw trade data from Comtrade Database, education data from [Barro and Lee \(2013\)](#), and GDP from Penn World Table 9.1 in the years $t = 1965, 1970, \dots, 2010$, for the set of countries with available data.⁹

It is likely that $\text{Unskill_Ex}_{i,t}$ and $\text{Skill_Ex}_{i,t}$ are endogenous, as more supply of skilled workers could result in higher skill content of exports. To address this endogeneity issue,

⁹We also experimented with restricting the sample to the set of countries we study in the quantitative analysis, which led to similar regression results.

we construct Bartik-type instruments as follows:

$$\begin{aligned} \text{Unskill_Ex}_{i,t}^{IV} &= \sum_s \sum_{j \neq i} (1 - \text{Col}_{US,s,2005}) \frac{\text{Ex}_{i,j,s,1965}}{\text{Ex}_{i,1965}} \frac{\text{Ex}_{-i,j,s,t}}{\text{Ex}_{-i,j,s,1965}} \\ \text{Skill_Ex}_{i,t}^{IV} &= \sum_s \sum_{j \neq i} \text{Col}_{US,s,2005} \frac{\text{Ex}_{i,j,s,1965}}{\text{Ex}_{i,j,1965}} \frac{\text{Ex}_{-i,j,s,t}}{\text{Ex}_{-i,j,s,1965}} \end{aligned} \quad (17)$$

where $\frac{\text{Ex}_{i,j,s,1965}}{\text{Ex}_{i,1965}}$ is the share of sectoral exports from country i to j in country i 's total exports in the initial year of our data set (1965). $\frac{\text{Ex}_{-i,j,s,t}}{\text{Ex}_{-i,j,s,1965}}$ is growth of sectoral exports to country j between 1965 and year t by countries other than country i . These two instruments are relevant for the corresponding independent variables, with a correlation coefficient of more than 0.5.¹⁰ Because we control for country fixed effects in the regression, identification is based on idiosyncratic growth rates of exports across sectors, as shown by [Borusyak and Jaravel \(2018\)](#).

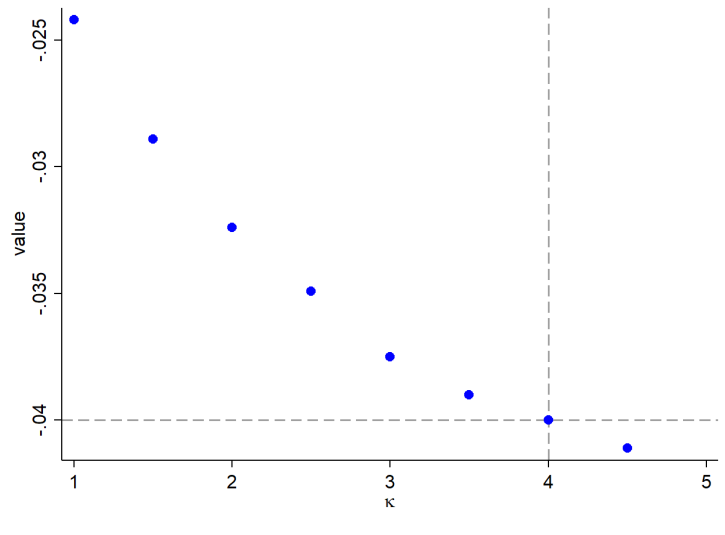
Table 3 presents the estimation results. Column (1) shows that increasing unskilled exports by 1% reduced the share of college graduates in the population by 0.04 percentage points after 10 years, whereas increasing skilled exports led to a larger share of college graduates in the population after 10 years. Column (2) uses Bartik-type instruments in equation (17) and still finds that growth in unskilled exports reduced the share of college graduates in the population after 10 years. Notably, the IV estimates are much larger in magnitude than the OLS estimates, which is in line with extant literature (e.g., [Blanchard and Olney 2016](#)), which also finds a stronger estimated effect of exports on schooling using instrumental variables rather than using OLS. In Columns (3) and (4), we choose the share of college graduates in the population for 15 years ahead ($h=15$) as the dependent variable. Due to fewer observations, the estimates are noisier but yet quantitatively similar compared with their counterparts in Columns (1) and (2). In conclusion, we find that increases in the skill demand from exports encouraged more education. The magnitude of our reduced-form estimates is comparable to similar evidence in the literature.¹¹

We use our reduced-form estimate in Column (1) of Table 3 to discipline parameter κ —which governs the density of population that is on the verge of switching their education

¹⁰The first-stage F values are larger than 500 in all our IV regressions.

¹¹For example, the OLS results in [Blanchard and Olney \(2016\)](#) show that increasing agriculture exports by 1% reduced years of schooling by 0.003 years, and increasing unskilled manufacturing exports by 1% reduced years of schooling by 0.0014 years. If we consider that college education requires 4 years of schooling, our OLS results suggest that increasing unskilled exports by 1% reduced average years of schooling by 0.0016 years. Because we only focus on two education levels, comparison of our reduced-form estimates and the reduced-form evidence on how trade affects years of schooling in the literature is imperfect.

Figure 1: Estimates Using Model-generated Data



The figure varies κ from 1 to 5 in the counterfactual exercise with changes in expenditure shares. The vertical line represents the baseline value of $\kappa = 4$, when the estimate from the model-generated data (-0.04) matches the estimate produced by the actual data (Column (1) of Table 3).

choices—using an indirect inference procedure. We proceed as follows. In our calibrated model, we assume that expenditure shares are subject to an exogenous demand shock $\beta_{is}^\epsilon = \beta_{is} \exp(\epsilon_s)$, in line with our regression results about the effects of skill demand on education choices. Exogenous shock ϵ_s is independent across sectors and distributed according to $\epsilon_s \sim \mathcal{N}(-\frac{\nu_s^2}{2}, \nu_s)$, where ν_s is chosen to be the actual standard deviation of 10-year export growth in sector s between 1965 and 2010. For each value of parameter κ , we simulate the model 100 times with different realizations of $\{\epsilon_s\}$ and then perform the same OLS regression as in Column (1) of Table 3.¹² We use the value of parameter κ to target coefficient $\beta_1 = -0.04$.

The intuition for this calibration is that a higher parameter κ corresponds to larger sensitivity of education choices to changes in the skill composition of exports. Figure 1 confirms this monotonic relationship between parameter κ and the reduced-form estimate from the model-generated data. The value $\kappa = 4$ minimizes the absolute difference between the model-generated estimate and its counterpart in the data. In Appendix C.6, we also report counterfactual results using other values of parameter κ .

¹²For each value of parameter κ , we recalibrate all other parameters to match the relevant moments in Table 1. When performing demand shocks in the calibrated model, we keep the 100 sequences of realizations of $\{\epsilon_s\}$ constant across different values of parameter κ .

III.C Gains from Trade

Armed with our calibrated model, we perform the counterfactual exercise of the autarkic economy, by setting bilateral trade costs to be infinite $d_{ijs} \rightarrow \infty \forall i \neq j$. We then compute the proportional change in real consumption from the autarkic economy to the observed equilibrium to derive the gains from trade. To understand how education choices and on-the-job learning shape the gains, we compute proportional changes in the number of college workers and lifetime wage growth from autarky to the observed equilibrium. We compute lifetime wage growth as the percent increase in the overall average wage relative to the young cohort's average wage, measuring the RTE in the model.

Table 4 reports the results for the largest 25 economies in our calibrated model. Column (1) of Table 4 reports the overall gains from trade. Columns (2) and (3) further decompose the overall gains from trade into the ACR formula and the gains due to changes in skill acquisition according to Proposition 1. Consistent with the trade literature (e.g., [Ramondo and Rodríguez-Clare 2013](#), [Costinot and Rodríguez-Clare 2014](#)), we find that the overall gains from trade are larger for small open economies, such as Canada, Netherlands, Malaysia, Sweden, and Denmark. In particular, the values in terms of the ACR formula in Column (2) are similar to the results in [Costinot and Rodríguez-Clare \(2014\)](#) who study the gains from trade in a multisector Eaton–Kortum model with input–output linkages.¹³ This result indicates that our quantitative results are reasonable.

