Skill Acquisition and the Gains from Trade: A Cross-country Quantitative Analysis

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Abstract

This paper studies the impact of trade openness on welfare through alterations in workers' skill acquisition. We integrate endogenous choices of learning investments into a multisector Eaton-Kortum model. In the model, workers can opt to become skilled through education and further enhance their human capital via on-the-job training. Both education and on-the-job training entail time and material costs. Our model reveals that trade openness influences skill acquisition by: (1) reallocating labor between sectors, as skill intensities and on-the-job learning opportunities vary across sectors; and (2) allowing producers in each country to source varieties from more cost-effective suppliers in other countries, thus reducing unit costs of material inputs and raising real wage rates. Our calibrated model indicates that the gains in skill acquisition account for 20% of the total gains from trade. We also find that the gains in skill acquisition primarily stem from increased real wage rates that encourage skill acquisition.

JEL Codes: F1; J2
Key Words: gains from trade; education; on-the-job learning

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1 Introduction

Freer trade, by altering the composition of economic activities and reducing input costs, affects returns and costs for schooling and on-the-job learning. Despite extensive empirical evidence on how trade influences schooling (e.g., Edmonds et al. 2010, Atkin 2016, Blanchard and Olney 2016, Li 2018, Ferriere et al. 2019), there is limited quantitative evidence on how educational choices impact welfare gains from trade across a broad range of countries. Moreover, the role of on-the-job learning, which has long been acknowledged as crucial in promoting human capital (Becker 1964) and has recently gained attention due to the availability of richer micro-level data (Islam et al. 2018, Lagakos et al. 2018), has seldom been associated with trade openness.

In this paper, we bridge this gap in the literature by developing a multisector Eaton-Kortum model that includes workers' endogenous choices of investments in education and on-the-job learning. The quantitative model, calibrated to correspond with cross-country trade, production, and education data, offers insights into how trade impacts skill acquisition and welfare across an extensive range of countries.

The production side of our model is built upon the multisector version of the framework developed by Eaton and Kortum (2002), enhanced with sectoral heterogeneity in skill intensities and on-the-job learning. Specifically, there is a final good in each country, assembled by competitive producers who combine sector-level varieties, each sourced from the most cost-effective supplier globally. The final good is utilized for consumption and as material inputs in learning. On the worker side, we incorporate an Overlapping Generations (OLG) model, where each worker has a two-period lifespan and can allocate time between working and learning, following the Ben-Porath model. Workers have the option to become skilled through education and can further advance their human capital through on-the-job training. Both education and on-the-job training entail time and material costs.

We show that this model enables an analytical solution for the gains from trade, measured by changes in real consumption from autarky to the observed economy. Our formula integrates the Arkolakis et al. (2012) (ACR) formula, augmented by the gains resulting from changes in skill acquisition. Our model reveals two main forces through which trade affects skill acquisition. Firstly, due to comparative advantages and sectoral heterogeneity in skill intensities and on-the-job learning opportunities, trade-induced sector reallocation alters education returns and average on-the-job learning opportunities. Secondly, in the model, the returns from learning depend on nominal wage rates, while a portion of learning costs are allocated for material inputs, and thus learning costs are determined by the final-good price. A decrease in unit costs of material inputs would lead to a relative increase in learning returns compared to learning costs, and this relative increase is reflected by rising real wage rates. Trade openness enables producers in each country to access more cost-effective varieties from suppliers in other countries, thereby reducing unit costs of material inputs and increasing real wage rates. This, in turn, encourages investments in learning activities.

We combine multiple data sources to calibrate the model to 54 countries and 20 sectors in 2005. We find that the gains from trade due to skill acquisition are considerable. For the 20 largest countries in our model, the average gains in real consumption resulting from trade-induced skill acquisition amount to 2.42%, accounting for 20% of the total gains in real consumption from trade (11.85%). The model-predicted magnitude of human capital in driving the gains from trade is consistent with recent literature that considers the role of both the number of skilled workers and human capital quality[1] in development accounting (e.g., Schoellman 2012, Jones 2014).[2]

Moreover, we find that the gains in skill acquisition are consistently positive but vary considerably across countries. For instance, the Netherlands and Canada benefit the most from trade-induced skill acquisition, with increases in real consumption of 13.47% and 5.22%, respectively. Conversely, China and Brazil gain the least, with increases in real consumption of 0.48% and 0.32%, respectively. Interestingly, we find a strong positive correlation between the ACR formula and the gains in skill acquisition across countries, suggesting that increased real wage rates (captured by the ACR formula) play a crucial role in encouraging skill acquisition.

We further perform a decomposition of the gains in skill acquisition into the two aforementioned forces: (1) comparative advantages that reallocate workers across sectors with varying learning opportunities; and (2) reduced material costs and increased real wage rates that promote skill acquisition. Our analysis shows that the second force is the main driver of the gains in skill acquisition. Moreover, we find that changes in skill acquisition driven by comparative advantages can be negative for some countries that have comparative advantages in low-skill sectors (e.g., agriculture), whereas changes in skill acquisition driven by real wage rates are consistently positive.

[1]In our model, human capital quality is captured by material investments.

[2]For instance, in a model that accounts for both education quantity and quality, Schoellman (2012) demonstrates that education accounts for about 20% of cross-country income differences.

Finally, we perform several robustness checks, such as evaluating different values for key parameters, incorporating input-output tables, considering multi-period OLG for workers, and allowing for destination-specific knowledge diffusion. Notably, we find that including input-output linkages amplifies the gains in skill acquisition because the gains in real wage rates from trade are generally larger in the model with input-output linkages (Costinot and Rodríguez-Clare 2014), which further promotes skill acquisition. Furthermore, the significance of materials in forming human capital plays a crucial role in shaping the gains in skill acquisition, as it determines the responses of skill acquisition to reduced material input costs and increased real wage rates. Nevertheless, across these robustness checks, the gains in skill acquisition from trade consistently account for a considerable portion of the total gains from trade.

In this paper, our contribution lies in extending the multisector Eaton–Kortum model by incorporating workers' endogenous skill acquisition. Through this model, we can analytically demonstrate how skill formation is integrated into the widely-used ACR formula of the gains from trade. Furthermore, we calibrate the model and provide quantitative evidence to enhance our understanding of how trade-induced sector reallocation and real wage gains influence skill acquisition.

This paper connects to several strands of literature. The first strand encompasses the extensive literature on the gains from trade. Existing studies highlight the significance of various factors in accounting for the gains from trade, such as multiple sectors, intermediate inputs, firm entry, nonlinearities, and productivity correlations (see e.g., Costinot and Rodríguez-Clare 2014, Caliendo and Parro 2015, Adão et al. 2017, Baqaee and Farhi 2019, Lind and Ramondo 2023). Building upon these earlier contributions, we investigate the impact of two additional factors—education choices and on-the-job learning—on the gains from trade. We demonstrate how the basic ACR formula is adapted to accommodate these two factors while maintaining its simplicity. We then perform quantitative analysis to highlight the importance of these two factors in driving the overall gains from trade.

Second, our work relates to the literature on how trade affects workers' skill acquisition. In addition to the aforementioned empirical evidence, many theoretical papers investigate the impact of trade on schooling. Findlay and Kierzkowski (1983) first incorporate education choices into a two-factor, two-good trade model. Several follow-up papers further expand this framework by introducing worker heterogeneity (e.g., Borsook 1987, Das 2006, Falvey et al. 2010) and other production factors (e.g., Bond et al. 2003). Our study differs from these papers in two aspects. First, besides education, we also consider on-the-job learning, drawing on the training literature (e.g., Acemoglu 1997, Acemoglu and Pischke 1998). Second, we embed endogenous choices of education and on-the-job learning into an Eaton-Kortum framework, which enables us to tractably include a greater number of countries and sectors in our analysis. Whereas some recent papers also employ Eaton-Kortum models with worker skill types (Parro 2013, Burstein and Vogel 2017, Reyes-Heroles et al. 2020), these studies largely overlook endogenous choices of skill acquisition, which are our primary focus in this paper. Compared to the empirical and theoretical literature, there are relatively fewer quantitative studies, primarily concentrating on the impact of trade on education choices in specific countries (e.g., Harris and Robertson 2013, Danziger 2017, Ferriere et al. 2019). We complement these studies by examining a large set of countries and by quantifying the less-explored impact of trade on on-the-job learning.

Lastly, we connect with recent papers that emphasize the importance of life-cycle human capital accumulation in development accounting (Manuelli and Seshadri 2014, Islam et al. 2018, Lagakos et al. 2018). Our paper is particularly related to Manuelli and Seshadri (2014), who also consider that skill acquisition requires both time and materials. They argue that lower TFP in developing economies increases the cost of material inputs for human capital accumulation, subsequently reducing households' incentives to invest in human capital. While our focus lies on the impact of trade openness, the primary driver of trade-induced skill acquisition operates similarly to theirs: trade openness allows producers in each country to access varieties from more cost-effective suppliers in other countries, thus lowering material input costs and promoting investments in learning activities.

This paper is structured as follows. Section 2 introduces the model. Section 3 presents the model calibration, and Section 4 quantitatively examines the impact of trade on workers' skill acquisition. Section 5 offers several robustness checks on the baseline results. Section 6 concludes.

2 Model

We consider a world consisting of I countries and S sectors, with i representing the country index and s representing the sector index. The production side is based on a multisector Eaton-Kortum model, featuring varying skill intensities and on-the-job learning opportunities across sectors. Regarding the workforce, we incorporate an OLG model. Each worker lives for two periods and can allocate time between working and learning, following the Ben-Porath model. Workers can choose to become skilled through education and further develop their human capital via on-the-job training. Both education and on-the-job training involve time and material costs. For tractability, we restrict our attention to a single dimension of general human capital.[3]

In what follows, we focus on the steady state of the model, in which aggregate variables are constant.

2.1 Production

2.1.1 Final Good Producers

In each country, there exists a nontradable final good produced by perfectly competitive manufacturers utilizing intermediate goods from every sector:

$$Q_i = \prod_s Q_{i,s}^{\beta_{i,s}}.$$

Here, $\beta_{i,s}$ denotes the expenditure share on intermediate goods from sector s, with $\sum_s \beta_{i,s} = 1$. The final good can be consumed or utilized to cover material costs. The price index for the final good is given by $P_i = \prod_s (P_{i,s}/\beta_{i,s})^{\beta_{i,s}}$, where $P_{i,s}$ represents the price index of intermediate goods from sector s.

2.1.2 Intermediate Good Producers

Within each country i and sector s, a nontradable intermediate good is produced by perfectly competitive manufacturers. The production combines a unit measure of varieties $\omega \in [0,1]$ using a Dixit-Stiglitz production function:

$$Q_{i,s} = \left(\int_0^1 q_{i,s}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{\sigma_s}{\sigma_s - 1}}.$$

[3] Firm-specific components of human capital have been found to be less relevant for wage growth than general human capital (e.g., Lazear 2009). A focus on general human capital is common in the quantitative literature on earnings dynamics (e.g., Bagger et al. 2014, Manuelli and Seshadri 2014).

To minimize costs, the intermediate-good producer in country i will purchase each variety ω in sector s from the most economical supplier worldwide:

$$p_{i,s}(\omega) = \min_{j} p_{j,i,s}(\omega),$$

where $p_{i,s}(\omega)$ denotes the purchase price of variety ω for the intermediate-good producer in country i, and $p_{j,i,s}(\omega)$ is the selling price of variety ω from country j to i.

Intermediate goods are utilized to create final goods. The price index for the intermediate good can be expressed as $P_{i,s}^{1-\sigma_s} = \int_0^1 p_{i,s}(\omega)^{1-\sigma_s} d\omega$. The quantity demanded for variety ω is $q_{i,s}(\omega) = p_{i,s}(\omega)^{-\sigma_s} P_{i,s}^{\sigma_s} Q_{i,s}$.

2.1.3 Production and Trade Costs for Varieties

Production Technology. In every country i, the technology to produce each variety ω of sector s is available, with the productivity level $z_{i,s}(\omega)$ drawn from a Fréchet distribution $F_{i,s}(z) = \exp(-A_{i,s} z^{-\vartheta_s})$. The scale parameter $A_{i,s} > 0$ determines the average productivity and thus the comparative advantage of sector s in country i. The shape parameter ϑ_s controls the dispersion of productivity draws, and it is required that $\vartheta_s > \sigma_s - 1$ to achieve a finite integral of sales. The production function is given by:

$$q = z_{i,s}(\omega) \left(\alpha_s u^{\frac{\phi-1}{\phi}} + (1-\alpha_s)\psi_i e^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}}, \tag{1}$$

where u and e denote efficiency units of time for unskilled and skilled workers, respectively. The parameter α_s governs the skill intensity of sector s's production. The parameter ψ_i accounts for skilled-biased technology in production for country i. The parameter ϕ is the elasticity of substitution between the two types of labor. This production technology is freely accessible to numerous potential entrants that take market prices as given.

We assume that the labor markets in country i are divided by skill types and sectors. Each labor market is perfectly competitive. Let $w_{i,s}^e$ and $w_{i,s}^u$ represent wage rates per unit of efficiency labor for skilled and unskilled workers, respectively. Cost minimization implies that labor costs per unit of output in country i and sector s, which are denoted by $w_{i,s}$, can be written as (when $z_{i,s}(\omega) = 1$):

$$w_{i,s} = \left(\alpha_s^{\phi} (w_{i,s}^u)^{1-\phi} + (1-\alpha_s)^{\phi} \psi_i^{\phi} (w_{i,s}^e)^{1-\phi} \right)^{1/(1-\phi)}.$$

Trade Costs. Shipping one unit of goods from country i to j involves iceberg transportation costs $d_{i,j,s} \geq 1$.

2.1.4 Solving Trade Shares

Given the unit cost $w_{j,s}$, the iceberg costs $d_{j,i,s}$, and the productivity draw $z_{j,s}(\omega)$, the selling price of variety ω from country j to i can be determined as:

$$p_{j,i,s}(\omega) = \frac{w_{j,s} d_{j,i,s}}{z_{j,s}(\omega)}.$$

Because the production technology is freely accessible to numerous potential entrants, there are no profits for the producers of varieties. Since the intermediate-good producer in country i will source the variety from the most cost-effective supplier, we can now determine the set of varieties sourced from country j:

$$\Omega_{j,i,s} = \{\omega \mid p_{j,i,s}(\omega) \leq p_{k,i,s}(\omega), \forall\, k \neq j\} = \{\omega \mid w_{j,s} d_{j,i,s}/z_{j,s}(\omega) \leq w_{k,s} d_{k,i,s}/z_{k,s}(\omega), \forall\, k \neq j\} \tag{2}$$

In the end, given the Dixit-Stiglitz demand system and that variety-level productivity levels follow a Fréchet distribution, we can calculate the share of country i's expenses in sector s that are sourced from country j (proof provided in Appendix B.1):

$$\Pi_{j,i,s} = \frac{\int_{\Omega_{j,i,s}} p_{j,i,s}(\omega)^{1-\sigma} d\omega}{\sum_k \int_{\Omega_{k,i,s}} p_{k,i,s}(\omega)^{1-\sigma} d\omega} = \frac{A_{j,s} \left(d_{j,i,s} w_{i,s}\right)^{-\vartheta_s}}{\sum_k A_{k,s} \left(d_{k,i,s} w_{k,s}\right)^{-\vartheta_s}}. \tag{3}$$

Thus, the model predicts trade shares identical to those in multisector Eaton-Kortum models, as seen in, for example, Burstein and Vogel (2017).