Column (3) exhibits the gains from trade due to changes in skill acquisition. In comparison to the overall gains from trade, the gains from trade due to changes in skill acquisition are relatively small, but nonetheless vastly different across countries. The United States and the United Kingdom are the two largest winners in trade-induced shifts in skill acquisition, largely due to their comparative advantage in high-skill services and skill-intensive manufacturing sectors. For example, the United States' gains from trade due to skill acquisition are 0.50%, which accounts for 7.2% of the overall gains from trade. Its share of employment in high-skill services increases from 47.0% in autarky to 49.0% with trade openness. Despite an overall shift of employment toward high-skill services, within manufacturing, the share of employment in sectors with higher skill intensities than the median also rises from 57.8% to 58.7% after trade openness. As a result, the

¹³For example, in our calibrated model, the gains from trade computed by the ACR formula are 6.5% and 10.0% for the United States and China respectively. In a multisector Eaton–Kortum model with input–output linkages in [Costinot and Rodríguez-Clare \(2014\)](#), the gains are 8.3% and 11.5% for the United States and China respectively. [Costinot and Rodríguez-Clare \(2014\)](#) tend to find larger gains from trade than ours, because their calibrated model considers more sectors.

Table 4: Gains from Trade

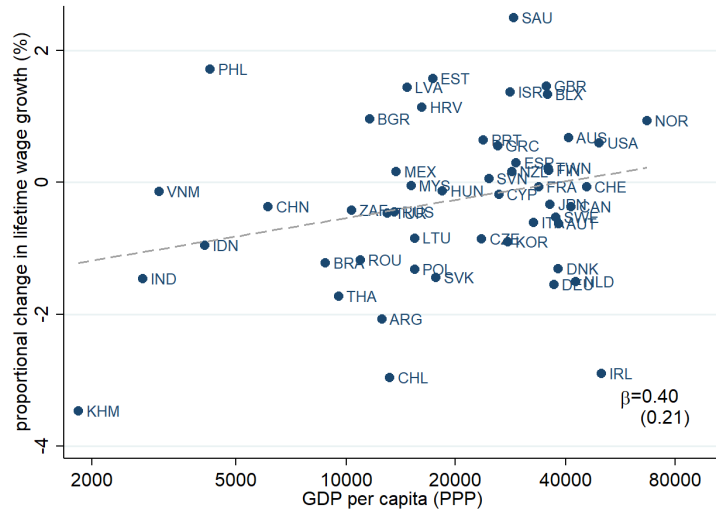
Country	Decomposition of gains from trade			Measures of skill acquisition	
	Gains from trade	ACR formula	Skill acquisition	# college workers	Lifetime wage growth
	(1)	(2)	(3)=(1)-(2)	(4)	(5)
USA	6.98%	6.48%	0.50%	0.87%	0.59%
CHN	9.88%	9.98%	-0.10%	-0.31%	-0.37%
JPN	4.05%	4.21%	-0.16%	-0.45%	-0.33%
IND	8.30%	7.81%	0.49%	3.45%	-1.46%
DEU	23.59%	24.33%	-0.74%	-1.33%	-1.55%
FRA	14.78%	14.77%	0.01%	0.55%	-0.07%
GBR	17.24%	16.36%	0.88%	2.33%	1.46%
RUS	16.23%	16.47%	-0.24%	-2.48%	-0.45%
ITA	10.87%	11.15%	-0.28%	-0.81%	-0.61%
BRA	7.00%	7.68%	-0.68%	-1.99%	-1.22%
MEX	12.29%	12.69%	-0.40%	-1.71%	0.16%
KOR	10.90%	11.15%	-0.25%	0.72%	-0.90%
CAN	27.12%	27.50%	-0.38%	-2.19%	-0.37%
ESP	15.60%	15.43%	0.17%	0.68%	0.29%
IDN	20.35%	20.69%	-0.34%	-3.09%	-0.96%
TUR	10.60%	10.81%	-0.21%	-0.89%	-0.47%
AUS	13.73%	13.47%	0.26%	-0.52%	0.68%
NLD	97.37%	97.92%	-0.55%	0.73%	-1.51%
POL	21.29%	21.81%	-0.52%	-1.23%	-1.32%
ZAF	22.25%	22.70%	-0.45%	-2.24%	-0.42%
ARG	12.84%	13.61%	-0.77%	-3.32%	-2.07%
MYS	61.79%	61.78%	0.01%	0.02%	-0.05%
POL	21.29%	21.81%	-0.53%	-1.23%	-1.32%
SWE	36.91%	37.42%	-0.49%	-1.14%	-1.73%
CHE	57.15%	56.96%	0.19%	2.03%	-0.07%
Average	22.42%	22.60%	-0.18%	-0.54%	-0.56%

United States enjoys more aggregate human capital from trade openness, with a 0.87% growth in the number of college workers and a 0.59% increase in lifetime wage growth, shown in Columns (4) and (5).

Another big winner is India, which gains a 0.49% increase in real consumption due to trade-induced shifts in skill acquisition. Most notably, the number of college workers increases by 3.45% if India moves from autarky to an open economy, which is partly induced by India's comparative advantage in services. However, India's lifetime wage growth tends to be lower after trade openness, because trade openness also induces reallocation of employment toward agriculture with low on-the-job learning opportunities.

Many countries experience losses from trade due to skill acquisition. Among the devel-

Figure 2: Changes in Lifetime Wage Growth after Trade Openness



oped countries reported in Table 4, Germany loses most with a 0.74% decrease in real consumption because of trade-induced shifts in skill acquisition. This is because after trade openness, Germany shifts employment from services to manufacturing sectors that tend to incur relatively lower skill requirements and on-the-job learning compared with services. Among the developing countries presented in Table 4, Argentina and Brazil experience the most losses (a 0.77% and 0.68% reduction in real consumption, respectively), because these two countries enjoy comparative advantage in agriculture that entails low skill intensity and few on-the-job learning opportunities.

Finally, Figure 2 plots proportional changes in lifetime wage growth from autarky to the observed equilibrium against log GDP per capita in 2005, for the set of countries in our quantitative analysis. Developed countries tend to enjoy better on-the-job learning opportunities after trade openness. This is because after trade openness, developed countries specialize in manufacturing sectors with higher RTE and have more college workers who enjoy faster on-the-job learning than unskilled workers.

IV Robustness

Our baseline model abstracts from job turnover and workers’ and firms’ internalization of benefits from human capital accumulation. To understand whether our quantitative results are robust to these simplifications, this section studies a more realistic extension

of our model with rich labor market dynamics. We first present the model extension in Section IV.A and then report quantitative findings of the extended model in Section IV.B.

IV.A Model Extension

We now discuss how we extend the model from Section II. We add the following features:

Labor Market. We assume that labor markets are separate by sectors and worker types. The matching function is $M(U_{is}^m, V_{is}^m) = \min\{U_{is}^m, V_{is}^m\}$. U_{is}^m and V_{is}^m are the total amount of searchers and vacancies, respectively, for workers of type $m \in \{l, h\}$ in country i and sector s . We still abstract from unemployment by assuming that vacancy costs are small enough.

Workers. We now assume that workers can live for potentially infinite periods with utility from consumption $\sum_{\tau=0}^{\infty} (1 + \rho)^{-\tau} \log(c_{\tau})$. The capital market is complete to avoid precautionary saving.¹⁴ A proportion δ_d of workers die in each period after production and consumption. In the beginning of each period, old workers who died in the last period are replaced by the same number of new entrants, who determine whether to become skilled and then start to search for jobs. To model that college education leads to less production time in addition to education costs in the pre-period, we assume that new skilled workers spend the first four years not working. Alive employed workers are exogenously separated from their employers with a possibility δ_p and become unemployed.