2.2 Workers

2.2.1 Setup

Age Structure. In country i, each generation consists of a measure L_i of workers. Every worker has a lifespan of two periods: young (Y) and old (O). During each period, a worker has efficiency units of time, which can be allocated between working and learning, following the Ben-Porath approach.

Utility. Workers derive linear utility from consuming the nontradable final good and apply a discount rate of ρ to their future consumption.

Education. In order for a worker to become skilled, they must undergo education, which involves both time and material costs. First, education reduces a young worker's production time by a proportion t_e. We assume this time cost remains constant across countries, and in our quantitative analysis, we define being skilled as obtaining a college education (typically lasting four years). Second, education requires material inputs in units of final goods, accounting for expenses such as medical care, nutrition, and tutoring fees, which can matter for human capital formation. For instance, Schoellman (2012) documents substantial heterogeneity in schooling quality for immigrants from different countries conditional on the same years of schooling.

Whereas the time costs of education are fixed, we assume that skilled workers in each country i can endogenously choose the amount of material inputs used in human capital formation, which determines their initial human capital:

$$h_i^{Y,e} = b_i t_e^{\gamma_1} y^{\gamma_2}. \tag{4}$$

y is the amount of material inputs, and b_i is country-specific and governs the cross-country heterogeneity in education efficiency for reasons other than material inputs. As typically assumed in the literature (Manuelli and Seshadri 2014, Hsieh et al. 2019), the human capital formed through education is a Cobb-Douglas function of both time spent and material inputs, with respective elasticities $0 < \gamma_1 < 1$ and $0 < \gamma_2 < 1$. As an unskilled person does not incur any investments in education, we normalize their initial human capital to 1, $h_i^{Y,u} = 1 \; \forall \, i$. It is worth noting that as unskilled and skilled people's efficiency units are imperfect substitutes in production, their human capital levels are thus in terms of different units and not directly comparable.

Aside from time and material inputs, workers in different countries may face different barriers τ_i (e.g., discrimination, quota on enrollments) to obtain an education. We model these frictions as proportional adjustments to utility from consumption (Hsieh et al. 2019). This setting helps the model exactly match the observed college enrollment ratio observed in the data. Moreover, to generate an imperfect elasticity of education choices to skill returns (as evidenced by Porzio et al. (2022)), we also incorporate idiosyncratic preferences, $\{\epsilon^e, \epsilon^u\}$, for becoming a skilled or unskilled worker, respectively. These preferences are i.i.d. and drawn from a Fréchet distribution, $G(\epsilon) = \exp(-\epsilon^{-\kappa})\ \forall\ \epsilon > 0$.[4] The preferences are also proportional adjustments to the worker's utility. For instance, $\epsilon^e < 1$ may represent that, for some workers, learning demands greater effort and results in higher disutility. Parameter κ controls the dispersion of preferences, with a smaller κ indicating a larger dispersion in preferences. As shown below, parameter κ determines the response of education choices to changes in skill returns. As the magnitude of this response is key to our quantitative results, we will use empirical evidence to discipline the value of parameter κ.

On-the-job Learning. For workers of each skill type $m \in \{e, u\}$, they can accumulate human capital while working on the job. We follow Manuelli and Seshadri (2014) and assume that the increment in human capital due to on-the-job training has the same Cobb-Douglas functional form as the human capital formation due to schooling. Given this assumption, the worker's human capital in old age is given by:

$$h_{i,s}^{O,m} = h_i^{Y,m} + \mu_{i,s}^m t^{\gamma_1} x^{\gamma_2}. \tag{5}$$

In contrast to the binary education choice, we assume that time investments in on-the-job learning are continuous variables. Workers decide the amount of efficiency units (t) and materials in units of final goods (x) to invest in learning. The parameter $\mu_{i,s}^m$ is country-sector-skill-specific and accounts for the heterogeneity in on-the-job learning opportunities across countries, sectors, and workers' education levels, as supported by extensive empirical evidence (e.g., Dix-Carneiro 2014, Lagakos et al. 2018).

Sectoral Choices. Workers freely choose their working sector. For tractability, we assume that each worker makes their sectoral choice after making the education choice during young age, and their job remains unchanged during their old age, as in Hsieh et al. (2019). As we show in Proposition 1 below, in equilibrium, the discounted present value of income at the beginning of young age must be equal across sectors.[5]

[4] This approach of introducing idiosyncratic preferences or abilities is now widely used in the literature studying worker sorting into locations, sectors, and occupations (e.g., Lagakos and Waugh 2013, Bryan and Morten 2019, Tombe and Zhu 2019).

[5] It is worth noting that if we allow workers to choose sectors again in old age, there can be kink solutions. In old age, all the workers will go to the sector with the highest wage rate, as they will not invest in human capital when old. The sector with the highest wage rate is not necessarily the sector with the highest discounted present value of income at the beginning of young age. In Section 5.2, we address this issue of kink solutions by introducing an imperfectly elastic labor supply at the sector level, allowing for sector-specific preferences (Galle et al. 2023).

2.2.2 Solving Worker's Problem

Upon birth, each worker initially decides whether to pursue an education and the amount of material inputs invested in the education process. Subsequently, the worker selects a sector to work in and determines the intensity of on-the-job training. We determine the worker's choices using backward induction.

Learning Investments and Sectoral Choices. Given education level $m \in \{e, u\}$ and education material investments y (which will be solved below), a young worker in country i selects consumption flows, the working sector, and investments in learning activities to optimize their utility, denoted as V_i^m:

$$\max_{c^Y, c^O, s, t, x} \quad V_i^m = c^Y + \frac{1}{1+\rho} c^O$$

$$\text{s.t.} \quad \underbrace{c^Y + \frac{1}{1+r} c^O}_{\text{present value of consumption}} = \underbrace{w_{i,s}^m \left(h_i^{Y,m} (1 - \mathcal{I}_e t_e) - t \right)}_{\text{wage income when young}} - \underbrace{(\mathcal{I}_e y + x) \, P_i}_{\text{material costs of learning}} + \underbrace{\frac{w_{i,s}^m \left(h_i^{Y,m} + \mu_{i,s}^m t^{\gamma_1} x^{\gamma_2} \right)}{1+r}}_{\text{wage income when old}} \tag{6}$$

With linear utility, the interest rate must be equal to the discount rate ($r = \rho$); otherwise, the worker would consume no goods in one period. Therefore, we assume $r = \rho$ and set the worker's consumption in each period to be equal to their income in the same period.[6] The right-hand side of the second row shows the present value of income for workers. When a worker chooses to work in sector s, they earn a wage income of $w_{i,s}^m \left(h_i^{Y,m} (1 - \mathcal{I}_e t_e) - t \right)$ while young. In this expression, $\mathcal{I}_e$ is a dummy variable indicating whether the worker receives an education. t_e represents the portion of production time lost due to education, and t represents the efficiency units dedicated to on-the-job learning. The term $(\mathcal{I}_e y + x) \, P_i$ denotes the associated material costs of learning. For an old worker, there are no incentives for learning, resulting in a wage income of $w_{i,s}^m \left(h_i^{Y,m} + \mu_{i,s}^m t^{\gamma_1} x^{\gamma_2} \right)$, where human capital $\left(h_i^{Y,m} + \mu_{i,s}^m t^{\gamma_1} x^{\gamma_2} \right)$ depends on the investments made in the previous period, as demonstrated in equation (5).

Proposition 1 (Learning Investments and Sectoral Choices). *Given the education choice $m \in \{e, u\}$ and education investments y, we can determine the optimal learning investments and the choice of sector as follows:*

[6] It should be noted that when $r = \rho$, the worker is indifferent between consuming in each period. Hence, we can set workers' consumption in each period to equal their income in the same period: $c^Y = w_{i,s}^m \left(h_i^{Y,m} (1 - \mathcal{I}_e t_e) - t \right) - (\mathcal{I}_e y + x) \, P_i$ and $c^O = w_{i,s}^m \left(h_i^{Y,m} + \mu_{i,s}^m t^{\gamma_1} x^{\gamma_2} \right)$. This setting avoids intertemporal borrowing, as commonly used in dynamic trade models (e.g., Caliendo et al. 2019).

(i) For workers in country i and sector s, the optimal time and material inputs for learning are:

$$t_{i,s}^{m} = \left[\frac{\gamma_1^{1-\gamma_2} \gamma_2^{\gamma_2} \mu_{i,s}^{m}}{1+r} \left(\frac{w_{i,s}^{m}}{P_i} \right)^{\gamma_2} \right]^{\frac{1}{1-\gamma_1-\gamma_2}}, \tag{7}$$

$$x_{i,s}^{m} = \left[\frac{\gamma_1^{\gamma_1} \gamma_2^{1-\gamma_1} \mu_{i,s}^{m}}{1+r} \left(\frac{w_{i,s}^{m}}{P_i} \right)^{1-\gamma_1} \right]^{\frac{1}{1-\gamma_1-\gamma_2}}. \tag{8}$$

(ii) In equilibrium, the present value of income is equalized across sectors:

$$\begin{aligned} & w_{i,s}^{m} \left(h_i^{Y,m}(1-\mathcal{I}_e t_e) - t_{i,s}^{m} \right) - \left(\mathcal{I}_e y + x_{i,s}^{m} \right) P_i + \frac{w_{i,s}^{m} \left(h_i^{Y,m} + \mu_{i,s}^{m} (t_{i,s}^{m})^{\gamma_1} (x_{i,s}^{m})^{\gamma_2} \right)}{1+r} \\ = {} & w_{i,s'}^{m} \left(h_i^{Y,m}(1-\mathcal{I}_e t_e) - t_{i,s'}^{m} \right) - \left(\mathcal{I}_e y + x_{i,s'}^{m} \right) P_i + \frac{w_{i,s'}^{m} \left(h_i^{Y,m} + \mu_{i,s'}^{m} (t_{i,s'}^{m})^{\gamma_1} (x_{i,s'}^{m})^{\gamma_2} \right)}{1+r} \ \forall\, s', \end{aligned} \tag{9}$$

which implies that workers are indifferent when selecting between various sectors.

Proof: See Appendix Section B.2.

Result (i) of Proposition 1 describes the optimal learning investments ($t_{i,s}^{m}$ and $x_{i,s}^{m}$). Under the constraint $\gamma_1 + \gamma_2 < 1$ (which implies diminishing returns to scale in learning and will be satisfied in our calibration), the optimal time and resources allocated to learning increase with $\mu_{i,s}^{m}$, which governs learning opportunities. Furthermore, the optimal learning investments also rise with real wage $w_{i,s}^{m}/P_i$. This occurs because the returns from training depend on nominal wage rates $w_{i,s}^{m}$, while a portion of training costs are paid for materials and are thus determined by the final-good price P_i. Consequently, an increase in real wage $w_{i,s}^{m}/P_i$ would lead to a relative increase in training returns compared to training costs, resulting in an increase in learning investments.

Result (ii) of Proposition 1 illustrates the present value of income across various sectors. In equilibrium, since workers can freely select sectors and the Fréchet-distributed productivity guarantees positive employment in each sector (due to the possibility of exceptionally large productivity draws),[7] workers will be indifferent in their utility when choosing between different sectors. This suggests that the present value of income should be equalized across all sectors.

[7]Positive employment can also be observed from equation (3), which indicates that for every level of wage rate $w_{i,s}^{m}$, the trade share always remains positive.

Education Choices Having solved the utility value of V_i^m in equation (6) for each education level m, we can now explore the education choice. As mentioned previously in Section 2.2.1, the worker will select an education level $m \in \{e, u\}$ and the amount of material investments y (if choosing to be educated) to maximize their utility, taking into account their individual preferences:

$$\max_{m \in \{e,u\}, y} \{\epsilon^u V_i^u, \epsilon^e V_i^e / \tau_i\}.$$

where V_i^e depends on investments y as shown in equation (6). Define $\Lambda_{i,s}^e$ ($\Lambda_{i,s}^u$) as the ratio of skilled (unskilled) workers' employment in sector s to the total employment of skilled (unskilled) workers: $\sum_s \Lambda_{i,s}^e = \sum_s \Lambda_{i,s}^u = 1$. We can obtain the following result.

Proposition 2 (Education Choices)**.** *The optimal education choices are:*
(i) For workers choosing to become skilled in country i, the optimal amount of material investments in education is given by:

$$y_i = \left[\gamma_2 b_i t_e^{\gamma_1} \frac{((1+\rho)(1-t_e)+1) \sum_s \Lambda_{i,s}^e w_{i,s}^e}{(1+\rho) P_i} \right]^{\frac{1}{1-\gamma_2}} \tag{10}$$

(ii) In country i, given Fréchet-distributed preferences, the proportion of workers opting to become skilled is given by:

$$\Lambda_i^e = \frac{(V_i^e/\tau_i)^\kappa}{(V_i^e/\tau_i)^\kappa + (V_i^u)^\kappa}. \tag{11}$$

Proof: See Appendix Section B.3.

Result (i) of Proposition 2 illustrates the optimal material investments in education, which grow with education efficiency, b_i. These investments also increase with the employment-weighted average real wage across sectors, $\sum_s \Lambda_{i,s}^e w_{i,s}^e / P_i$, as education entails material inputs, akin to the earlier finding on on-the-job learning. Result (ii) indicates that the proportion of workers opting to become skilled relies on the utility of being skilled (V_i^e) in comparison to being unskilled (V_i^u). The parameter κ regulates the reactions of education choices to changes in the relative returns of being skilled. We will calibrate κ to correspond with the empirically estimated responses of education choices to changes in skill returns. We denote $L_i^e = \Lambda_i^e L_i$ and $L_i^u = (1 - \Lambda_i^e) L_i$ as the number of skilled and unskilled workers in country i, respectively.

2.3 Equilibrium

We assume that trade is balanced at the national level for each period. The labor-market clearing conditions imply:

$$L_i^e \Lambda_{i,s}^e \left(h_i^{Y,e}(1-t_e) - t_{i,s}^e + h_{i,s}^{O,e} \right) = \frac{(1-\alpha_s)^\phi \psi_i^\phi (w_{i,s}^e)^{-\phi}}{(w_{i,s})^{1-\phi}} \sum_j \Pi_{i,j,s} \beta_{j,s} I_j, \tag{12}$$

$$L_i^u \Lambda_{i,s}^u \left(h_i^{Y,u} - t_{i,s}^u + h_{i,s}^{O,u} \right) = \frac{\alpha_s^\phi (w_{i,s}^u)^{-\phi}}{(w_{i,s})^{1-\phi}} \sum_j \Pi_{i,j,s} \beta_{j,s} I_j. \tag{13}$$

$I_i = \sum_s \left[L_i^e \Lambda_{i,s}^e w_{i,s}^e \left(h_i^{Y,e}(1-t_e) - t_{i,s}^e + h_{i,s}^{O,e} \right) + L_i^u \Lambda_{i,s}^u w_{i,s}^u \left(h_i^{Y,u} - t_{i,s}^u + h_{i,s}^{O,u} \right) \right]$ represents the total labor income in country j, which is aggregated across both young and old workers in all sectors. The left-hand side of each equation indicates the supply of each type of worker to each sector, while the right-hand side represents the demand for each type of worker, aggregated across destinations. It is important to note that, according to equation (3), $\Pi_{i,j,s}$ also depends on $\{w_{i,s}^e, w_{i,s}^u\}$. Thus, by combining equations (7) through (13), we can determine each country's wage rates $w_{i,s}^m$, learning investments $\{y_i, t_{i,s}^m, x_{i,s}^m\}$, worker shares in each sector $\{\Lambda_{i,s}^u, \Lambda_{i,s}^e\}$, and the share of skilled workers Λ_i^e. With the wages and worker measures, we can compute all other endogenous variables, such as $\{P_{i,s}, P_i, p_{i,j,s}(\omega), \Pi_{i,j,s}\}$.

2.4 Gains from Trade

We follow Costinot and Rodríguez-Clare (2014) to evaluate welfare based on workers' real consumption (excluding learning costs). For country i, let GT_i represent the ratio of real consumption in the observed economy to that in the autarkic economy, where bilateral trade costs are infinite ($d_{i,j,s} \to \infty \; \forall \; i \neq j$). We use the superscript aut to denote variables in the autarkic economy.

Proposition 3 (Gains from Trade). *Assume that trade is balanced at the national level. The gains from trade in country i are:*

$$GT_i = \underbrace{\prod_s (\Pi_{i,i,s})^{-\frac{\beta_{i,s}}{\vartheta_s}}}_{\text{ACR formula}} \times \underbrace{\frac{L_i^u \sum_s \Lambda_{i,s}^u \lambda_{i,s}^u \bar{h}_{i,s}^u + L_i^e \sum_s \Lambda_{i,s}^e \lambda_{i,s}^e \bar{h}_{i,s}^e - \mathcal{F}_i}{L_i^{u,aut} \sum_s \Lambda_{i,s}^{u,aut} \lambda_{i,s}^{u,aut} \bar{h}_{i,s}^{u,aut} + L_i^{e,aut} \sum_s \Lambda_{i,s}^{e,aut} \lambda_{i,s}^{e,aut} \bar{h}_{i,s}^{e,aut} - \mathcal{F}_i^{aut}}}_{\text{Gains in skill acquisition from trade}}. \tag{14}$$

$\bar{h}_{i,s}^u = \left(h_i^{Y,u} - t_{i,s}^u + h_{i,s}^{O,u} \right)/2$ *and* $\bar{h}_{i,s}^e = \left(h_i^{Y,e}(1-t_e) - t_{i,s}^e + h_{i,s}^{O,e} \right)/2$ *are average efficiency* *units used in production per unskilled and skilled worker in sector s, respectively.* $\lambda_{i,s}^m = w_{i,s}^m / \prod_s w_{i,s}^{\beta_{i,s}}$ *measures the effect of relative wages. The expenditures on the material inputs of learning are denoted as* $\mathcal{F}_i = \left[L_i^u \sum_s \Lambda_{i,s}^u x_{i,s}^u + L_i^e (y_i + \sum_s \Lambda_{i,s}^e x_{i,s}^e)\right] P_i / \prod_s w_{i,s}^{\beta_{i,s}}$.

Proof: See Appendix Section B.4.

The first term on the right-hand side of equation (14) precisely corresponds to the multisector version of the formula found in ACR. This term illustrates the gains resulting from alterations in wage rates and prices following trade liberalization.

Our key contribution is the second term that captures two primary forces through which trade influences skill acquisition. First, due to comparative advantage, trade openness reallocates workers between sectors that offer varying on-the-job learning opportunities and have different demands for skilled workers. This force is demonstrated by changes in the sectoral shares of workers ($\Lambda_{i,s}^e$ and $\Lambda_{i,s}^u$) and changes in relative wages between skill types and across sectors ($\lambda_{i,s}^m$) following trade liberalization.

Secondly, trade enables producers in each country to source varieties from more affordable suppliers in other countries, thereby reducing the unit cost of material inputs P_i and increasing real wages. The increase in real wages encourages skill acquisition, as shown earlier by equations (7), (8) and (10), because both education and on-the-job training involve material costs. While our focus is on the impact of trade openness, this force operates similarly to Manuelli and Seshadri (2014), who argue that lower TFP in developing economies increases the cost of inputs for human capital accumulation, consequently diminishing households' incentives to invest in human capital.

Overall, the two forces consequently lead to changes in skill acquisition, as reflected by changes in the number of skilled and unskilled workers (L_i^e and L_i^u) and their average efficiency units utilized in production ($\bar{h}_{i,s}^e$ and $\bar{h}_{i,s}^u$), with the corresponding changes in the material costs of learning $\mathcal{F}_i$.

3 Calibration

In this section, we take the model to the data. We discuss the calibration of model parameters and subsequently present the calibration results.

3.1 Calibration

We calibrate our model to 53 countries and the Rest of the World in 2005. We consider 20 sectors—agriculture, mining, 16 manufacturing sectors, low-skill services, and high-skill services. Appendix Section C provides the details of countries and sectors.

Due to data limitations, we do not solve the model using the "Exact Hat Algebra" approach (Dekle et al. 2008), which offers the advantage of reducing the number of model parameters requiring calibration but necessitates observed data on an extensive set of variables.[8] Instead, we directly calibrate all the model parameters and solve the model using the iterative algorithm developed by Alvarez and Lucas (2007).

The calibration must determine the following parameter values: discount rate ρ, elasticities of human capital gains to time and materials $\{\gamma_1, \gamma_2\}$, the elasticity of substitution between skilled/unskilled labor ϕ, trade elasticities $\{\vartheta_s\}$, employment $\{L_i\}$, origin-destination-sector-specific trade costs $\{d_{i,j,s}\}$, spending shares $\{\beta_{i,s}\}$, on-the-job learning strength $\{\mu^m_{i,s}\}$, sectoral skill intensities $\{\alpha_s\}$, productivity of skilled labor $\{\psi_i\}$, education efficiency and barriers $\{b_i, \tau_i\}$, productivity levels $\{A_{i,s}\}$, and the shape parameter of the distribution of education preferences κ. We use the subscript or the superscript to denote the dimension of parameter values (s: sector; i, j: country; m: skill type) if the parameter is multi-valued along any dimension.

3.1.1 Externally Calibrated Parameters

We first draw some common parameters directly from the literature, as presented in Panel A of Table 1. We consider 20 years to be one period. We follow Manuelli and Seshadri (2014) to set the elasticity of human capital gains regarding time to be $\gamma_1 = 0.48$ and an annual interest rate of 5.5%,[9] implying the discount rate $\rho = (1 + 0.055)^{20} - 1$. We assign the portion of time during young age spent on education as $t_e = 0.2$, reflecting the typical 4-year duration of college education. The labor literature typically finds the elasticity of substitution between skilled and unskilled labor to be around 1.5 (e.g., Katz and Murphy 1992), and thus we set $\phi = 1.5$.

[8] We lack data on certain variables, such as country-sector-level shares of labor payments separately for skilled and unskilled workers, and country-sector-level experience-wage profiles, making it impossible to directly solve the model using the "Exact Hat Algebra" approach (Dekle et al. 2008).

[9] Manuelli and Seshadri (2014) also offer an estimate of γ_2, which determines the elasticity of human capital gains to materials. However, due to the critical importance of γ_2 for our results, we will rely on data to calibrate the value of this parameter. We will use the estimate of γ_2 in Manuelli and Seshadri (2014) to perform a robustness check in Section 5.5.

Table 1: Parameter Values and Sources

Parameters			Sources or Targeted Moments
Symbol	Value	Description	Description
Panel A: Externally Calibrated Parameters			
γ_1	0.48	Elast of human capital gains to time	Estimate in Manuelli and Seshadri (2014)
ρ	1.92	Discount rate (20 years)	Annualized interest rate of 5.5%
t_e	0.2	Time spent on college education	Data
ϕ	1.5	Elasticity of substitution btw skilled/unskilled	Estimate in Katz and Murphy (1992)
ϑ_s	8.07 (10.86)	Sector-specific trade elasticity	Estimates in Caliendo and Parro (2015)
L_i	0.37 (1.01)	Country-specific employment ($L_{US} = 1$)	World Bank Database
$d_{i,j,s}$	23.85 (71.93)	Origin-destination-sector-specific trade costs	Imputed from trade shares
$\beta_{i,s}$	0.05 (0.09)	Country-sector-specific consumption shares	World I/O Table 2005
b_i	3.93 (0.92)	Education efficiency in each country	Evidence from Schoellman (2012)
Panel B: Internally Calibrated Parameters			
γ_2	0.23	Elast of human capital gains to materials	Higher education spending in the U.S.
$A_{i,s}$	1.65 (1.86)	Country-sector-specific productivity ($A_{US,s} = 1$)	Country-sector-specific output in 2005
α_s	0.38 (0.09)	Parameters about sectoral skill intensities	Sectoral college employment share in the U.S.
ψ_i	0.39 (0.17)	Country-specific productivity of skilled workers	Country-specific college premium
τ_i	2.37 (1.30)	Country-specific frictions to obtain education	Share of college edu, Barro and Lee (2013)
μ_s^m	1.03 (0.12)	Sector-skill-specific on-the-job HC increment	RTE by sector/skill in the U.S.
μ_i	5.30 (0.63)	Country-specific on-the-job HC increment	Country-specific RTE in Lagakos et al. (2018)
κ	2.75	Shape parameter of dist of education preferences	Coefficient in Column (2) of Table A.2

Notes: Parameter values for $\{\vartheta_s, L_i, d_{i,j,s}, \beta_{i,s}, b_i, A_{i,s}, \alpha_s, \psi_i, \tau_i, \mu_s^m, \mu_i\}$ refer to averages across all the pairs with specific values. Standard deviations are in parenthesis. In all simulations, we consider balanced trade at the national level and normalize the wage rate of unskilled worker in the United States to be 1.

We use sector-specific trade elasticities ϑ_s from Caliendo and Parro (2015).[10] We obtain employment L_i for each country in 2005 from the World Bank Database. We follow Head and Ries (2001) to assume symmetric trade costs $d_{i,j,s} = d_{j,i,s}$ and infer them from observed bilateral trade shares $d_{i,j,s} = \left(\frac{\Pi_{i,j,s}\Pi_{j,i,s}}{\Pi_{i,i,s}\Pi_{j,j,s}}\right)^{-1/2\vartheta_s}$.[11] We calibrate consumption share $\beta_{i,s} = \frac{Y_{i,s}+IM_{i,s}-EX_{i,s}}{\sum_s Y_{i,s}+IM_{i,s}-EX_{i,s}}$, where $Y_{i,s}$, $EX_{i,s}$ and $IM_{i,s}$ represent sector-specific output, exports, and imports, respectively.

Finally, we calibrate education efficiency $\{b_i\}$. Using Schoellman (2012)'s data on immigrants' returns to schooling (which are estimated from Mincer regressions controlling for experience), we find that the elasticity of returns to schooling on GDP per

[10]Because 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).

[11]We compute observed trade shares in 2005 by combining OECD Bilateral Trade Database for Goods and Services with OECD Input-Output Tables.

capita of immigrants' original countries is 0.27, suggesting higher education quality in richer countries. In our model, the initial human capital level of skilled labor in country i is given by $b_i t_e^{\gamma_1} y_i^{\gamma_2}$, which is driven by both material investments y_i, as evidenced by equation (10), and education efficiency b_i. We find that the investment-driven elasticity of skilled workers' initial human capital regarding GDP per capita is $0.79 \times \frac{\gamma_2}{1-\gamma_2}$ according to our model and data.[12] Thus, we choose the elasticity of b_i to GDP per capita to be $0.27 - 0.79 \times \frac{\gamma_2}{1-\gamma_2}$, such that our model can generate the same elasticity of skilled labor's quality to GDP per capita as suggested by evidence from Schoellman (2012). We normalize the US's b_i to be 3, which ensures the initial human capital of skilled labor in the US to be roughly 1 under the baseline calibration.

3.1.2 Internally Calibrated Parameters

We combine the method of moments (in the inner loop) and the indirect inference (in the outer loop) to calibrate the remaining parameters.

Inner Loop. Given a choice of parameter κ (which will be calibrated using the indirect inference), we jointly calibrate the elasticity of human capital gains to materials γ_2, country-sector-specific productivity levels $\{A_{i,s}\}$, sector-specific skill intensities $\{\alpha_s\}$, country-specific productivity levels of skilled workers $\{\psi_i\}$, country-specific education frictions $\{\tau_i\}$, and country-sector-specific learning opportunities $\{\mu_{i,s}^m\}$ to match the targeted data moments. To reduce the number of parameters, we assume that on-the-job learning parameters can be decomposed into $\mu_{i,s}^m = \mu_i \mu_s^m$, where μ_s^m is the sector-skill-specific component and μ_i is the country-specific component.

We iterate on the parameter values to minimize the sum of absolute differences between the data moments and the model moments. Specifically, we target the following moments in the data: (1) the ratio of higher education spending to total labor income in the U.S.;[13] (2) country-sector-specific output, drawn from OECD Input–Output Ta-

[12] According to initial capital level $b_i t_e^{\gamma_1} y_i^{\gamma_2}$ and optimal solution of investment y_i in equation (10), the elasticity of initial human capital to skilled worker's wages is $\gamma_2/(1-\gamma_2)$. Using the collected cross-country data on college premium and GDP per capita, we find that the elasticity of skilled workers' wages to GDP per capita is 0.79. Thus, the investment-driven elasticity of skilled workers' initial human capital regarding GDP per capita is $0.79 \times \frac{\gamma_2}{1-\gamma_2}$.

[13] According to the OECD Database, the share of higher education spending (including both private and public spending on higher education) in GDP is 2.5% in the U.S.. Meanwhile, the FRED data indicates that the labor share of GDP in the U.S. is approximately 60%. Consequently, the ratio of higher education spending to total labor income is around 4.2%. We observe that the benefits of human capital accumulation are higher future labor income flows; given wage levels, capital income would not directly influence human capital decisions. Since our model only focuses on labor and abstracts from

bles in 2005;[14] (3) the share of college-educated workers in employment for each sector in the U.S., computed from the ACS data in 2005; (4) country-specific college premium, collected from multiple data sources summarized in Appendix Section C; (5) the country-specific share of college graduates in 2005 from Barro and Lee (2013); and (6) relative returns to experience (RTE) across 20 sectors and two education groups,[15] which are estimated using the U.S. Census and ACS in the years 1980–2017 (the estimation method is discussed in detail in Appendix Section C.4). Finally, we match the overall average wage relative to the average wage of the young cohort in the model and in the data, which is informative of life-cycle human capital accumulation (Manuelli and Seshadri 2014):

$$\underbrace{\frac{\sum_s L_i^e \Lambda_{i,s}^e w_{i,s}^e \left(h_i^{Y,e} - t_{i,s}^e + h_{i,s}^{O,e}\right)/2 + \sum_s L_i^u \Lambda_{i,s}^u w_{i,s}^u \left(h_i^{Y,u} - t_{i,s}^u + h_{i,s}^{O,u}\right)/2}{\sum_s L_i^e \Lambda_{i,s}^e w_{i,s}^e \left(h_i^{Y,e} - t_{i,s}^e\right) + \sum_s L_i^u \Lambda_{i,s}^u w_{i,s}^u \left(h_i^{Y,u} - t_{i,s}^u\right)}}_{\text{model: avg wage relative to avg wage of young cohort}} = \underbrace{\sum_{x\in\mathcal{X}} \Lambda_{x,i} \left(1 + \frac{\phi_{x,i}}{\phi_{20-24,i}} \times \phi_{20-24,i}\right)}_{\text{data: avg wage relative to avg wage of young cohort}}. \tag{15}$$

The left-hand side represents the overall average wage relative to the average wage of the young cohort in the model.[16] 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 $x \in \mathcal{X}$ ={0–4,...,35–39}, with the youngest cohort's RTE $\phi_{0-4,i} = 0$. To calculate the data moment in equation (15), as many countries lack data estimates on RTE, we use: (a) the relationship between RTE and GDP per capita for 20–24 years of experience in Lagakos et al. (2018): $\phi_{20-24} = 0.89 + 0.26 \log(\text{GDPPC}_i/\text{GDPPC}_{US})$; (b) relative RTE across different experience groups in the United States, $\frac{\phi_{x,i}}{\phi_{20-24,i}} = \frac{\phi_{x,US}}{\phi_{20-24,US}}$; and (c) country-specific populations of different age groups from Barro and Lee (2013) to obtain $\Lambda_{x,i}$.