New entrants and laid-off workers choose the sector to look for jobs. To generate upward-sloping labor supply curves on the sector level, we follow Tombe and Zhu (2019) to assume that workers maximize cash flow from the job, facing idiosyncratic taste shocks y that are i.i.d. across sectors and individuals, according to a Fréchet distribution $\exp(-y^{-\chi})$. The parameter $\chi > 0$ captures the dispersion of idiosyncratic tastes and therefore the elasticity of labor supply to wage rates. One period working in sector s generates a proportional increase of τ_{is}^m in human capital. Therefore, for workers of type $m \in \{l, h\}$ in country i , the probability to look for jobs in sector s is:

$$\Lambda_{is}^m = \frac{(W_{is}^m)^{\chi}}{\sum_s (W_{is}^m)^{\chi}}$$

¹⁴Because our extended model allows for exogenous separation, workers have motives for precautionary saving. If the capital market is incomplete, workers' consumption will rely on their amount of assets, which complicates the model solutions and is beyond the scope of this paper. With complete capital markets and no aggregate uncertainty, the prices of Arrow–Debreu securities in country i are determined by the interest rate r_i and the probability of each event. Workers' consumption is not state-contingent.

where $W_{is}^m = \sum_{t=0}^{\infty} \left(\frac{(1+\tau_{is}^m)(1-\delta_d)(1-\delta_p)}{1+r_i} \right)^t w_{is}^m$ is the discounted cash flow for a job in sector s , with w_{is}^m denoting the wage rate per efficiency unit of time. Searchers' original human capital does not show up in probability Λ_{is}^m , as its effects on wage returns are identical across sectors. Because separation rates are identical across sectors, Λ_{is}^m also represents sectoral employment share in country i for workers of type $m \in \{l, h\}$.

Firms. Firms post vacancies each period to attract job searchers. Instead of assuming that firms are myopic as in Section II, we now assume that firms post vacancies by considering the present value of workers' future benefits to the firm. This means that firms internalize the benefits from workers' on-the-job human capital accumulation, weighted by workers' potential death and exogenous separations.

IV.B Quantitative Results

We then take this extended model to the data. One period in the model is one year, with the yearly discount rate $\rho = 0.04$. The death rate $\delta_d = 0.025$ matches the working life of 40 years, and $\delta_p = 0.2$ is based on 1.5–3% monthly job separation rates in the US (Shimer 2012, Faberman, Mueller, Sahin and Topa 2017). We recalibrate $\{\tau_i, \alpha_s, \psi_i, e_i, A_{is}, \kappa\}$ in Table 1, jointly with the newly introduced elasticity of labor supply χ . In addition to the relevant moments specified in Table 1, we use the new parameter χ to target the between-sector dispersion of average wages in the U.S. in 2005. Our intuition is that larger labor-supply elasticity χ implies stronger responses of sectoral employment to sectoral wage changes and therefore lower between-sector wage dispersion. Appendix C provides the parameter values and the comparison of the targeted moments.

Due to the lack of an analytical solution for the gains from trade, we perform two counterfactual exercises to obtain the gains from trade due to changes in skill acquisition. In the first exercise, we set bilateral trade costs to be infinite $d_{ijs} \rightarrow \infty \forall i \neq j$. With this exercise, we quantify the overall gains from trade. In the second exercise, we assume that for workers of type $m \in \{l, h\}$ in country i , on-the-job learning opportunities are identical across sectors by letting $\tau_{is}^m = \bar{\tau}_i^m \forall s$, where $\bar{\tau}_i^m$ is the employment-weighted average of τ_{is}^m across sectors. We also fix the share of college workers in each country. Under these restrictions, we recalibrate the model to match all data moments specified earlier.¹⁵ We then set bilateral trade costs to be infinite $d_{ijs} \rightarrow \infty \forall i \neq j$. With this exercise, we quantify the

¹⁵We keep the elasticity of labor supply χ unchanged as in the original calibration and thus do not target the between-sector wage dispersion in the recalibration, because the gains from trade are sensitive to the labor-supply elasticity (see e.g., Galle et al. 2017).

Table 5: Gains from Trade (Extended Model)

Country	Decomposition of gains from trade			Measures of skill acquisition	
	Gains from trade	Without changes in skill acquisition	Skill acquisition	# college workers	Lifetime wage growth
	(1)	(2)	(3)=(1)-(2)	(4)	(5)
USA	10.64%	9.98%	0.66%	0.76%	0.98%
CHN	12.39%	12.48%	-0.09%	-0.01%	-0.12%
JPN	5.49%	5.61%	-0.12%	-0.32%	0.07%
IND	14.58%	14.08%	0.50%	3.96%	-0.02%
DEU	19.52%	20.66%	-1.14%	-0.42%	-1.25%
FRA	19.69%	19.71%	-0.02%	0.14%	0.45%
GBR	22.11%	20.87%	1.24%	2.57%	1.37%
RUS	21.72%	21.49%	0.23%	-4.43%	0.17%
ITA	13.73%	14.19%	-0.46%	-0.97%	-0.06%
BRA	6.75%	7.58%	-0.83%	-2.44%	-0.41%
MEX	12.41%	12.79%	-0.38%	-1.64%	0.03%
KOR	13.35%	13.66%	-0.31%	1.60%	-0.27%
CAN	28.46%	28.60%	-0.14%	-2.80%	-0.10%
ESP	21.30%	21.13%	0.17%	-0.03%	0.83%
IDN	28.81%	29.41%	-0.60%	-4.91%	0.16%
TUR	14.41%	14.72%	-0.31%	-1.42%	0.20%
AUS	21.45%	20.80%	0.65%	-1.74%	1.43%
NLD	90.86%	92.80%	-1.94%	0.56%	-1.51%
POL	19.21%	20.52%	-1.31%	-0.36%	-1.26%
ZAF	28.80%	29.52%	-0.72%	-3.06%	0.10%
ARG	13.06%	14.01%	-0.95%	-5.21%	-0.34%
MYS	76.42%	76.79%	-0.37%	-0.87%	0.38%
POL	19.21%	20.52%	-1.31%	-0.36%	-1.26%
SWE	42.17%	42.89%	-0.72%	-1.51%	-0.49%
CHE	55.85%	56.00%	-0.15%	1.58%	0.33%
Average	25.30%	25.63%	-0.33%	-0.85%	-0.02%

gains from trade without changes in skill acquisition. By deducting the gains from trade without changes in skill acquisition from the overall gains from trade, we obtain the gains from trade due to changes in skill acquisition. To understand how education levels and on-the-job learning change due to trade openness, for the first counterfactual exercise, we also measure changes in skill acquisition from autarky to the observed equilibrium in the same way as in Table 4.

Table 5 presents the results for the largest 25 economies in our calibrated model. Column (1) reports the overall gains from trade in our extended model, which are slightly larger than the gains from trade in our baseline model shown in Table 4, with a correlation coefficient of 0.98. The gains from trade in the extended model are larger than in the

baseline model, possibly caused by the difficulty of employment adjustments in the extended model, for which the sectoral labor supply is upward-sloping. In line with [Galle, Rodríguez-Clare and Yi \(2017\)](#), we find that as sectoral labor supply becomes more elastic ($\chi \rightarrow \infty$), the gains from trade tend to become smaller in the extended model.

Column (3) of Table 5 reports the gains from trade due to changes in skill acquisition in the extended model, which are quantitatively similar to our results shown in Table 4 for the baseline model, with a correlation coefficient of 0.87.¹⁶ Still, the United States, the United Kingdom, and India experience gains from trade-induced skill acquisition, whereas Germany, Brazil, and Argentina suffer losses. Reassuringly, in Columns (4) and (5) of Table 5, trade-induced proportional changes in the number of college workers and lifetime wage growth are also analogous to the corresponding results for the baseline model, with correlation values of 0.94 and 0.84, respectively. These results suggest that our quantitative findings in the baseline model are robust.