To inform our choice of moments for the determination of parameters, we trace the dependence of certain parameters to specific moments. In line with Hsieh et al. (2019), we employ education expenditures in the data as a proxy of material costs spent on ed-

capital, using the share of higher education spending in GDP (in the data, GDP also includes capital income) as the target would underestimate the importance of materials for human capital in our model.

[14] We draw observed 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.

[15] As we also target the overall lifetime wage growth, which already provides information on the absolute levels of RTE, we only target relative levels here. We normalize the RTE for high-skill services of skilled workers to be 1.

[16] We exclude the time costs of education from the expression, as our analysis of wage-experience profiles in the data focuses on employed workers who have completed their schooling.

ucation. A greater elasticity of human capital gains to materials, γ_2, would suggest that workers invest more in material inputs, leading to a higher ratio of spending on college education relative to labor income. The country-sector-specific productivity levels, $\{A_{i,s}\}$, directly influence the country-sector-specific output, while sector-specific skill intensities, $\{\alpha_s\}$, determine the share of college-educated workers in sectoral employment. Country-specific productivity levels of college-educated workers, $\{\psi_i\}$, govern the skill premium in each country. Given the skill returns, we deduce the country-specific education frictions, $\{\tau_i\}$, from the share of college-educated workers in each country. Finally, the extent of lifetime wage growth across sectors, skill types, and countries is informative of their respective returns from on-the-job training $\{\mu_s^m, \mu_i\}$.

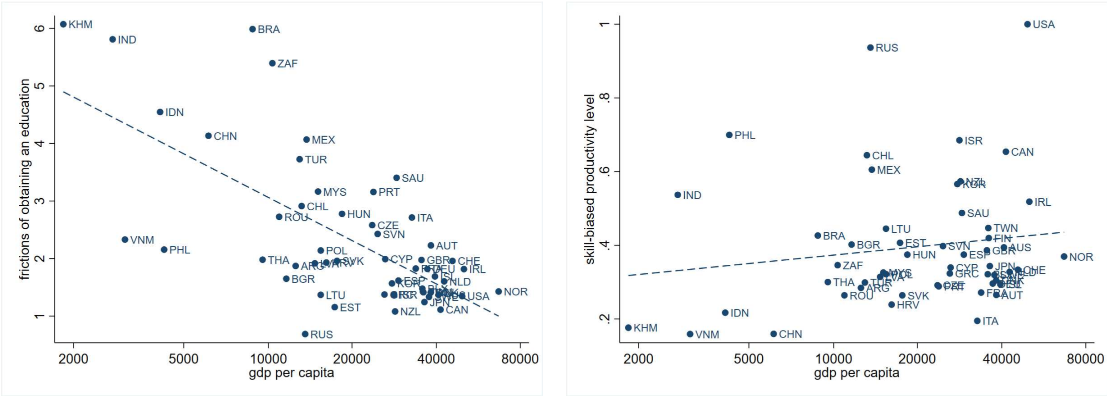
Outer Loop. In Appendix Table A.2, we use the global trade and education data between 1965–2010 and present the reduced-form analysis for the impact of exports' skill composition on workers' education choices. We use our reduced-form estimate in Table A.2 to discipline parameter κ—which governs the responses of education choices to economic shocks—using an indirect inference procedure. We proceed as follows. With the calibrated parameters from the inner loop, we assume that expenditure shares are subject to an exogenous demand shock $\beta_{i,s}^{\epsilon} = \beta_{i,s}\exp(\epsilon_s)$, in line with our regression results about the effects of changes in export demand on education choices. Exogenous shock ϵ_s is independent across sectors and distributed according to $\epsilon_s \sim \mathcal{N}(-\nu_s^2/2, \nu_s^2)$, where ν_s is chosen to be the observed 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, each time using a new realization of $\{\epsilon_s\}$. We then use the model-generated data on education choices, GDP, and trade flows to perform the same regression as in Column (2) of Table A.2.[17]

Procedure. We now describe the overall procedure to combine the method of moments and the indirect inference to calibrate all internally calibrated parameters.

- From the interval $[0, 4]$,[18] we choose evenly distributed values for parameter value κ. For each value of parameter κ: we perform the inner loop to calibrate the model to the targeted moments on production, skill returns, and skill acquisition; and we then use the outer loop to obtain the model-generated regression coefficient of ed-

[17]We opt to focus on Column (2) of Table A.2, as the coefficient on unskilled exports in this column has the smallest magnitude among all columns. This enables us to provide a conservative evaluation of the gains in skill acquisition from trade.

[18]Numerically, we find that this range is large enough for us to find the parameter value of κ that matches the reduced-form evidence.



(a) Frictions of Obtaining Education (τ_i) (b) Skill-biased Productivity (ψ_i)

Figure 1: Calibrated Education Frictions and Skill-biased Productivity

ucation choices on trade flows.

- We gather all the regression coefficients for different values of parameter κ. We compare the model-generated regression coefficients with the data coefficient in Column (2) of Table A.2, and choose the value of κ that minimizes the absolute distance between the model moment and the data moment.

3.2 Calibration Results

Panel B of Table 1 displays the internally calibrated parameter values. These values are reasonbale compared with the existing literature. For instance, Figure 1a illustrates the frictions in obtaining an education (τ_i) across various countries, indicating that participating in schooling is considerably more challenging in developing countries compared to developed ones. This observation is consistent with the widely reported low enrollment rates and underutilization of talent in the developing world (e.g., Fujimoto et al. 2023). Furthermore, Figure 1b demonstrates that skill-biased technology levels (ψ_i) rise with development, aligning with the findings of Acemoglu and Zilibotti (2001), who reveal that countries with a higher abundance of skilled labor are more likely to adopt skill-biased technology.

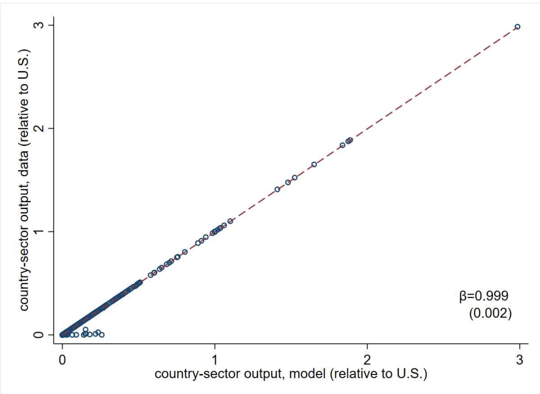
With the calibrated parameters, our model effectively matches the targeted data moments in the inner loop, as demonstrated in Table 2. Additionally, Figure 2 compares the country-sector output (targeted using A_{is}) and the origin-destination-sector trade shares (untargeted, although the symmetric trade costs are inferred from observed trade shares) between the model and the data. We observe that our model

Table 2: Targeted Moments in the Model and the Data

Moments	Data	Model
1. Ratio of higher education spending to total labor income in the U.S.	4.2%	4.2%
2. Country-specific ratio of average wage to average wages of young cohort	1.51 (0.18)	1.51 (0.18)
3. Relative RTE across sectors and education groups in the U.S.	0.68 (0.21)	0.68 (0.21)
4. Country-sector-specific output (relative to US)	0.11 (0.24)	0.11 (0.24)
5. Sector-specific college employment share in the U.S.	0.43 (0.14)	0.43 (0.14)
6. Country-specific college premium	2.06 (0.73)	2.05 (0.72)
7. 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.

performs quite well, as the regression coefficient of the data moments on the model moments is nearly equal to unity.



(a) Country-sector Output

(b) Origin-destination-sector Trade Share

Figure 2: Comparison of Output and Trade Shares between the Model and the Data

The intuition for the calibration of parameter κ is that a larger value of parameter κ corresponds to higher sensitivity of education choices to changes in the skill composition of exports. Figure 3 confirms this monotonic relationship between parameter value κ and the reduced-form response of education choices to increases in unskilled exports from the model-generated data. The value $\kappa = 2.75$ minimizes the absolute difference between the model-generated estimate and its counterpart in the data (Column (2) of Table A.2).

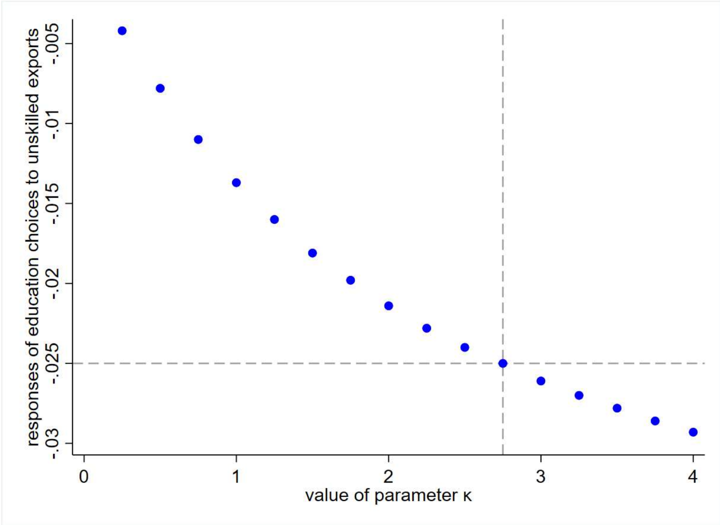


Figure 3: Estimates Using Model-generated Data

Note: The figure varies κ from 0 to 4 in the counterfactual exercise with changes in expenditure shares. The vertical line represents the baseline value of $\kappa = 2.75$, when the estimate from the model-generated data (-0.025) matches the estimated response of education choices to increases in unskilled exports produced by the observed data (Column (2) of Table A.2).

4 Quantitative Results

We now employ our calibrated model to examine the impact of skill acquisition on the gains from trade in Section 4.1 and to break down the primary drivers behind the changes in skill acquisition in Section 4.2.

4.1 Gains from Trade

Armed with our calibrated model, we conduct a counterfactual analysis of the autarkic economy by setting bilateral trade costs to be infinite $d_{i,j,s} \to \infty \; \forall \; i \neq j$. We then calculate the proportional change in real consumption from the autarkic economy to the observed equilibrium to determine the gains from trade. To comprehend how education choices and on-the-job learning influence these gains, we compute proportional changes in the number of college-educated workers and workers' lifetime wage growth from autarky to the observed equilibrium.[19]

Table 3 shows the results for the 20 largest economies in our calibrated model. In Column (1) of Table 3, the overall gains from trade are displayed. Columns (2) and (3) further divide the overall gains from trade into the ACR formula and the gains due

[19]In line with the calibration procedure, we calculate lifetime wage growth as the percent increase in the overall average wage relative to the young cohort's average wage, which represents the RTE in the model.

to changes in skill acquisition, as outlined in Proposition 3. 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 more significant for small open economies, such as Canada and the Netherlands. In particular, the values related to the ACR formula in Column (2) are similar to the results discovered in Costinot and Rodríguez-Clare (2014), who investigate the gains from trade in a multisector model.[20] This finding suggests that our quantitative results are reasonable.

Column (3) of Table 3 displays the gains from trade resulting from changes in skill acquisition, which are notably significant. The average gains in real consumption due to trade-induced skill acquisition amount to 2.42%, accounting for 20% of the total gains in real consumption from trade (11.85%). Our model-predicted magnitude of human capital in triggering the gains from trade aligns with the findings in recent literature that considers the role of both the number of skilled workers and human capital quality (represented by material investments in our model) in development accounting (e.g., Schoellman 2012, Jones 2014).

We find that the gains in skill acquisition are consistently positive but vary considerably across countries. For instance, the Netherlands and Canada benefit the most from trade-induced skill acquisition, with increases in real consumption of 13.47% and 5.22%, respectively. Conversely, China and Brazil gain the least, with increases in real consumption of 0.48% and 0.32%, respectively. This considerable cross-country heterogeneity in gains reflects the combined effects of (1) comparative advantages that reallocate workers across sectors with varying learning opportunities, and (2) increased real wage rates that promote skill acquisition, as discussed earlier in Section 2.4. In Figure 4, we plot the ACR formula and the gains in skill acquisition across countries. Since the ACR formula primarily captures changes in real wage rates, the strong positive correlation between the ACR formula and the gains in skill acquisition across countries suggests that increased real wage rates play a crucial role in encouraging skill acquisition. Recognizing the importance of understanding these two distinct forces, we will conduct a formal decomposition of these forces in the subsequent subsection.

In line with the considerable gains in skill acquisition from trade, we observe that trade openness has on average raised the number of college graduates and lifetime

[20]For example, in our calibrated model, the gains from trade calculated by the ACR formula are 3.7% and 4.0% for the United States and China, respectively. In a multisector model in Costinot and Rodríguez-Clare (2014), the gains are 4.4% and 4.0% for the United States and China, respectively. Costinot and Rodríguez-Clare (2014) generally report larger gains from trade than ours, as their calibrated model includes more sectors.

Table 3: Gains from Trade

		Decomposition of gains from trade		Measures of skill acquisition	
	Gains from trade	**ACR formula**	**Skill acquisition**	**# college graduates**	**Lifetime wage growth**
Country	(1)	(2)	(3)=(1)-(2)	(4)	(5)
USA	5.46%	3.73%	1.72%	0.68%	3.38%
CHN	4.47%	3.99%	0.48%	-0.05%	3.24%
JPN	3.15%	2.50%	0.65%	0.17%	2.10%
IND	5.60%	5.01%	0.60%	1.26%	3.09%
DEU	18.00%	14.13%	3.87%	0.86%	10.94%
FRA	10.76%	8.45%	2.31%	0.84%	7.32%
GBR	11.82%	8.71%	3.11%	2.46%	8.81%
RUS	11.30%	8.78%	2.52%	-0.91%	4.87%
ITA	6.95%	5.66%	1.28%	-0.37%	4.67%
BRA	4.52%	4.20%	0.32%	-1.34%	1.44%
MEX	9.71%	8.00%	1.71%	-0.21%	5.61%
KOR	7.50%	5.80%	1.70%	1.20%	4.31%
CAN	20.17%	14.96%	5.22%	-0.24%	11.39%
ESP	9.41%	7.41%	2.00%	0.32%	6.36%
IDN	12.62%	11.74%	0.88%	-3.08%	7.14%
TUR	6.04%	5.32%	0.73%	-1.41%	3.72%
AUS	9.11%	6.96%	2.15%	-0.26%	6.55%
NLD	53.80%	40.33%	13.47%	4.37%	31.61%
THA	18.36%	15.73%	2.63%	0.20%	11.62%
ARG	8.32%	7.32%	1.00%	-1.76%	3.65%
Mean	11.85%	9.44%	2.42%	0.14%	7.09%

wage growth by 0.14% and 7.09%, respectively, as shown in Columns (4) and (5) of Table 3. The minimal average impact on education choices demonstrates the influence of comparative advantage, as trade-induced reallocation across sectors with varying skill intensities directly influences skill returns in different directions for different countries, with counterbalancing effects between nations. We find that the number of college-educated workers tends to decrease in developing countries (such as China, Brazil, and Indonesia) following trade openness, reflecting the fact that these countries typically possess comparative advantages in agriculture and other low-skill industries.