V Cross-Country Evidence on Exports and OTJ Learning

This section presents suggestive empirical evidence on the relationship between trade and on the job skill acquisition that supports our quantitative findings.

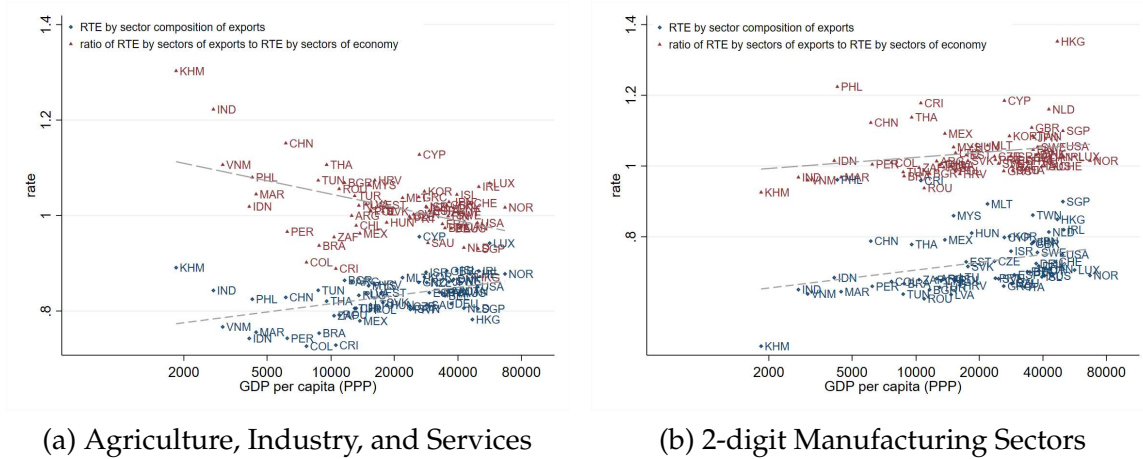
We measure on-the-job learning opportunities by using returns to experience (RTE).¹⁷ The recent literature suggests large differences in RTE between sectors. In an extensive study, [Islam et al. \(2018\)](#) use 1,041 household surveys that include 23 million individuals from 145 countries (which accounts for 95% of the world population). They find population-weighted RTE for an extra year of experience is 2.6% (services), 2% (industry), and 1.3% (agriculture). These sectoral differences hold for developing and developed countries (see Table 1 in [Islam et al. \(2018\)](#)). [Herrendorf and Schoellman \(2015\)](#) use the Current Population Survey and also document that in the United States, the wage-experience profile for nonagricultural workers is two times as steep as for agricultural workers.

We document new evidence by connecting on-the-job learning with trade. To isolate the

¹⁶In this extended model, we need recalibration to isolate the gains from trade due to changes in skill acquisition. This process may introduce additional computation errors especially for countries with large trade openness (e.g., Netherlands and Malaysia), and therefore we interpret the results with caution and mostly as a robustness check.

¹⁷We interpret RTE as reflecting on-the-job learning opportunities. In principle, RTE may also reflect changes in workers' bargaining power. There is still much debate on how to decompose RTE into changes in human capital and changes in bargaining power, which usually relies on the structure of the model (e.g., [Bagger, Fontaine, Postel-Vinay and Robin 2014](#), [Gregory 2019](#)).

Figure 3: Weighted Average RTE across Sectors



effects of trade-induced sector reallocation, we use the average RTE for agriculture, industry (manufacturing, mining, and public utility), and services from Islam et al. (2018) and normalize RTE in services to be 1 for ease of description. We compute RTE for each country's exports, which is an employment-weighted average RTE across three sectors' exports, by combining data from OECD Input–Output Tables and the World Bank.¹⁸ To shed light on how trade affects RTE, we also compute RTE by sectors for each country's overall economy, adjusted for export intensity¹⁹ to avoid that different tradability of sectors²⁰ drives the results. We compute all these measures for the year 2005.

Figure 3a presents the results. We highlight three findings. First, RTE by sectors of exports increased with GDP per capita, as developed countries tended to export more in services that embody the highest RTE among three sectors. Second, poor countries appeared to shift employment toward sectors with higher RTE by exporting, as their RTE by sectors of exports tended to be higher than RTE by sectors of the overall economy. Third, the relative ratio of RTE by sectors of exports to RTE by sectors of the economy varied markedly across countries, suggesting large heterogeneity in countries' benefits from on-the-job learning.

Finally, using aggregate sectors may mask the vast amount of heterogeneity in RTE across

¹⁸We draw output and export data from OECD Input–Output Tables and employment data from the World Bank. By assuming that output per capita is identical between producing domestic sales and producing exports, we compute the amount of employment used to produce exports in each sector for each country.

¹⁹For each country, we first multiply each sector's output with the global average export intensity for that sector to compute the hypothetical sector composition of exports. Then we compute RTE for this hypothetical sector composition of exports.

²⁰In the data, manufacturing is much more export-intensive than agriculture and services.

detailed sectors, especially for manufacturing that is export-intensive. With this in mind, we use the U.S. Census and the American Community Survey (ACS) in the years 1980–2017 to estimate RTE after 35–40 years of experience for 16 2-digit ISIC manufacturing sectors²¹ in the United States, by applying Mincer regressions and the Heckman–Locker–Taber method (Lagakos et al. 2018) detailed in Appendix C.4.

We use the RTE estimates from U.S. manufacturing sectors to compute an export-weighted average RTE and an output-weighted average RTE for each country in 2005.²² Figure 3b presents the results.²³ The results show that even though rich countries already produced more in manufacturing sectors with higher RTE, they shifted employment toward manufacturing sectors with even higher RTE by exporting. This result suggests that accounting for detailed manufacturing sectors could increase gains in human capital from trade for developed countries. Due to different implications of Figures 3a and 3b about which countries gained more RTE after trade openness. Our quantitative analysis answers this question.

The calibrated model shows that indeed developed countries tend to enjoy better on-the-job learning opportunities after trade openness, which is driven by developed countries specializing in manufacturing sectors with higher RTE and having more college workers who enjoy faster on-the-job learning than unskilled workers.

VI Conclusion

Whereas researchers have devoted much attention to the gains from trade, mostly taking workers’ skills as given, it is reasonable to think that trade can bring additional benefits (losses) by changing workers’ education choices and on-the-job learning opportunities. In this paper, we have taken a step in this direction by developing a multisector Eaton–Kortum model with heterogeneous skill intensities and on-the-job learning opportunities across sectors. In the model, workers decide whether to become skilled and accumulate

²¹ISIC stands for International Standard Industrial Classification, and we use ISIC Revision 3.0. These 2-digit manufacturing sectors include: Food Products, Beverages, and Tobaccos (ISIC 15–16), Textiles (ISIC 17–19), Wood (ISIC 20), Paper Products (ISIC 21–22), Coke, Refined Petroleum Products and Nuclear Fuel (ISIC 23), Chemicals (ISIC 24), Rubber and Plastics Products (ISIC 25), Other Non-metallic Mineral Products (ISIC 26), Basic Metals (ISIC 27), Fabricated Metal Products (ISIC 28), Machinery and Equipment (ISIC 29), Computer, Electronic, and Optical Products (ISIC 30, 32, 33), Electrical Machinery and Apparatus (ISIC 31), Motor Vehicles, Trailers, and Semi-trailers (ISIC 34), Other Transport Equipment (ISIC 35), and Manufacturing n.e.c and Recycling (ISIC 36–37).

²²Employment shares for detailed manufacturing sectors are not available in our data set.

²³We normalize the U.S.’s export-weighted average RTE for manufacturing sectors to be 0.75, to be consistent with Figure 3a, which normalizes RTE in industry to be 0.75.

human capital on the job. Our model can analytically solve for the gains from trade, through an ACR formula, augmented by gains due to changes in skill acquisition.

The calibrated model reveals that the gains from trade due to changes in skill acquisition are vastly different across countries, with large gains for the United States, the United Kingdom, and India, as well as big losses for Germany, Brazil, and Argentina. The important reason for these countries' different outcomes is their different specialization patterns after trade openness. Finally, the quantitative results show that developed countries enjoy better on-the-job learning opportunities after trade openness. We provide empirical support for the channels studied in this paper. Particularly, we document some evidence on how exporting may alter on-the-job learning opportunities. In particular, rich countries specialized in manufacturing sectors and services with higher on-the-job learning opportunities by exporting.

Our paper emphasizes how trade-induced sector reallocation affects welfare by changing workers' education choices and, more importantly, on-the-job learning opportunities. Many questions remain quantitatively unexplored about trade and skill acquisition, such as how trade affects skill specialization through shifts in the demand for different occupations or reallocation of workers across firms.

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Appendix A Proofs

Appendix A.1 Share of College Graduates

Note that in country i , a worker would choose to become skilled if and only if $\epsilon^h \exp(\mathbb{E}U(\mathbf{c}_i^h))(1 - e_i) \geq \epsilon^l \exp(\mathbb{E}U(\mathbf{c}_i^l))$. Given that ϵ^l and ϵ^h are distributed according to $G(\epsilon) = \exp(-\epsilon^{-\kappa})$, we can compute the share of workers who decide to become skilled as:

$$\begin{aligned} \Lambda_i^h &= \int_0^\infty G\left(\frac{\epsilon^h \exp(\mathbb{E}U(\mathbf{c}_i^h))(1 - e_i)}{\exp(\mathbb{E}U(\mathbf{c}_i^l))}\right) dG(\epsilon^h) \\ &= \int_0^\infty \kappa(\epsilon^h)^{-\kappa-1} \exp\left\{-\left[\left(\frac{\exp(\mathbb{E}U(\mathbf{c}_i^h))(1 - e_i)}{\exp(\mathbb{E}U(\mathbf{c}_i^l))}\right)^{-\kappa} + 1\right](\epsilon^h)^{-\kappa}\right\} d\epsilon^h \\ &= \frac{\exp(\kappa \mathbb{E}U(\mathbf{c}_i^h))(1 - e_i)^\kappa}{\exp(\kappa \mathbb{E}U(\mathbf{c}_i^h))(1 - e_i)^\kappa + \exp(\kappa \mathbb{E}U(\mathbf{c}_i^l))} \end{aligned}$$

The first equality uses the definition of the share of skilled workers. The second equality uses the definition of $G(\epsilon)$. The third equality computes the integral.

Appendix A.2 CES Trade Shares and Prices

Note that $p_{ijs}(\omega) = d_{ijs}p_{iis}(\omega) = \frac{d_{ijs}w_{is}}{\beta z_{is}(\omega)}$. Due to CES Preferences, the share of country j 's expenses in sector s that source from country i is:

$$\Pi_{ijs} = \frac{\int_{\Omega_{ijs}} p_{ijs}(\omega)^{1-\sigma} d\omega}{\sum_k \int_{\Omega_{kjs}} p_{kjs}(\omega)^{1-\sigma} d\omega} \quad (18)$$

where $\Omega_{ijs} = \{\omega \in [0, 1], p_{ijs}(\omega) \leq p_{kjs}(\omega) \forall k \neq i\}$ is the set of goods sourced from country i .

Note that $z_{is}(\omega)$ follows the *Fréchet* distribution $F_{is}(z) = \exp(-A_{is}z^{-\vartheta_s})$. We can obtain:

$$\begin{aligned} \int_{\Omega_{ijs}} p_{ijs}(\omega)^{1-\sigma} d\omega &= \int_0^\infty \left(\frac{d_{ijs}w_{is}}{\beta z}\right)^{1-\sigma} \prod_{k \neq i} F_{ks}\left(\frac{w_{ks}d_{kjs}z}{w_{is}d_{ijs}}\right) dF_{is}(z) \\ &= \int_0^\infty \left(\frac{d_{ijs}w_{is}}{\beta}\right)^{1-\sigma} A_{is}\vartheta_s z^{\sigma-\vartheta_s-2} \exp\left(-\sum_k A_{ks}\left(\frac{w_{ks}d_{kjs}z}{w_{is}d_{ijs}}\right)^{-\vartheta_s}\right) dz \\ &= \int_0^\infty \beta^{\sigma-1} (d_{ijs}w_{is})^{-\vartheta_s} A_{is} \left(\sum_k A_{ks} (w_{ks}d_{kjs})^{-\vartheta_s}\right)^{\frac{\sigma-\vartheta_s-1}{\vartheta_s}} \exp(-y)y^{\frac{\vartheta_s+1-\sigma}{\vartheta_s}-1} dy \\ &= \Gamma\left(1 - \frac{\sigma-1}{\vartheta_s}\right) \beta^{\sigma-1} (d_{ijs}w_{is})^{-\vartheta_s} A_{is} \left(\sum_k A_{ks} (w_{ks}d_{kjs})^{-\vartheta_s}\right)^{\frac{\sigma-\vartheta_s-1}{\vartheta_s}} \end{aligned} \quad (19)$$

The first equality uses the definition of p_{ijs} and Ω_{ijs} . The second equality uses the distribution of $F_{is}(z)$. The third equation changes the variable by letting $y = \sum_k A_{ks} \left(\frac{w_{ks} d_{kjs} z}{w_{is} d_{ijs}} \right)^{-\vartheta_s}$. The final equality uses the definition of the Gamma function $\Gamma(z) = \int_0^\infty x^{z-1} \exp(-x) dx$. By plugging $\int_{\Omega_{ijs}} p_{ijs}(\omega)^{1-\sigma} d\omega$ into equation (18), we obtain trade shares in equation (10). Also note that CES preferences imply:

$$P_{js} = \left(\sum_k \int_{\Omega_{kjs}} p_{kjs}(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}} = \left(\Gamma \left(1 - \frac{\sigma-1}{\vartheta_s} \right) \beta^{\sigma-1} \right)^{\frac{1}{1-\sigma}} \left(\sum_k A_{ks} (w_{ks} d_{kjs})^{-\vartheta_s} \right)^{-\frac{1}{\vartheta_s}} \quad (20)$$

where we plug in $\int_{\Omega_{ijs}} p_{ijs}(\omega)^{1-\sigma} d\omega$ in the second equality.

Appendix A.3 The Gains from Trade

With little abuse of notation, we define W_i as the real consumption in the economy, which is

$$\begin{aligned} W_i &= 2 \frac{w_i^l L_i \sum_s \Lambda_{is}^l (1 + \tau_{is}^l / 2) + w_i^h H_i \sum_s \Lambda_{is}^h (1 + \tau_{is}^h / 2)}{P_i} \\ &= C_i \frac{w_i^l L_i \sum_s \Lambda_{is}^l (1 + \tau_{is}^l / 2) + w_i^h H_i \sum_s \Lambda_{is}^h (1 + \tau_{is}^h / 2)}{\prod_s \left(\sum_k A_{ks} (w_{ks} d_{kis})^{-\vartheta_s} \right)^{-\frac{\beta_{is}}{\vartheta_s}}} \\ &= C_i \frac{w_i^l L_i \sum_s \Lambda_{is}^l (1 + \tau_{is}^l / 2) + w_i^h H_i \sum_s \Lambda_{is}^h (1 + \tau_{is}^h / 2)}{\prod_s (A_{is} w_{is}^{-\vartheta_s} / \Pi_{iis})^{-\frac{\beta_{is}}{\vartheta_s}}} \\ &= C_i \frac{\frac{w_i^l}{\prod_s w_{is}^{\beta_{is}}} L_i \sum_s \Lambda_{is}^l (1 + \tau_{is}^l / 2) + \frac{w_i^h}{\prod_s w_{is}^{\beta_{is}}} H_i \sum_s \Lambda_{is}^h (1 + \tau_{is}^h / 2)}{\prod_s (A_{is} / \Pi_{iis})^{-\frac{\beta_{is}}{\vartheta_s}}} \end{aligned} \quad (21)$$

where C_i is some country-specific constant. The first equality uses the definition of real consumption. The second equality uses $P_i = \prod_s (P_{is} / \beta_{is})^{\beta_{is}}$ and price index in equation (20). The third equality uses the expression for trade shares in equation (10). The fourth equality divides the numerator and the denominator by $\prod_s w_{is}^{\beta_{is}}$.