Nevertheless, we discover that trade-induced alterations in lifetime wage growth are consistently positive across all countries. This occurs because the decrease in material input costs following trade openness encourages investments in on-the-job learning for both skilled and unskilled workers. Furthermore, we find that the magnitude of changes in lifetime wage growth is larger than that of the number of college graduates. This can be ascribed to two factors. First, since the time allocated to on-the-job

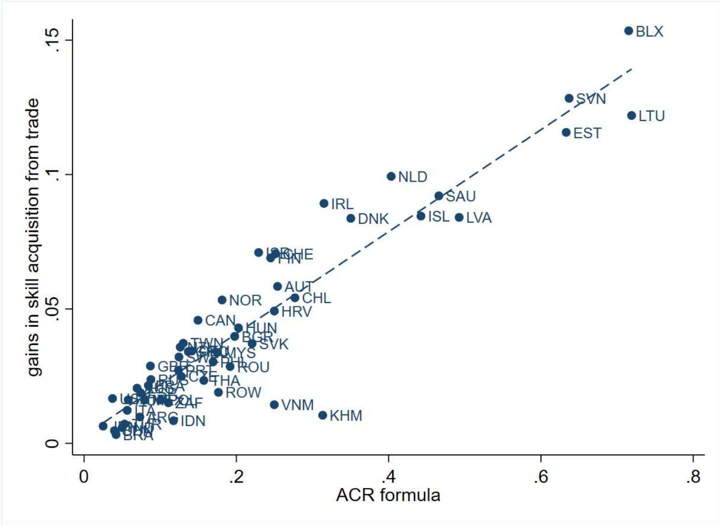


Figure 4: ACR Formula and Gains in Skill Acquisition from Trade

learning can also be adjusted, the elasticity of on-the-job human capital increment in response to changes in real wage rates exceeds the elasticity of education choices to real wage rates. Second, the increase in time dedicated to on-the-job learning results in reduced working time at a young age, which naturally contributes to higher lifecycle wage growth. These findings indicate that including on-the-job learning is crucial for comprehending the gains in skill acquisition resulting from trade.

Additional Results. We present two supplementary results in the appendix. Firstly, we observe that our formula for the gains from trade does not encompass workers' preferences and frictions associated with obtaining an education. In Appendix B.5, we calculate workers' average utility (after accounting for tastes and frictions) and provide the decomposition of utility gains from trade into the ACR formula and the component attributed to skill acquisition. Appendix Table D.1 displays the decomposition results. We discover that the gains in skill acquisition constitute 10% of the total utility gains from trade in our calibrated model. The diminished role of skill acquisition in accounting for utility gains, compared to its role in accounting for gains in real consumption, is due to the fact that as skill returns increase, workers with lower preferences for being skilled would opt for acquiring skills.

Secondly, we observe that the ACR formula is derived based on the assumption of a single skill type. As a result, our formula for the gains in skill acquisition essentially captures the difference in the gains from trade between the model with a single skill type and no learning investments, and the model with two skill types and endogenous learning investments. Considering that Eaton-Kortum models with two skill types are also widely utilized, it may be intriguing to view the gains in skill acquisition as reflecting endogenous skill acquisition in such models. Due to the absence of an analytical solution for calculating the gains from trade with fixed learning in models with two skill types, in Appendix Table D.2, we numerically recompute the gains from trade when fixing all learning investments in autarky to the baseline levels.[21] Comparing these results with the gains from trade from our baseline results in Table 3 (which allow for endogenous skill acquisition), we discover that the gains attributable to endogenous skill acquisition account for 17% of the total gains from trade.[22]

4.2 Main Forces behind Changes in Skill Acquisition

We now differentiate between the two forces that contribute to changes in skill acquisition: comparative advantages that reallocate workers across sectors with diverse learning opportunities, and increased real wage rates that encourage skill acquisition. From equations (7), (8), and (10), we observe that when the elasticity of human capital gains to materials $\gamma_2 = 0$, real wage rates no longer influence on-the-job learning and education investments.[23] Based on this observation, we employ the model with $\gamma_2 = 0$ to determine the changes in skill acquisition that exclusively result from comparative advantage. To achieve this, we first recalibrate the model with $\gamma_2 = 0$ following our calibration procedure outlined in Section 3 and then calculate trade-induced changes in workers' skill acquisition. We interpret the trade-induced changes in the model with $\gamma_2 = 0$ as solely representing the effects of comparative advantages. Consequently, the remaining portion of the trade-induced changes found in our baseline model reflects the effects of increased real wage rates that promote skill acquisition.

Table 4 presents the decomposition results, from which we can highlight three

[21]The learning investments include the amount of time and material inputs spent on education, the sector-specific amount of time and material inputs spent on on-the-job training, and the share of skilled workers. By fixing all learning investments, we assume that these investments are fixed to the baseline levels and not chosen by workers in autarky.

[22]In the scenario with fixed learning investments, trade openness influences not only real wage rates but also reduces the material costs of learning. The latter gain was captured by the formula for the gains in skill acquisition when we decomposed the gains from trade into the ACR formula and the gains in skill acquisition.

[23]In the case of on-the-job learning, this absence of effects occurs because, when $\gamma_2 = 0$, on-the-job learning only leads to reductions in production time. Thus, the increase in wage rates changes both marginal benefits and marginal costs of learning in the same proportions, not affecting the optimal time spent on learning. In the case of education choices, the absence of effects is due to the fact that, when $\gamma_2 = 0$, the human capital of skilled labor relies solely on education time, which remains constant.

Table 4: Decomposition of Skill Acquisition Changes

	Gains in skill acquisition		# college graduates		Lifetime wage growth	
	CA	b/c real wage	CA	b/c real wage	CA	b/c real wage
Country	(1)	(2)	(3)	(4)	(5)	(6)
USA	0.23%	1.49%	0.50%	0.18%	0.59%	2.79%
CHN	-0.03%	0.51%	-0.27%	0.22%	0.05%	3.19%
JPN	-0.08%	0.73%	-0.05%	0.22%	-0.10%	2.20%
IND	0.06%	0.54%	1.05%	0.21%	-0.73%	3.82%
DEU	-0.33%	4.20%	-0.41%	1.27%	-1.27%	12.21%
FRA	-0.06%	2.37%	0.07%	0.77%	-0.05%	7.37%
GBR	0.43%	2.68%	1.81%	0.65%	1.45%	7.36%
RUS	-0.07%	2.59%	-1.25%	0.34%	-0.42%	5.29%
ITA	-0.16%	1.44%	-0.99%	0.62%	-0.55%	5.22%
BRA	-0.46%	0.78%	-1.64%	0.30%	-0.95%	2.39%
MEX	-0.16%	1.87%	-0.64%	0.43%	0.39%	5.22%
KOR	-0.03%	1.73%	0.85%	0.35%	-0.23%	4.54%
CAN	-0.23%	5.45%	-1.22%	0.98%	-0.26%	11.65%
ESP	-0.06%	2.06%	-0.31%	0.63%	0.08%	6.28%
IDN	-0.32%	1.20%	-3.69%	0.61%	-0.59%	7.73%
TUR	-0.31%	1.04%	-1.88%	0.47%	-0.48%	4.20%
AUS	0.00%	2.15%	-0.87%	0.61%	0.57%	5.98%
NLD	-0.24%	13.71%	1.36%	3.01%	-1.41%	33.02%
THA	-0.18%	2.81%	-0.65%	0.85%	0.03%	11.59%
ARG	-0.40%	1.40%	-2.34%	0.58%	-1.66%	5.31%
Mean	-0.12%	2.54%	-0.53%	0.67%	-0.28%	7.37%

main findings. First, changes in skill acquisition driven by comparative advantages are considerably smaller in magnitude compared to those driven by real wage rates. Specifically, the average gains in skill acquisition induced by comparative advantages amount to -0.12%, which is not significantly different from zero. This minor average impact is intuitive, as trade-induced global production reallocation would generate counterbalancing effects between countries.[24] However, the average gains in skill acquisition induced by real wage rates are 2.54%, accounting for nearly 100% of the overall gains in skill acquisition from trade.

Second, changes in skill acquisition driven by comparative advantages can be negative for some countries. Argentina and Brazil experience the most losses with a reduction of 0.40% and 0.46% in real consumption respectively, mainly because these two countries enjoy comparative advantages in agriculture that entails low-skill require-

[24]Due to the Cobb-Douglas production function for the final good, the relative aggregate demand for each sector's output remains unchanged. The assumption of a Cobb-Douglas production function is a standard approach in the trade literature (e.g., Caliendo and Parro 2015).

ments and few on-the-job learning opportunities. In comparison, the United States and the United Kingdom are the two largest winners, with an increase in real consumption of 0.23% and 0.43%, largely due to these two countries' comparative advantages in high-skill services.

Finally, changes in skill acquisition driven by real wage rates are consistently positive. This is due to the fact that real wage gains are always positive in classical Eaton-Kortum models according to the ACR formula, which promotes skill acquisition investments. Furthermore, even without any changes in learning investments (which means that $x^m_{i,s}$, $t^m_{i,s}$, y_i, and Λ^e_i remain constant), as real wages rise, material costs of skill acquisition would constitute a smaller percentage of the overall output, which would result in higher real consumption levels.

5 Robustness

In this section, we provide several robustness checks for our baseline results. In Sections 5.1–5.4, we discuss how several model extensions affect our quantitative findings, while in Section 5.5, we analyze the effects of alterations in parameter values on our results. Lastly, in Section 5.6, we discuss other potential channels not captured by our model and through which trade may influence workers' skill acquisition.

5.1 Input-output Linkages

As input-output linkages play a vital role in comprehending the gains from trade (e.g., Costinot and Rodríguez-Clare 2014, Baqaee and Farhi 2019), we now expand the model to include intermediate inputs. Specifically, we revise firms' production function in equation (1) as follows:

$$q = z_{i,s}(\omega)\left(\alpha_s u^{\frac{\phi-1}{\phi}} + (1-\alpha_s)\psi_i e^{\frac{\phi-1}{\phi}}\right)^{\frac{\zeta^l_{i,s}\phi}{\phi-1}} \prod_{s'} (x_{s'})^{\zeta^{s'}_{i,s}}. \tag{16}$$

In this equation, $x_{s'}$ denotes expenditures on intermediate goods from sector s'. The parameter $\gamma^{s'}_{i,s}$ signifies the proportion of production costs in industry s allocated to materials from sector s', while the parameter $\gamma^l_{i,s}$ represents the share of costs dedicated to labor. In Appendix Section B.6, we expand Proposition 3 (the formula for the gains from trade and its decomposition into the ACR formula and the gains in skill

Table 5: Comparison of Gains in Skill Acquisition across Alternative Models

	Gains in skill acquisition from trade				
	Baseline	**With I/O linkages**	**Multi-period OLG with sectoral shifts**	**Edu composition of unskilled labor**	**Destination-specific knowledge diffusion**
Country	(1)	(2)	(3)	(4)	(5)
USA	1.72%	3.37%	3.78%	1.71%	0.98%
CHN	0.48%	1.55%	0.80%	0.49%	3.42%
JPN	0.65%	1.29%	1.38%	0.65%	0.25%
IND	0.60%	1.50%	3.31%	0.51%	2.80%
DEU	3.87%	6.60%	2.53%	3.85%	3.12%
FRA	2.31%	5.04%	4.01%	2.31%	2.08%
GBR	3.11%	6.31%	5.40%	3.09%	2.86%
RUS	2.52%	6.65%	3.61%	2.54%	4.22%
ITA	1.28%	3.17%	2.24%	1.30%	1.09%
BRA	0.32%	1.12%	-0.27%	0.38%	1.83%
MEX	1.71%	2.93%	1.33%	1.81%	4.81%
KOR	1.70%	4.12%	2.31%	1.69%	1.54%
CAN	5.22%	10.58%	5.16%	5.20%	5.25%
ESP	2.00%	4.97%	4.57%	2.02%	2.15%
IDN	0.88%	2.55%	2.92%	0.94%	4.55%
TUR	0.73%	2.35%	1.96%	0.79%	2.02%
AUS	2.15%	5.57%	5.60%	2.14%	1.04%
NLD	13.47%	35.47%	12.47%	13.41%	10.53%
THA	2.63%	7.62%	3.52%	2.70%	6.62%
ARG	1.00%	2.34%	1.38%	1.04%	2.31%
Mean	2.42%	5.75%	3.40%	2.43%	3.17%
% of total gains	20%	21%	27%	20%	25%

acquisition) to accommodate input-output linkages.

We calibrate input–output linkages $\{\gamma^l_{i,s}, \gamma^{s'}_{i,s}\}$ for each country according to OECD Input–Output Tables in 2005. With the addition of intermediate inputs, we need to adjust consumption shares, $\beta_{i,s} = \frac{Y_{i,s}+IM_{i,s}-EX_{i,s}-INT_{i,s}}{\sum_s Y_{i,s}+IM_{i,s}-EX_{i,s}-INT_{i,s}}$, where $Y_{i,s}$, $EX_{i,s}$, $IM_{i,s}$, and $INT_{i,s}$ represent sector-specific output, exports, imports, and usage as raw materials in production in the data. We then recalibrate all internal parameters according to the calibration procedure outlined in Section 3.

Column (2) of Table 5 displays the gains in skill acquisition from trade in this alternative model. We observe larger average gains in skill acquisition (5.75%) compared to the baseline model (2.42%). This finding is intuitive, as the reductions in material input costs and the gains in real wage rates are typically greater in the model with input-output linkages (Costinot and Rodríguez-Clare 2014), which would further encourage skill acquisition in our model with endogenous choices of skill acquisition.

Interestingly, due to the larger gains in real wage rates simultaneously, the gains in skill acquisition from trade contribute a similar proportion (21%) to the overall gains from trade when compared to the baseline result (20%).

5.2 Multi-period OLG with Workers' Sectoral Adjustments

Our baseline model omits job turnover and workers' sectoral reallocation. To evaluate the robustness of our quantitative results against these simplifications, we expand the model in two aspects. First, considering that job destruction and adjustments occur at high frequency, we assume that workers can potentially live for many periods, adopting a Blanchard-Yaari "perpetual youth" structure. Second, to circumvent the kink solutions of workers' sorting into different sectors when workers can vary in their ages and human capital levels (as discussed in footnote 5), we assume that workers sort into sectors imperfectly, following Galle et al. (2023). In Appendix B.7, we offer detailed mathematical derivations and discuss the recalibration of this model extension.

Column (3) of Table 5 displays the gains in skill acquisition from trade in this alternative model. We observe larger average gains in skill acquisition (3.40%) in this case compared to the baseline model (2.42%), with the gains in skill acquisition constituting 27% of the total gains from trade in this extended model. The increased gains in skill acquisition primarily result from the assumption in our baseline model that workers live for two periods and only invest time in learning during their youth, causing a significant portion of wage profiles to stem from changes in learning time. However, in the OLG model with multiple periods, the alterations in learning time are less drastic than in the two-period OLG, leading to a more prominent role of on-the-job human capital accumulation in explaining wage profiles and driving the gains from trade.

5.3 Education Composition within Unskilled Workers

In our baseline calibration, we consider the time spent on becoming skilled (obtaining college degrees) to be homogeneous across countries. However, in reality, the education composition of unskilled workers varies across countries,[25] and therefore the time required to become a college graduate relative to being an unskilled worker also dif-

[25]Despite potential differences in education composition, we normalize unskilled workers' initial human capital to be homogeneous across countries following Jones (2014). Any cross-country differences in human capital levels of unskilled labor would be absorbed by country-specific productivity levels and thus do not affect quantitative outcomes.

fers across countries. Taking this into account, we use data from Barro and Lee (2013) to calculate each country's difference in years of schooling between college graduates and non-college workers, using this difference to calibrate country-specific time required to become educated, t_e. We then recalibrate all internal parameters following the calibration procedure outlined in Section 3.