Note that the gains from trade is $GT_i = \frac{W_i}{W_i^o}$. By evaluating W_i and W_i^o with equation (21), we can obtain the formula in Proposition 1.

Appendix A.4 The Gains of Trade with Intermediate Inputs

Now consider the case in which there are intermediate inputs in firm production

$$y_{is} = z \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1 - \alpha_s) \psi_i h^{\frac{\phi-1}{\phi}} \right) \gamma_{is}^{\frac{\phi}{\phi-1}} \prod_{s'} (m_{s'})^{\gamma_{is}^{s'}}$$

Then the unit cost of producing with $z = 1$ is:

$$c_{is} = \left(\frac{w_{is}}{\beta \gamma_{is}^l} \right)^{\gamma_{is}^l} \prod_{s'} \left(\frac{P_{is'}}{\gamma_{is}^{s'}} \right)^{\gamma_{is}^{s'}}$$

Using the similar procedure as in [Appendix A.2](#), we can obtain:

$$\Pi_{iis} = C_{is} \frac{A_{is}(c_{is})^{-\vartheta_s}}{P_{is}^{-\vartheta_s}}$$

where C_{is} is a constant.

Let $\hat{x} = \log(x'/x)$ denote the log change of variable x from the observed equilibrium to the counterfactual case. Taking the log changes of c_{is} and Π_{iis} , we can obtain:

$$\hat{P}_{is} = \frac{\hat{\Pi}_{iis}}{\vartheta_s} + \gamma_{is}^l \hat{w}_{is} + \sum_{s'} \gamma_{is}^{s'} \hat{P}_{is'}$$

As a result,

$$\hat{P}_{is} = \sum_{s'} \alpha_{iss'} \left(\frac{\hat{\Pi}_{iis'}}{\vartheta_{s'}} + \gamma_{is'}^l \hat{w}_{is'} \right)$$

where $\alpha_{iss'}$ is the (s, s') element of the Leontief inverse matrix $(I - \Gamma_i)^{-1}$. Let S be the number of industries. I is a $S \times S$ identity matrix, and Γ_i is a $S \times S$ matrix with the (s, s') element being $\gamma_{is}^{s'}$.

Using this formula, we can show that the gains from trade are:

$$GT_i = \underbrace{\prod_s \prod_{s'} (\Pi_{iis'})^{-\frac{\alpha_{iss'} \beta_{is}}{\vartheta_{s'}}}}_{\text{ACR formula}} \times \underbrace{\frac{\frac{w_i^l}{\beta_{is} \alpha_{iss'} \gamma_{is'}^l} L_i \sum_s \Lambda_{is}^l (1 + \tau_{is}^l/2) + \frac{w_i^h}{\beta_{is} \alpha_{iss'} \gamma_{is'}^l} H_i \sum_s \Lambda_{is}^h (1 + \tau_{is}^h/2)}{\frac{w_i^{l,o}}{\beta_{is} \alpha_{iss'} \gamma_{is'}^l} L_i \sum_s \Lambda_{is}^{l,o} (1 + \tau_{is}^l/2) + \frac{w_i^{h,o}}{\beta_{is} \alpha_{iss'} \gamma_{is'}^l} H_i \sum_s \Lambda_{is}^{h,o} (1 + \tau_{is}^h/2)}}_{\text{Gains due to changes in skill acquisition}}$$

Appendix B Extensions of the Model

Appendix B.1 Ben–Porath Model for On-the-job Learning

In this section, we model on-the-job learning endogenously using a Ben–Porath model. For ease of description, we abstract from superscripts for workers' types. Assume that learning for $0 \leq t \leq 1$ units of time increases human capital by $b_{is} t^\gamma$, where b_{is} measures returns to investments in learning for country i and sector s . For example, in developed countries, b_{is} is typically higher due to factors such as more available knowledge. $0 < \gamma < 1$ captures the diminishing returns of learning.

A worker that maximizes lifetime income solves:

$$\max_t w_i(1 - t) + \frac{1}{1 + r_i} w_i(1 + b_{is}t^\gamma)$$

Assuming that b_{is} is small enough such that there is an internal solution. The first-order condition implies:

$$w_i = \frac{\gamma b_{is} t^{\gamma-1} w_i}{1 + r_i}$$

where the left-hand side is the costs of learning (less production time), while the right-hand side is the gains of learning (higher future wages). Because wages appear in both marginal costs and marginal benefits, they cancel out. Clearly, in this setting, the optimal learning time t_{is}^* is:

$$t_{is}^* = \left(\frac{\gamma b_{is}}{1 + r_i} \right)^{\frac{1}{1-\gamma}}$$

which is pinned down by parameters. Therefore, trade openness will not affect on-the-job learning if b_{is} (which captures available knowledge) remains constant after trade openness. Without loss of generality, we can normalize the production time for young workers to be 1 for each sector and country (by redefining A_{is}), and $1 + \tau_{is} = \frac{1 + b_{is}(t_{is}^*)^\gamma}{1 - t_{is}^*}$ captures changes in efficiency units between young and old. With these changes, the model with endogenous on-the-job learning decisions of the Ben–Porath type is identical to our baseline model with exogenous on-the-job learning.

Appendix C Data Description and Robustness Checks

Appendix C.1 Countries

We consider the following 53 countries in the calibration: Argentina, Australia, Austria, Bulgaria, Belgium-Luxembourg, Brazil, Canada, Switzerland, Chile, China, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, the United Kingdom, Greece, Croatia, Hungary, Indonesia, India, Ireland, Iceland, Israel, Italy, Japan, Cambodia, Korea, Lithuania, Latvia, Mexico, Malaysia, Netherlands, Norway, New Zealand, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, Slovak Republic, Slovenia, Sweden, Thailand, Turkey, Taiwan, the United States, Viet Nam, and South Africa.

Appendix C.2 Sector Decomposition

Table 6 lists the set of sectors we consider in the calibrated model. The raw data from OECD Input–Output Tables contains 34 sectors—agriculture, mining, 16 manufacturing sectors, and 16 service sectors. For precision of estimating RTE, we collapse 16 service sectors into high-skill and low-skill services, based on the share of college workers in employment in each service sector. Specially, we use the U.S. ACS 2005 data and classify a service sector to belong to high-skill services if its share of college workers in employment

lies above the median among all service sectors.