Column (4) of Table 5 displays the gains in skill acquisition from trade using this alternative calibration. We observe that the results are quantitatively very similar to the baseline results, with the average gains in skill acquisition accounting for 20% of the total gains from trade in this extended model.

5.4 Incorporating Destination-specific Knowledge Diffusion

In our baseline model, the parameter $\mu_{i,s}^m$, which governs the human capital increase from on-the-job learning, remains constant with trade exposure. However, there is much evidence on the gains of direct knowledge diffusion associated with different trade partners (e.g., Coe and Helpman 1995, Eaton and Kortum 1999), as reviewed by Keller (2021). In a companion paper (Ma et al. forthcoming), we utilized Brazilian employer-employee and customs data, demonstrating that Brazilian workers experience higher human capital growth when firms export to high-income destinations.

We now investigate the impact of destination-specific knowledge flows on the gains in skill acquisition from trade within our current model. To integrate destination-specific knowledge flows into the model, we assume that:

$$\mu_{i,s}^m = \bar{\mu}_{i,s}^m (X_{i,s})^{\xi}. \tag{17}$$

$\bar{\mu}_{i,s}^m$ represents the part that remains constant with trade exposure, which was considered in the baseline model. $X_{i,s}$ represents the external set of productive ideas and is accessible to all workers in country i and sector s. Let $k_{i,j,s}$ be the share of output sold to destination j in the total sectoral output, and Λ_j denote the stock of knowledge obtainable when selling to market j. Then $X_{i,s} = \sum_j k_{i,j,s}\Lambda_j$ is a weighted average of knowledge across destinations.

In accordance with Ma et al. (forthcoming), we approximate each country's knowledge stock Λ_j using its GDP per capita and set the elasticity $\xi = 0.21$. We then recalibrate all internal parameters following the calibration procedure outlined in Section

3.[26] Although the calibration in Ma et al. (forthcoming) is based on Brazilian data, this exercise can still offer indicative evidence of how destination-specific knowledge flows may alter the gains in skill acquisition from trade.

Column (5) of Table 5 presents the gains in skill acquisition from trade in this extended model. We observe that the gains remain significant, with the average gains in skill acquisition constituting 25% of the total gains from trade. Furthermore, in the presence of cross-country knowledge flows, developed countries tend to experience lower gains, as they may export to some poorer countries after trade openness. For instance, the U.S. gains decrease from 1.72% in the baseline model to 0.98% in this extended model. Conversely, compared to the baseline results, developing countries tend to benefit more from skill acquisition gains through trade. For example, China's gains rise from 0.48% in the baseline model to 3.42% in this extended model, as China heavily exports to wealthy countries.

5.5 Parameter Values

In our baseline model, we calibrated κ (the dispersion of education preferences) to be 2.75, based on empirically estimated responses of education choices to changes in skill returns. We now investigate alternative values of κ. In Columns (2) and (3) of Table 6, we display the gains in skill acquisition under $\kappa = 1$ and $\kappa = 4$, respectively.[27] We find that the average gains in skill acquisition from trade remain relatively similar with different values of κ (if anything, the average gains tend to slightly increase with the value of κ). The minor impact of κ aligns with the subtle average effects of trade on college enrollments observed in our baseline results (Table 3). This is because trade-induced reallocation across sectors with varying skill intensities directly influences skill returns in different directions for different countries, leading to counterbalancing effects between nations. We find that for countries that benefit significantly from the trade-induced expansion of college education, such as the UK and the Netherlands, their gains in skill acquisition increase with the value of κ, as a larger κ implies that more workers are at the margin of switching education choices.

As shown in equations (7), (8), and (10) and also discussed in Section 4.2, the elasticity of human capital gains to materials, γ_2, plays a crucial role in determining the

[26]In this extended model, we break down the constant part of learning returns into the country-specific component and the sector-skill-specific component, represented as $\bar{\mu}_{i,s}^m = \bar{\mu}_i \bar{\mu}_s^m$.

[27]For each scenario with a different value of κ, we recalibrate all other internally calibrated parameters to match the corresponding moments in Table 1.

responses of on-the-job learning and education investments to real wage rates. In our baseline calibration, we calibrated γ_2 to match the share of higher education spending in labor income for the U.S.. We now conduct a robustness check by following Manuelli and Seshadri (2014) and considering $\gamma_2 = 0.4$. We recalibrate all other internally calibrated parameters to match the corresponding moments in Table 1.

Column (4) of Table 6 presents the gains in skill acquisition from trade in this alternative calibration. Consistent with increased responses of on-the-job learning and education investments to real wage rates, the gains are substantially larger compared to the baseline results. In this scenario, the average gains in skill acquisition account for 46% of the total gains from trade. This finding implies a significant dependency of the gains in skill acquisition on the parameter value of γ_2, which can also be deduced from our analytical results. For example, combining equations (7) and (8), we find that the elasticity of on-the-job human capital increment to real wage rates is $\frac{\gamma_2}{1-\gamma_1-\gamma_2}$, which increases from 0.84 in our baseline calibration with $\gamma_2 = 0.23$ to 3.64 with $\gamma_2 = 0.4$.

5.6 Discussion of Other Possible Channels

In Section 5.4, we examined knowledge flows from destination markets. Knowledge diffusion might also originate from foreign sellers in domestic markets (Alvarez et al. 2013, Buera and Oberfield 2020) or superior domestic sellers (Sampson 2016, Perla et al. 2021). These existing studies demonstrate that such knowledge flows significantly enhance domestic firms' productivity. These knowledge flows may potentially amplify the gains in skill acquisition from trade as well.

Our model does not account for the firm environment. Recent literature has empirically demonstrated that learning opportunities are more abundant in highly productive firms (e.g., Gregory 2021, Engbom 2022). This pattern might reflect that workers have better supervisors and more learning-by-doing opportunities in firms with advanced technology, as suggested by a vast body of previous literature (e.g., Arrow 1962, Hopenhayn and Chari 1991). Quantitatively analyzing the firm learning environment typically requires adopting a heterogeneous firm model and modeling the interaction between workers and firms in determining learning investments. Although incorporating the firm environment is limited by our model choice of the Eaton-Kortum framework, we conjecture that considering the firm environment can further amplify the gains in skill acquisition from trade. This is because trade would encourage labor reallocation toward more productive firms (Melitz 2003).

Table 6: Comparison of Gains in Skill Acquisition with Different Parameter Values

	Gains in skill acquisition from trade			
	Baseline **($\kappa = 2.75$, $\gamma_2 = 0.23$)**	**Dispersion of edu preferences $\kappa = 1$**	**Dispersion of edu preferences $\kappa = 4$**	**Elasticity of HC to materials, $\gamma_2 = 0.4$**
Country	(1)	(2)	(3)	(4)
USA	1.72%	1.66%	1.74%	5.29%
CHN	0.48%	0.48%	0.48%	1.73%
JPN	0.65%	0.65%	0.65%	2.69%
IND	0.60%	0.54%	0.62%	1.14%
DEU	3.87%	3.85%	3.88%	14.46%
FRA	2.31%	2.30%	2.32%	8.67%
GBR	3.11%	3.01%	3.14%	9.87%
RUS	2.52%	2.49%	2.54%	7.45%
ITA	1.28%	1.29%	1.28%	5.33%
BRA	0.32%	0.40%	0.29%	1.37%
MEX	1.71%	1.73%	1.71%	4.53%
KOR	1.70%	1.65%	1.71%	5.80%
CAN	5.22%	5.22%	5.21%	17.78%
ESP	2.00%	2.00%	2.00%	7.38%
IDN	0.88%	0.93%	0.86%	2.85%
TUR	0.73%	0.76%	0.71%	3.23%
AUS	2.15%	2.15%	2.15%	7.68%
NLD	13.47%	13.37%	13.50%	41.84%
THA	2.63%	2.63%	2.63%	7.88%
ARG	1.00%	1.02%	0.99%	3.97%
Mean	2.42%	2.40%	2.42%	8.05%
% of total gains	20%	20%	20%	46%

Finally, in our model, we assumed that unskilled workers' human capital is homogeneous across countries,[28] which is a common assumption in the development literature (e.g., Jones 2014, Caselli and Ciccone 2019). Considering the diverse education compositions across countries, it is plausible that trade openness could also promote education investments for unskilled workers, particularly in developing countries where the average years of schooling for unskilled workers remain low.

[28] Assuming uniformity of unskilled workers' skills would not directly impact our findings, since any cross-country variations in human capital levels of unskilled labor would be absorbed by country-specific productivity levels, and therefore would not influence quantitative results.

6 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) through changes in workers' skill acquisition. In this paper, we develop a multisector Eaton–Kortum model with workers' endogenous choices of investments in education and on-the-job training. The calibrated model demonstrates that the gains from trade, resulting from changes in skill acquisition, are considerable and consistently positive across countries. The main driver of these countries' gains is the reduction in the unit cost of material inputs and the increase in real wage rates following trade openness, which stimulates investments in learning activities.

Our paper has investigated the effects of trade-induced sector reallocation and real wage gains on education choices and on-the-job learning. There are many other potential channels through which trade impacts human capital. For instance, trade may reallocate workers toward firms offering superior learning opportunities or expose workers to knowledge diffusion from sellers in domestic markets. A promising area for future research is to determine whether these additional channels are present in the data and hold quantitative significance.

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A Motivating Evidence for Quantitative Analysis

This section presents some facts on the relationship between trade and skill acquisition and key regressions to pin down important model parameters for the quantitative analysis. We start by describing the main data sources and then proceed to provide empirical evidence on how exporting may alter human capital formation.

A.1 Data Sources

To provide empirical evidence on how trade affects training and education, we assemble multiple micro-level and macro-level datasets. Here we briefly describe the data sources.

Firm-level Training Data. We use the European Union Continuing Vocational Training (EU-CVT) Enterprise Survey, which provides information on enterprises' investments in their staff's continuing vocational training in the last year. The data provides information on participation, time spent, and the costs of training. We rely on the EU-CVT conducted in 2005, 2010, and 2015, and the survey covers all EU member states and Norway.

Worker-level Training Data. Given the concern that firm-level evidence may not reflect workers' overall learning activities, we also complement firm-level findings with worker-level evidence. For the worker-level data, we rely on data from the Adult Education Survey (EU-AES). The EU-AES collects information on participation in education and learning activities within the last 12 months. The AES is one of the main data sources for EU lifelong learning statistics, and it covers around 666,000 adults aged 25–64. The data was collected during 2007, 2011, and 2017 in 26, 27, and 28 EU member states, respectively.

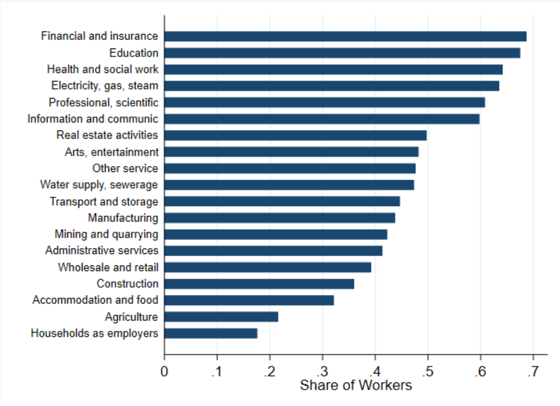
Output, Trade, and Schooling Data. To estimate how trade openness affects schooling choices, we draw trade data from Comtrade Database, education data from Barro and Lee (2013), and GDP from Penn World Table 9.1.

A.2 On-the-Job Training

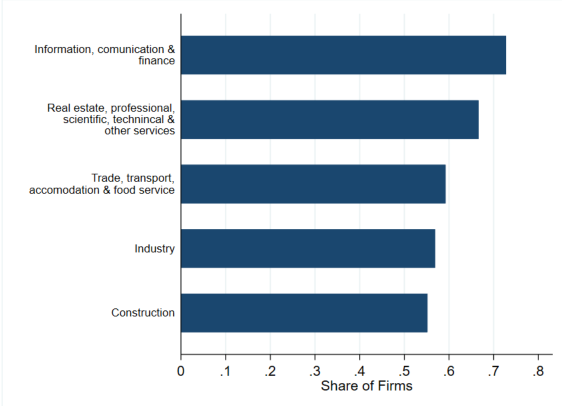
In this section, we show that on-the-job training levels vary across sectors, and thus trade-induced sector reallocation affects average levels of on-the-job learning.

Using the EU-CVT survey and the EU-AES survey, Figure A.1 shows the share of European workers reporting having participated in on-the-job training in Panel (a) and the share of European firms reporting having invested in on-the-job training in Panel (b). The EU-AES survey provides information for 19 sectors, while the EU-CVT provides information for only 5 sectors. It is clear that on-the-job training investments vary largely across sectors: there are low training investments in agriculture, higher investments in manufacturing and very high levels of on-the-job training in high-skill service sectors such as information and communication, education, and financial services. Even though our sample only covers European countries, this variation across sectors is consistent with estimates on returns to experience in Islam et al. (2018) who use worker-level surveys covering both developing and developed countries and show that returns to experiences are larger in services than manufacturing than agriculture.

Figure A.1: Training Participation Rates by Sector



(a) Share of Workers in Training - AES



(b) Share of Firms Offering Training - CVT

Notes: These figures show employees' and firms' participation rates in training by sector categories. Panel (a) shows the proportion of workers who participate in training activities, by sector, under AES classification. Results come from two AES survey waves: AES 2011 and AES 2016. Data from AES 2007 is not comparable due to different sector and training classifications. Weighting factors are used in order to calculate proportions for each wave. Panel (b) shows the proportion of firms which participate in training activities, by sector, under CVT classification. Results are population-weighted averages of respective proportions in Europe.

Moreover, considering that higher levels of training investments in some sectors may be due to different compositions of workers, we show that after controlling for workers' observable characteristics, sectors still vary vastly in training participation of their workers. Table A.1 estimates the linear probability model of having participated in training using worker-level information from the EU-AES survey. We regress the dummy of training participation on sector dummies, occupation dummies, schooling, socio-economic characteristics (i.e., gender and age), countries' GDP per capita, and country and year fixed effects. We demonstrate that, after controlling for all those characteristics, there still remain vastly different training levels across sectors.

A.3 The Impact of Exports on Education Choices

We present reduced-form evidence on how trade openness affects schooling levels. This evidence will not only confirm the impact of trade on schooling as similarly found by the literature (e.g., Blanchard and Olney 2016), but will also help us discipline the model parameter that governs the education responses through the indirect inference.