Table 6: Sector Decomposition

Sector name	ISIC Rev.3	% college workers (U.S. ACS 2005)
1. Agriculture, hunting, forestry, and fishing	01–05	31.9
2. Mining and quarrying	10–14	36.6
<i>Manufacturing sectors:</i>		
3. Food products, beverages, and tobacco	15–16	31.5
4. Textiles, textile products, leather and footwear	17–19	25.8
5. Wood and products of wood and cork	20	25.5
6. Pulp, paper, paper products, printing and publishing	21–22	49.2
7. Coke, refined petroleum products, and nuclear fuel	23	56.8
8. Chemicals and chemical products	24	61.7
9. Rubber and plastics products	25	33.6
10. Other non-metallic mineral products	26	31.7
11. Basic metals	27	32.4
12. Fabricated metal products, except machinery and equipment	28	33.1
13. Machinery and equipment n.e.c	29	40.7
14. Computer, electronic, and optical products	30, 32, 33	64.4
15. Electrical machinery and apparatus n.e.c	31	57.9
16. Motor vehicles, trailers, and semi-trailers	34	38.9
17. Other transport equipment	35	59.7
18. Manufacturing n.e.c.; recycling	36, 37	36.3
19. Low-skill services (utility, construction, wholesale, hotel, transport, and personal services)	40–63, 90–95	37.7
20. High-skill services (telecommunications, finance, real estate, renting of machinery, computer activities, research and business activities, public administration, education, and health work)	64–89	68.7

Appendix C.3 College Premium

We collect the college premium for each country in 2005 (or the nearest year when the data is available) from multiple data sources, as shown by Table 7.

Appendix C.4 Estimating RTE from US

In our empirical analysis, we present evidence on RTE after 40 years of experience. To estimate RTE for detailed sectors, we use the U.S. Census and ACS from IPUMS for the years 1980, 1990, 2000–2017 for which we have data on earnings and hours worked. We first build a measure of potential experience for each individual that we define as the minimum of age minus 18 and age minus years of schooling minus 6 ($\min\{\text{age}-18, \text{age}-6-\text{educ}\}$). We calculate the wage-experience profile for each industry by computing the

Table 7: Data Sources of the College Premium

Country	Source
Argentina, Bulgaria, Croatia, Malaysia, Philippines, Saudi Arabia, Thailand, Japan	Statistical Yearbook
Australia, Austria, Belgium-Luxembourg, Brazil, Canada, Switzerland, Chile, Czech Republic, Denmark, Spain, Estonia, Finland, the United Kingdom, Hungary, Ireland, Israel, Italy, Korea, Mexico, Netherlands, Norway, New Zealand, Poland, Portugal, Slovak Republic, Sweden	OECD Database
China, Greece, India, Iceland, Russia, Taiwan, the United States, South Africa	Luxembourg Income Study
Cyprus, Germany, France, Latvia, Lithuania, Romania, Slovenia, Turkey	Eurostat
Indonesia	IPUMS
Cambodia	Lall and Sakellariou (2010)
Viet Nam	Moock et al. (1997)

average wage increase in 5-year experience bins relative to the first bin (0–4 years of potential experience) of which the average wage increase is normalized to 0. Specifically, we estimate the following Mincer regression (we omit subscripts for sectors to save notation):

$$\log(w_{ict}) = \sum_{x \in X} \phi^x D_{ict}^x + \mathbf{bX}_{ict} + \gamma_t + \gamma_c + \epsilon_{ict}, \quad (22)$$

where i and t represent individuals and years respectively. $\log(w_{ict})$ denotes the log hourly wage for an individual i . γ_t represents time fixed effects, and γ_c is cohort fixed effect. D_{ict}^x are dummies for each experience bin, and finally \mathbf{X}_{ict} are individual controls. Note that there is a well-known collinearity problem if we include year and cohort fixed effects and potential experience in the regression ([Deaton 1997](#)), as wage growth over time can be induced by either experience or time effects. To construct the wage-experience profile, we rely on the [Deaton \(1997\)](#) and [Heckman et al. \(1998\)](#) method used by [Lagakos et al. \(2018\)](#). Specifically, we first decompose time effects into a trend and a cyclical component:

$$\gamma_t = gt + e_t. \quad (23)$$

where g denotes aggregate time trends. Specially, we restrict the cyclical component e_t to average zero over the time period $\sum_t e_t = 0$ and to be orthogonal to the time trend $\sum_t e_t t = 0$. These assumptions are also made in [Deaton \(1997\)](#) and [Aguiar and Hurst \(2013\)](#) in estimating life-cycle profiles. To pin down the time trend g , we build on the assumptions from [Heckman et al. \(1998\)](#). The idea of this approach is to assume that there are no experience effects at the end of the working life of agents, and thus, all wage growth in this last period has to come from other sources which are assumed to be common across all cohorts. This approach requires two parameter values: the value for human capital depreciation rate and the amount of years at the end of the worker’s life cycle

Table 8: Targeted Moments in the Model vs Data

Moments	Data	Model
1. Country-specific ratio of average wage to average wages of young cohort	1.51 (0.18)	1.51 (0.18)
2. Country-sector-specific output (relative to US)	0.11 (0.24)	0.11 (0.24)
3. Sector-specific college employment share in the U.S.	0.43 (0.14)	0.42 (0.14)
4. Country-specific college premium	2.06 (0.73)	2.09 (0.74)
5. Country-specific college employment share	0.21 (0.12)	0.21 (0.12)

Notes: When we compare output between the model and the data, we normalize each country's sectoral output by the U.S.'s sectoral output in the model and in the data. The moments refer to averages across all the pairs with specific values. Standard deviations are in parenthesis.

with no wage growth from experience. We assume that there is no depreciation in human capital. And there is no experience effect in the last 10 years of workers' life cycle, which is between 30 and 40 years of experience (as we censor experience at 40 years of experience), following the main specification by [Lagakos et al. \(2018\)](#). Thus, for each one sector in [Table 6](#) and each type of worker (skilled/unskilled), we separately estimate regression (22) by imposing $\gamma_t = gt + e_t$ such that there is no wage growth coming from experience in the last 10 years of individuals' working life in this sector. More details of this approach can be found in [Lagakos et al. \(2018\)](#).

Appendix C.5 Comparison of Moments in the Model and in the Data

In [Table 8](#), we compare the targeted moments in the baseline and in the data. In general, we find that our model matches the targeted data moments very well. In [Figure 4](#), we further compare the country-sector output (targeted using A_{is}) and the origin-destination-sector trade shares (untargeted though the trade costs are inferred from actual trade shares) in the model and in the data. We find that our model does a pretty good job with the regression coefficient of the data moments on the model moments being almost unity.

Appendix C.6 Robustness Checks for Parameter κ

In [Table 9](#), we report the gains from trade due to changes in skill acquisition for different values of parameter κ . It is worth noting that when we perform the counterfactual exercise for each value of parameter κ , we recalibrate all other parameters to match the relevant moments in [Table 1](#). We highlight two main findings. First, as parameter κ becomes larger, the gains from trade due to changes in skill acquisition are more volatile across countries. This is because a higher value of parameter κ makes education choices more responsive to trade openness. Second, the gains from trade due to changes in skill acquisition are not very sensitive to the value of parameter κ , as the gains are also determined by trade-induced changes in on-the-job learning opportunities.

Figure 4: Comparison of Output and Trade Shares in the Model and in the Data

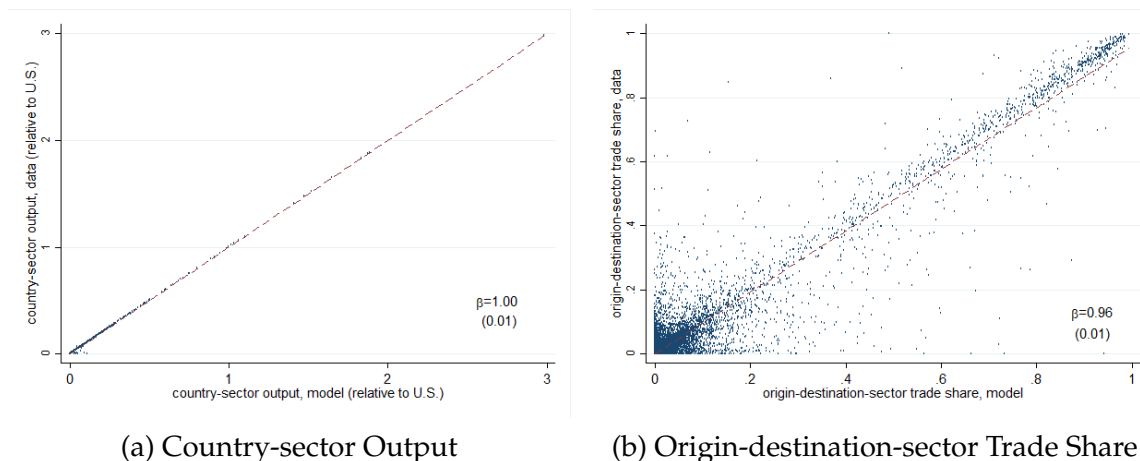


Table 9: Gains from Trade Due to Changes in Skill Acquisition

Country	baseline ($\kappa = 4$) (1)	$\kappa = 1$ (2)	$\kappa = 3$ (3)	$\kappa = 5$ (4)	$\kappa = 10$ (5)	$\kappa = 100$ (6)
USA	0.50%	0.38%	0.49%	0.52%	0.55%	0.60%
CHN	-0.10%	-0.09%	-0.09%	-0.10%	-0.10%	-0.10%
JPN	-0.16%	-0.14%	-0.16%	-0.16%	-0.14%	-0.15%
IND	0.49%	0.24%	0.45%	0.52%	0.60%	0.66%
DEU	-0.74%	-0.68%	-0.73%	-0.75%	-0.76%	-0.78%
FRA	0.01%	-0.01%	0.00%	0.01%	0.02%	0.03%
GBR	0.88%	0.71%	0.84%	0.89%	0.93%	0.98%
RUS	-0.24%	-0.10%	-0.20%	-0.23%	-0.30%	-0.54%
ITA	-0.28%	-0.26%	-0.28%	-0.28%	-0.28%	-0.29%
BRA	-0.68%	-0.57%	-0.66%	-0.71%	-0.74%	-0.79%
MEX	-0.40%	-0.20%	-0.36%	-0.42%	-0.45%	-0.50%
KOR	-0.25%	-0.31%	-0.27%	-0.25%	-0.20%	-0.18%
CAN	-0.38%	-0.21%	-0.36%	-0.40%	-0.45%	-0.49%
ESP	0.17%	0.13%	0.16%	0.17%	0.18%	0.19%
IDN	-0.34%	-0.26%	-0.32%	-0.34%	-0.37%	-0.39%
TUR	-0.21%	-0.17%	-0.20%	-0.21%	-0.22%	-0.23%
AUS	0.26%	0.29%	0.26%	0.25%	0.24%	0.24%
NLD	-0.55%	-0.60%	-0.57%	-0.56%	-0.67%	-0.66%
POL	-0.52%	-0.46%	-0.51%	-0.52%	-0.54%	-0.56%
ZAF	-0.45%	-0.29%	-0.42%	-0.46%	-0.50%	-0.54%
ARG	-0.77%	-0.64%	-0.75%	-0.78%	-0.81%	-0.84%
MYS	0.01%	0.01%	0.01%	0.01%	0.00%	0.01%
POL	-0.53%	-0.46%	-0.51%	-0.52%	-0.54%	-0.56%
SWE	-0.49%	-0.48%	-0.51%	-0.52%	-0.54%	-0.55%
CHE	0.19%	0.07%	0.17%	0.20%	0.06%	0.09%
Average	-0.18%	-0.16%	-0.18%	-0.19%	-0.20%	-0.21%
Std	0.42%	0.34%	0.40%	0.43%	0.45%	0.48%

Notes: In this table, we vary parameter κ from 1 to 100 in the baseline model and then compute the gains from trade due to changes in skill acquisition. When we perform the counterfactual exercise for each value of parameter κ , we recalibrate all other parameters to match the relevant moments in Table 1.

Appendix C.7 Parameter Values and Moments in the Extended Model

Table 10 and 11 present the parameter values and the targeted moments in the extended model. Overall, our model matches the data moments pretty well. It is worth mentioning that we also recalibrate the parameter κ to match the reduced-form estimate in Section ??, following the same procedure as in Section III.B. The new calibrated value $\kappa = 4.2$ is close to the value ($\kappa = 4$) in the baseline model.

Table 10: Parameter Values in the Extended Model

Parameters			Moments
Notation	Value	Description	Description
ρ	0.04	Discount rate (one year)	Annualized discount rate of 4%
δ_d	0.025	Death rate	Working life of 40 years
δ_p	0.20	Exogenous separation rate	1.5-3% U.S. monthly separation rates
β	2/3	Labor share	Estimates in Gollin (2002)
ϕ	1.5	Elasticity of substitution btw skilled/unskilled	Katz and Murphy (1992)
f^m	0.1	Vacancy costs by skill types	Normalization
ϑ_s	8.07 (10.86)	Sector-specific trade elasticity	Estimates in Caliendo and Parro (2015)
N_i	0.37 (1.01)	Country-specific employment ($N_{US} = 1$)	World Bank
d_{ijs}	23.85 (81.99)	Origin-destination-sector-specific trade costs	Trade shares between j and i
γ_{is}^l	0.36 (0.14)	Country-sector-specific value added share	World I/O Table 2005
γ_{is}^s	0.03 (0.07)	Country-sector-specific input-output linkages	World I/O Table 2005
β_{is}	0.05 (0.10)	Country-sector-specific consumption shares	World I/O Table 2005
τ_s^m	0.73 (0.22)	On-the-job learning returns by sectors/skill types	RTE by sectors/skill types in the U.S.
τ_i	0.01 (0.003)	Country-specific on-the-job learning returns	Relation between RTE and GDPPC in Lagakos et al. (2018)
α_s	0.45 (0.12)	Parameters governing sector-specific skill intensities	Sector-specific college employment share in the U.S. ACS 2005
ψ_i	0.35 (0.16)	Country-specific relative productivity of college workers ($\psi_{US} = 1$)	Country-specific college premium
e_i	0.46 (0.24)	Time costs of becoming skilled	Country-specific college population share in Barro and Lee (2013)
A_{is}	1.25 (1.08)	Country-sector-specific productivity ($A_{US,s} = 1$)	Country-sector-specific output in 2005
κ	4.2	Shape parameter of <i>Fréchet</i> distribution for idiosyncratic education preferences	Reduced-form estimate in Section ??
χ	5.1	Shape parameter of <i>Fréchet</i> distribution for idiosyncratic sector preferences	Between-sector dispersion of average wages

Notes: Parameter values for $\{\vartheta_s, N_i, d_{ijs}, \gamma_{is}^l, \gamma_{is}^s, \beta_{is}, \tau_s^m, \tau_i, \alpha_s, \psi_i, e_i, A_{is}\}$ refer to averages across all the pairs with specific values. Standard deviations are in parenthesis.

Table 11: Targeted Moments in the Extended Model vs Data

Moments	Data	Model
1. Country-specific ratio of average wage to average wages of young cohort	1.51 (0.18)	1.51 (0.18)
2. Country-sector-specific output (relative to US)	0.11 (0.24)	0.11 (0.24)
3. Sector-specific college employment share in the U.S.	0.43 (0.14)	0.41 (0.14)
4. Country-specific college premium	2.06 (0.73)	2.04 (0.72)
5. Country-specific college employment share	0.21 (0.12)	0.19 (0.10)
6. Reduced-form estimate in Section ??	-0.04	-0.04
7. Between-sector dispersion of log average wage in the U.S.	0.24	0.24

Note: When we compare output between the model and the data, we normalize each country's sectoral output by the U.S.'s sectoral output in the model and in the data. The first five moments refer to averages across all the pairs with specific values. Standard deviations are in parenthesis. We compute the between-sector dispersion of log average wage separately for skilled and unskilled workers using the U.S. ACS 2005, and then take the average of the between-sector dispersion across two types of workers.