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

Table A.1: Workers' Training Across Sectors

	Workers' Training Participation Dummy		
	(1)	(2)	(3)
Financial and insurance	0.304***	0.302***	0.295***
	(0.010)	(0.010)	(0.010)
Education	0.271***	0.273***	0.276***
	(0.009)	(0.009)	(0.009)
Health and social work	0.296***	0.279***	0.279***
	(0.009)	(0.009)	(0.009)
Electricity, gas, steam	0.263***	0.312***	0.311***
	(0.013)	(0.013)	(0.013)
Professional, scientific	0.188***	0.179***	0.174***
	(0.010)	(0.010)	(0.010)
Information and communication	0.188***	0.188***	0.177***
	(0.010)	(0.010)	(0.010)
Real estate activities	0.147***	0.137***	0.137***
	(0.013)	(0.013)	(0.013)
Arts, entertainment	0.138***	0.147***	0.143***
	(0.011)	(0.011)	(0.011)
Other service	0.206***	0.207***	0.201***
	(0.010)	(0.010)	(0.010)
Water supply, sewerage	0.187***	0.237***	0.233***
	(0.013)	(0.013)	(0.013)
Transport and storage	0.177***	0.203***	0.199***
	(0.009)	(0.010)	(0.010)
Manufacturing	0.154***	0.184***	0.177***
	(0.009)	(0.009)	(0.009)
Mining and quarrying	0.159***	0.200***	0.195***
	(0.012)	(0.013)	(0.013)
Administrative services	0.170***	0.176***	0.170***
	(0.010)	(0.010)	(0.010)
Wholesale and retail	0.110***	0.139***	0.130***
	(0.009)	(0.009)	(0.009)
Construction	0.113***	0.136***	0.128***
	(0.009)	(0.009)	(0.009)
Accommodation and food	0.090***	0.102***	0.092***
	(0.009)	(0.009)	(0.009)
Agriculture	0.056***	0.166***	0.165***
	(0.010)	(0.010)	(0.010)
Observations	247,380	247,380	206,364
R-squared	0.123	0.203	0.202
Schooling and occupation controls	YES	YES	YES
Year FE	NO	YES	YES
Country FE	NO	YES	YES
Socio-economic controls	NO	NO	YES

Notes: This table shows the effects of working in each sector (ranked by their unconditional means) on the probability of taking part in training activities in the last 12 months. Socio-economic controls are as follows: log of per capita GDP (PPP), age, squared age, and gender dummies. The individual-level data is from AES 2011 and 2016. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: The Impact of Exports on Education Choices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Years ahead	10	10	10	10	15	15	15	15
log(unskilled exports)	-0.049***	-0.025**	-0.019	-0.088	-0.050***	-0.025**	-0.051*	-0.145
	(0.014)	(0.010)	(0.028)	(0.080)	(0.016)	(0.011)	(0.031)	(0.091)
log(skilled exports)	0.071***	0.025***	0.044*	0.089	0.073***	0.024**	0.075***	0.146
	(0.013)	(0.010)	(0.026)	(0.088)	(0.016)	(0.021)	(0.029)	(0.099)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Obs	878	848	878	848	773	744	773	744
R-squared	0.400	0.936	0.393	0.932	0.393	0.940	0.393	0.929
First-stage F			40.08	6.30			33.16	5.56

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)–(4) show the results for $h = 10$, and Columns (5)–(8) 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: country fixed effects, year fixed effects, log GDP, log population, and log import in year t. For IV regressions, we also report the Kleibergen-Paap statistic for the underidentification test. Robust standard errors are in parenthesis: * 10%, ** 5%, *** 1%.

following regression,

$$\text{Col}_{i,t+h} = \beta_0 + \beta_1 \ln(\text{Unskill\_Ex}_{i,t}) + \beta_2 \ln(\text{Skill\_Ex}_{i,t}) + \beta_3 X_{i,t} + \gamma_i + v_t + \epsilon_{i,t}, \quad \text{(A.1)}$$

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 exports' skill composition on education choices of h years ahead. The control variables X_{it} include a logarithm of GDP, imports, and population in the year t. γ_i and v_t refer to country and year fixed effects respectively. The independent variables $\text{Unskill\_Ex}_{i,t}$ and $\text{Skill\_Ex}_{i,t}$ are the amount of unskilled and skilled exports, constructed as follows,

$$\text{Unskill\_Ex}_{i,t} = \sum_s (1 - \text{Col}_{US,s,2005})\text{Ex}_{i,s,t},$$
$$\text{Skill\_Ex}_{i,t} = \sum_s \text{Col}_{US,s,2005}\text{Ex}_{i,s,t}.$$

We proxy the sector-specific skill intensity using the share of college-educated workers in employment for each sector in 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.'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.'s sector-specific share of college-educated workers in employment, representing the export exposure of skilled workers. For estimation, we use trade, education, and GDP data in the years $t = 1965, 1970, ...2010$, for the set of countries with available data.[29]

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

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, we construct Bartik-type instruments as follows:

$$\begin{aligned}\text{Unskill\_Ex}_{i,t}^{IV} &= \sum_s \sum_{j \neq i} (1 - \text{Col}_{US,s,2005}) \frac{\text{Ex}_{i,j,s,1965}}{\text{Ex}_{i,1965}} \frac{\text{Ex}_{-i,j,s,t}}{\text{Ex}_{-i,j,s,1965}} \\ \text{Skill\_Ex}_{i,t}^{IV} &= \sum_s \sum_{j \neq i} \text{Col}_{US,s,2005} \frac{\text{Ex}_{i,j,s,1965}}{\text{Ex}_{i,1965}} \frac{\text{Ex}_{-i,j,s,t}}{\text{Ex}_{-i,j,s,1965}}\end{aligned} \tag{A.2}$$

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 dataset (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. 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 A.2 presents the estimation results. Columns (1)–(2) show the OLS results for the impact of exports on education for 10 years ahead. Depending on the controls, we find that a 1% increase in unskilled exports reduced the share of college graduates in the population by 0.02–0.05 percentage points after 10 years, whereas an increase in skilled exports led to a larger share of college graduates in the population after 10 years. Columns (3)–(4) use Bartik-type instruments constructed in equation (A.2) and still find that growth in unskilled exports reduced the share of college graduates in the population after 10 years, though the results are much noisier, especially in the case with controls (when the instruments tend to be weak). In Columns (5)–(8), we choose the share of college graduates in the population for 15 years ahead ($h = 15$) as the dependent variable. The estimates are quantitatively similar compared with their counterparts in Columns (1)–(4). The magnitude of our reduced-form estimates is comparable to similar evidence in the literature.[30]

[30]For 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 0.008–0.0020 years.

B Proofs

B.1 CES Trade Shares and Prices

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

$$\Pi_{j,i,s} = \frac{\int_{\Omega_{j,i,s}} p_{j,i,s}(\omega)^{1-\sigma} d\omega}{\sum_k \int_{\Omega_{k,i,s}} p_{k,i,s}(\omega)^{1-\sigma} d\omega}, \tag{B.1}$$

where $\Omega_{j,i,s} = \{\omega \mid p_{j,i,s}(\omega) \leq p_{k,i,s}(\omega), \forall\, k \neq j\} = \{\omega \mid w_{j,s}d_{j,i,s}/z_{j,s}(\omega) \leq w_{k,s}d_{k,i,s}/z_{k,s}(\omega), \forall\, k \neq j\}$ is the set of goods sourced from country j.

As $z_{i,s}(\omega)$ follows the Fréchet distribution $F_{i,s}(z) = \exp(-A_{i,s}z^{-\vartheta_s})$, we can obtain:

$$\begin{aligned}
\int_{\Omega_{j,i,s}} p_{j,i,s}(\omega)^{1-\sigma} d\omega &= \int_0^\infty \left(\frac{d_{j,i,s}w_{j,s}}{z}\right)^{1-\sigma} \prod_{k\neq j} F_{k,s}\left(\frac{w_{k,s}d_{k,i,s}z}{w_{j,s}d_{j,i,s}}\right) dF_{j,s}(z) \\
&= \int_0^\infty (d_{j,i,s}w_{j,s})^{1-\sigma} A_{j,s}\vartheta_s z^{\sigma-\vartheta_s-2} \exp\left(-\sum_k A_{k,s}\left(\frac{w_{k,s}d_{k,i,s}z}{w_{j,s}d_{j,i,s}}\right)^{-\vartheta_s}\right) dz \\
&= \int_0^\infty (d_{j,i,s}w_{j,s})^{-\vartheta_s} A_{j,s}\left(\sum_k A_{k,s}(w_{k,s}d_{k,i,s})^{-\vartheta_s}\right)^{\frac{\sigma-\vartheta_s-1}{\vartheta_s}} \exp(-y)y^{\frac{\vartheta_s+1-\sigma}{\vartheta_s}-1}dy \\
&= \Gamma\left(1-\frac{\sigma-1}{\vartheta_s}\right)(d_{j,i,s}w_{j,s})^{-\vartheta_s} A_{j,s}\left(\sum_k A_{k,s}(w_{k,s}d_{k,i,s})^{-\vartheta_s}\right)^{\frac{\sigma-\vartheta_s-1}{\vartheta_s}}.
\end{aligned} \tag{B.2}$$

The first equality uses the definition of $p_{j,i,s}$ and $\Omega_{j,i,s}$. The second equality uses the distribution of $F_{i,s}(z)$. The third equation changes the variable by letting $y = \sum_k A_{k,s}\left(\frac{w_{k,s}d_{k,i,s}z}{w_{j,s}d_{j,i,s}}\right)^{-\vartheta_s}$. The final equality uses the definition of the Gamma function $\Gamma(z) = \int_0^\infty x^{z-1}\exp(-x)dx$.

By plugging $\int_{\Omega_{j,i,s}} p_{j,i,s}(\omega)^{1-\sigma}d\omega$ into equation (B.1), we obtain trade shares in equation (3). Also note that CES preferences imply:

$$P_{i,s} = \left(\sum_k \int_{\Omega_{k,i,s}} p_{k,i,s}(\omega)^{1-\sigma}d\omega\right)^{\frac{1}{1-\sigma}} = \Gamma\left(1-\frac{\sigma-1}{\vartheta_s}\right)^{\frac{1}{1-\sigma}}\left(\sum_k A_{k,s}(w_{k,s}d_{k,i,s})^{-\vartheta_s}\right)^{-\frac{1}{\vartheta_s}}. \tag{B.3}$$

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

B.2 Proof of Proposition 1

After plugging the present value of consumption from the budget constraint under $r = \rho$, we can rewrite the maximization problem in equation (6) as:

$$\max_{s,t,x} V_i^m = w_{i,s}^m (h_i^{Y,m}(1-\mathcal{I}_e t_e) - t) - (\mathcal{I}_e y + x)\, P_i + \frac{w_{i,s}^m \left(h_i^{Y,m} + \mu_{i,s}^m t^{\gamma_1} x^{\gamma_2}\right)}{1+r}. \tag{B.4}$$

Thus, the first-order condition with regard to t and x implies:

$$-w_{i,s}^m + \frac{w_{i,s}^m}{1+r}\gamma_1 \mu_{i,s}^m t^{\gamma_1 - 1} x^{\gamma_2} = 0,$$

$$-P_i + \frac{w_{i,s}^m}{1+r}\gamma_2 \mu_{i,s}^m t^{\gamma_1} x^{\gamma_2 - 1} = 0.$$

Combining these two first-order conditions, we can solve for the optimal values of t and x, which are exactly the formula of $t_{i,s}^m$ and $x_{i,s}^m$ shown in equations (7)–(8).

Note that in equilibrium, there will be positive employment in each sector of country i. Otherwise, if the employment in sector s is zero, then the wage rate in this sector shall be infinity. This is because according to equation (3), for every finite level of wage rate $w_{i,s}^m$, the expenditure share on goods sourced from country i in sector s always remains positive. Because workers in country i can freely choose sectors, the utility value shall thus be equalized across sectors, as shown by equation (9).

B.3 Proof of Proposition 2

We first compute the optimal material investments in education, y, which maximizes the utility for the skilled person:[31]

$$\max_{y} \sum_s \Lambda_{i,s}^e \left[w_{i,s}^e (h_i^{Y,e}(1-t_e) - t_{i,s}^e) - \left(y + x_{i,s}^e\right) P_i + \frac{w_{i,s}^e \left(h_i^{Y,e} + \mu_{i,s}^e (t_{i,s}^e)^{\gamma_1} (x_{i,s}^e)^{\gamma_2}\right)}{1+r} \right],$$
$$\text{s.t. } h_i^{Y,e} = b_i t_e^{\gamma_1} y^{\gamma_2}.$$

The first-order condition implies:

$$-P_i + \frac{(1+r)(1-t_e)+1}{1+r}\gamma_2 b_i t_e^{\gamma_1} y^{\gamma_2 - 1} \sum_s \Lambda_{i,s}^e w_{i,s}^e = 0.$$

[31] Here, we assume that sectoral choices are unresolved when the worker makes material investments in education. This reflects the reality that many college graduates are unsure about their future career trajectories and might not even pursue jobs related to their majors. Alternatively, we can assume that when workers make education investments, they already take future sectoral choices into consideration. In this alternative case, the arbitrary condition in equation (9) still holds, but now education investments would be country-sector-specific: the formula for education investments is analogous to equation (10) except for depending on country-sector-specific wage rates. These two modeling choices of material investments in education have only minor differences, and we prefer to use the first approach.

With $r = \rho$ in equilibrium, we can solve for the formula of optimal investment (which is identical to all skilled workers in country i), y_i, as shown in equation (10).

In country i, a worker would choose to become skilled if and only if $\epsilon^e V_i^e/\tau_i \geq \epsilon^u V_i^u$, which implies $\epsilon^u \leq \frac{\epsilon^e V_i^e}{\tau_i V_i^u}$. Given that ϵ^e and ϵ^u are distributed according to $G(\epsilon) = \exp(-\epsilon^{-\kappa})$, we can compute the share of workers who decide to become skilled as:

$$\begin{aligned}
\Lambda_i^e &= \int_0^\infty G\left(\frac{\epsilon^e V_i^e}{\tau_i V_i^u}\right) dG(\epsilon^e) \\
&= \int_0^\infty \kappa(\epsilon^e)^{-\kappa-1} \exp\left\{ - \left[\left(\frac{V_i^e}{\tau_i V_i^u}\right)^{-\kappa} + 1\right] (\epsilon^e)^{-\kappa} \right\} d\epsilon^e \\
&= \frac{(V_i^e/\tau_i)^\kappa}{(V_i^e/\tau_i)^\kappa + (V_i^u)^\kappa}.
\end{aligned}$$

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.

B.4 The Gains from Trade

We define $\mathcal{W}_i$ as the real consumption in the economy, which is

$$\begin{aligned}
\mathcal{W}_i &= \frac{L_i^u \sum_s \Lambda_{i,s}^u w_{i,s}^u \bar{h}_{i,s}^u + L_i^e \sum_s \Lambda_{i,s}^e w_{i,s}^e \bar{h}_{i,s}^e - \left[L_i^u \sum_s \Lambda_{i,s}^u x_{i,s}^u + L_i^e (y_i + \sum_s \Lambda_{i,s}^e x_{i,s}^e)\right] P_i}{P_i} \\
&= C_i \frac{L_i^u \sum_s \Lambda_{i,s}^u w_{i,s}^u \bar{h}_{i,s}^u + L_i^e \sum_s \Lambda_{i,s}^e w_{i,s}^e \bar{h}_{i,s}^e - \left[L_i^u \sum_s \Lambda_{i,s}^u x_{i,s}^u + L_i^e (y_i + \sum_s \Lambda_{i,s}^e x_{i,s}^e)\right] P_i}{\prod_s \left(\sum_k A_{k,s} \left(w_{k,s} d_{k,i,s}\right)^{-\vartheta_s}\right)^{-\frac{\beta_{i,s}}{\vartheta_s}}} \\
&= C_i \frac{L_i^u \sum_s \Lambda_{i,s}^u w_{i,s}^u \bar{h}_{i,s}^u + L_i^e \sum_s \Lambda_{i,s}^e w_{i,s}^e \bar{h}_{i,s}^e - \left[L_i^u \sum_s \Lambda_{i,s}^u x_{i,s}^u + L_i^e (y_i + \sum_s \Lambda_{i,s}^e x_{i,s}^e)\right] P_i}{\prod_s \left(A_{i,s} w_{i,s}^{-\vartheta_s}/\Pi_{i,i,s}\right)^{-\frac{\beta_{i,s}}{\vartheta_s}}} \\
&= C_i \frac{L_i^u \sum_s \Lambda_{i,s}^u \frac{w_{i,s}^u}{\prod_s (w_{i,s})^{\beta_{i,s}}} \bar{h}_{i,s}^u + L_i^e \sum_s \Lambda_{i,s}^e \frac{w_{i,s}^e}{\prod_s (w_{i,s})^{\beta_{i,s}}} \bar{h}_{i,s}^e - \left[L_i^u \sum_s \Lambda_{i,s}^u x_{i,s}^u + L_i^e (y_i + \sum_s \Lambda_{i,s}^e x_{i,s}^e)\right] P_i / \prod_s (w_{i,s})^{\beta_{i,s}}}{\prod_s \left(A_{i,s}/\Pi_{i,i,s}\right)^{-\frac{\beta_{i,s}}{\vartheta_s}}}.
\end{aligned} \tag{B.5}$$

$C_i = \prod_s (\beta_{i,s})^{\beta_{i,s}} \Gamma\left(1 - \frac{\sigma-1}{\vartheta_s}\right)^{-\frac{\beta_{i,s}}{1-\sigma}}$ is a country-specific constant. The first equality defines real consumption. The second equality uses $P_i = \prod_s \left(P_{i,s}/\beta_{i,s}\right)^{\beta_{i,s}}$ and price index in equation (B.3). The third equality uses the expression for trade shares in equation (3). The fourth equality divides the numerator and the denominator by $\prod_s w_{i,s}^{\beta_{i,s}}$.

Note that the gains from trade is $\text{GT}_i = \frac{\mathcal{W}_i}{\mathcal{W}_i^{aut}}$. By evaluating $\mathcal{W}_i$ and $\mathcal{W}_i^{aut}$ with equation (B.5), we can obtain the formula in Proposition 3.

B.5 Workers' Utility

Our calculation of the gains from trade does not account for workers' preferences and the obstacles associated with obtaining an education. To incorporate preferences and frictions, we now compute the average utility (after considering tastes and frictions) of skilled labor:

$$
\begin{aligned}
\mathcal{U}_i^e &= \int_0^\infty \epsilon^e \frac{V_i^e}{\tau_i} G\left(\frac{\epsilon^e V_i^e}{\tau_i V_i^u}\right) dG(\epsilon^e)/\Lambda_i^e \\
&= \int_0^\infty \kappa \frac{V_i^e}{\tau_i} (\epsilon^e)^{-\kappa} \exp\left\{ - \left[\left(\frac{V_i^e}{\tau_i V_i^u}\right)^{-\kappa} + 1\right] (\epsilon^e)^{-\kappa} \right\} d\epsilon^e/\Lambda_i^e \\
&= \int_0^\infty \left[(V_i^e/\tau_i)^\kappa + (V_i^u)^\kappa\right]^{1/\kappa} y^{-\frac{1}{\kappa}} \exp(-y) dy \\
&= \Gamma\left(1 - \frac{1}{\kappa}\right) \left[(V_i^e/\tau_i)^\kappa + (V_i^u)^\kappa\right]^{1/\kappa}.
\end{aligned}
$$

The first equality defines the average utility for skilled labor. The second equality uses the definition of $G(\epsilon)$. The third equality changes the variable by letting $y = \left[(V_i^e/\tau_i V_i^u)^{-\kappa} + 1\right] (\epsilon^e)^{-\kappa}$. The final equality uses the definition of the Gamma function $\Gamma(z) = \int_0^\infty x^{z-1} \exp(-x) dx$. Similarly, we can obtain the average utility of unskilled labor as $\mathcal{U}_i^u = \Gamma\left(1 - \frac{1}{\kappa}\right) \left[(V_i^e/\tau_i)^\kappa + (V_i^u)^\kappa\right]^{1/\kappa}$.

Thus, the average utility of workers in country i is:

$$
\begin{aligned}
\mathcal{U}_i &= \mathcal{U}_i^u (1 - \Lambda_i^e) + \mathcal{U}_i^e \Lambda_i^e \\
&= \Gamma\left(1 - \frac{1}{\kappa}\right) \left[(V_i^e/\tau_i)^\kappa + (V_i^u)^\kappa\right]^{1/\kappa}.
\end{aligned}
$$

We observe that without education choices and on-the-job learning, the average utility of workers is determined by the real wage, and therefore the gains from trade will be represented by the ACR formula. Consequently, we decompose the proportional changes in utility between autarky and the observed economy as follows:

$$
\frac{\mathcal{U}_i}{\mathcal{U}_i^{aut}} = \underbrace{\prod_s (\Pi_{i,i,s})^{-\frac{\beta_{i,s}}{\vartheta_s}}}_{\text{ACR formula}} \times \underbrace{\frac{\mathcal{U}_i}{\mathcal{U}_i^{aut} \prod_s (\Pi_{i,i,s})^{-\frac{\beta_{i,s}}{\vartheta_s}}}}_{\text{Gains in skill acquisition}}.
$$

B.6 The Gains of Trade with Intermediate Inputs

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

$$
q = z_{i,s}(\omega) \left(\alpha_s u^{\frac{\phi-1}{\phi}} + (1-\alpha_s)\psi_i e^{\frac{\phi-1}{\phi}}\right)^{\frac{\zeta_{i,s}^l \phi}{\phi-1}} \prod_{s'} (x_{s'})^{\zeta_{i,s}^{s'}}. \tag{B.6}
$$

Then the unit cost of producing with $z_{i,s}(\omega) = 1$ is:

$$c_{i,s} = \left(\frac{w_{i,s}}{\gamma^l_{i,s}}\right)^{\gamma^l_{i,s}} \prod_{s'} \left(\frac{P_{i,s'}}{\gamma^{s'}_{i,s}}\right)^{\gamma^{s'}_{i,s}}.$$

Using the similar procedure as in Appendix B.1, we can show:

$$\Pi_{i,i,s} = \frac{A_{i,s}(c_{i,s})^{-\vartheta_s}}{\sum_j A_{j,s}(d_{j,i,s}c_{j,s})^{-\vartheta_s}} = \Gamma_{i,s}\frac{A_{i,s}(c_{i,s})^{-\vartheta_s}}{P^{-\vartheta_s}_{i,s}},$$

where $\Gamma_{i,s}$ 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 $c_{i,s}$ and $\Pi_{i,i,s}$, we can obtain:

$$\hat{P}_{i,s} = \frac{\hat{\Pi}_{i,i,s}}{\vartheta_s} + \gamma^l_{i,s}\hat{w}_{i,s} + \sum_{s'} \gamma^{s'}_{i,s}\hat{P}_{i,s'}.$$

Consequently, by performing some matrix calculations, we can derive

$$\hat{P}_{i,s} = \sum_{s'} \alpha_{i,s,s'}\left(\frac{\hat{\Pi}_{i,i,s'}}{\vartheta_{s'}} + \gamma^l_{i,s'}\hat{w}_{i,s'}\right),$$

where $\alpha_{i,s,s'}$ 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 $\gamma^{s'}_{i,s}$.

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

$$\mathrm{GT}_i = \underbrace{\prod_s \prod_{s'} (\Pi_{i,i,s'})^{-\frac{\alpha_{i,s,s'}\beta_{i,s}}{\vartheta_{s'}}}}_{\text{ACR formula}} \times \underbrace{\frac{L^u_i \sum_s \Lambda^u_{i,s}\frac{w^u_{i,s}}{x_i}\bar{h}^u_{i,s} + L^e_i \sum_s \Lambda^e_{i,s}\frac{w^e_{i,s}}{x_i}\bar{h}^e_{i,s} - \mathcal{F}_i}{L^{u,aut}_i \sum_s \Lambda^{u,aut}_{i,s}\frac{w^{u,aut}_{i,s}}{x^{aut}_i}\bar{h}^{u,aut}_{i,s} + L^{e,aut}_i \sum_s \Lambda^{e,aut}_{i,s}\frac{w^{e,aut}_{i,s}}{x^{aut}_i}\bar{h}^{e,aut}_{i,s} - \mathcal{F}^{aut}_i}}_{\text{Gains due to changes in skill acquisition}},$$

where $x_i = \prod_s \prod_{s'} (w_{i,s'})^{\beta_{i,s}\alpha_{i,s,s'}\gamma^l_{i,s'}}$, and $\mathcal{F}_i = \left[L^u_i \sum_s \Lambda^u_{i,s}x^u_{i,s} + L^e_i(y_i + \sum_s \Lambda^e_{i,s}x^e_{i,s})\right] P_i/x_i$.

B.7 Multi-period OLG with Sectoral Adjustments

Model Extension. As job destruction and adjustments happen at high frequency, we need to adjust the model setting for workers. We assume that workers can live for potentially many periods. Each period is one year. For convenience, we adopt a Blanchard-Yaari "perpetual youth" structure, in which workers die with a probability

δ_d in the end of each period. Workers enjoy utility from consumption $\sum_{t=0}^{\infty}(1+\rho)^{-t}c_t$. 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 work. To model that college education leads to less production time in this model extension, 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 work in. To generate imperfect mobility between sectors, we follow Galle et al. (2023) to assume that the share of workers choosing sector s is given by:

$$\Lambda_{i,s}^m = \frac{\left(w_{i,s}^m\right)^\chi}{\sum_s \left(w_{i,s}^m\right)^\chi}.$$

The parameter χ captures the responses of sectoral choices to wage rates.

Worker's Problem in Model Extension. In this setting, as workers could live for many periods, the current-period value of a worker with human capital h in country i and sector s is:

$$\max_{t,x} V_{i,s}^m(h) = w_{i,s}^m(h-t) - xP_i + (1-\delta_d)\frac{(1-\delta_p)V_{i,s}^m(h') + \delta_p \sum_s \Lambda_{i,s}^m V_{i,s}^m(h')}{1+r},$$
$$\text{s.t.} \quad h' = h + \mu_{i,s}^m t^{\gamma_1} x^{\gamma_2}.$$

Given the present value of consumption shall be equal to the present value of income, we directly plug in the present value of income in this equation. By using the first-order conditions, we can solve for optimal learning investments as:

$$t_{i,s}^m = \left[\gamma_1^{1-\gamma_2}\gamma_2^{\gamma_2}\mu_{i,s}^m \frac{\partial V_{i,s}^m/\partial h'}{w_{i,s}^m}\left(\frac{w_{i,s}^m}{P_i}\right)^{\gamma_2}\right]^{\frac{1}{1-\gamma_1-\gamma_2}},$$

$$x_{i,s}^m = \left[\gamma_1^{\gamma_1}\gamma_2^{1-\gamma_1}\mu_{i,s}^m \frac{\partial V_{i,s}^m/\partial h'}{w_{i,s}^m}\left(\frac{w_{i,s}^m}{P_i}\right)^{1-\gamma_1}\right]^{\frac{1}{1-\gamma_1-\gamma_2}}.$$

We can characterize the education choices for a new-born worker as:

$$\max_{m\in\{e,u\},y}\left\{\epsilon^u \sum_s \Lambda_{i,s}^u V_{i,s}^u(1), \epsilon^e\left[\sum_s \Lambda_{i,s}^e \frac{(1-\delta_d)^4}{(1+r)^4} V_{i,s}^e(b_i t_e^{\gamma_1} y^{\gamma_2}) - P_i y\right]/\tau_i\right\},$$

where $\frac{(1-\delta_d)^4}{(1+r)^4}$ captures that it takes 4 years to obtain a college degree, thus inducing time costs and the discounted value of income from working. We can compute the optimal material investments in education as:

$$y_i = \left[\frac{(1-\delta_d)^4}{(1+r)^4}\frac{\sum_s \Lambda_{i,s}^e \partial V_{i,s}^e(b_i t_e^{\gamma_1} y^{\gamma_2})/\partial(b_i t_e^{\gamma_1} y^{\gamma_2})}{P_i} b_i t_e^{\gamma_1}\gamma_2\right]^{\frac{1}{1-\gamma_2}}.$$

And we can compute the share of workers choosing to be skilled as:

$$\Lambda_i^e = \frac{\left[\sum_s \Lambda_{i,s}^e \left(\frac{(1-\delta_d)^4}{(1+r)^4} V_{i,s}^e (b_i t_e^{\gamma_1} y_i^{\gamma_2}) - P_i y_i\right) / \tau_i\right]^\kappa}{\left[\sum_s \Lambda_{i,s}^e \left(\frac{(1-\delta_d)^4}{(1+r)^4} V_{i,s}^e (b_i t_e^{\gamma_1} y_i^{\gamma_2}) - P_i y_i\right) / \tau_i\right]^\kappa + \left[\sum_s \Lambda_{i,s}^u V_{i,s}^u (1)\right]^\kappa}.$$

Model Equilibrium Conditions. The production side of the model remains unchanged. With changes in the assumptions about the worker's problem, we can adjust the left-hand side of labor clearing conditions in equations (12) and (13) to take into account that the labor supply is aggregated across workers of different human capital levels.

Model Parameters. 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 U.S. (Shimer 2012, Faberman et al. 2017). We calibrate the new parameter χ (which governs the elasticity of sectoral choices to sectoral wage rates) to target the between-sector dispersion of average wages in the U.S. in 2005. We calibrate all other parameters following the calibration procedure in Section 3.[32]

C Data Description

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.

C.2 Sector Decomposition

Table C.1 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 manu-

[32] In this scenario, we find that the inclusion of persistent death rates even during younger ages causes workers to discount the benefits from acquiring education more heavily than in the baseline model. As a result, matching the share of higher education spending in labor income requires a significantly larger value of parameter γ_2 in this model extension. To facilitate a better comparison of this model extension with the baseline results, we maintain the same value of parameter γ_2 from the baseline calibration. Alternatively, we also experimented with calibrating γ_2 to match the share of higher education spending in labor income, resulting in a value of $\gamma_2 = 0.43$. With $\gamma_2 = 0.43$, the model generates considerably large gains in skill acquisition, as demonstrated in Section 5.5.

facturing 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-educated 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-educated workers in employment lies above the median among all service sectors.

Table C.1: Sector Decomposition

Sector name	ISIC Rev.3	% college-educated workers (U.S. ACS 2005)
1. Agriculture, hunting, forestry, and fishing	01–05	31.9
2. Mining and quarrying	10–14	36.6
Manufacturing sectors:		
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

C.3 College Premium

We manually 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 C.2.

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, and 2000–2017 with available data on earnings and hours

Table C.2: 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
Cyrus, Germany, France, Lativa, Lithuania, Romania, Slovenia, Turkey	Eurostat
Indonesia	IPUMS
Cambodia	Lall and Sakellariou (2010)
Viet Nam	Moock et al. (1997)

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 ($\min${age-18,age-6-educ}). We calculate the wage-experience profile for each sector by computing the 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):

$$\log(w_{ict}) = \sum_{x \in X} \phi^x D^x_{ict} + \mathbf{b}\mathbf{X}_{ict} + \gamma_t + \gamma_c + \epsilon_{ict}, \tag{C.1}$$

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^x_{ict} 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:

$$\gamma_t = gt + e_t. \tag{C.2}$$

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 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 C.1 and each type of worker (skilled/unskilled), we separately estimate regression (C.1) 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).

D Additional Results

Table D.1: Gains from Trade Based on Workers' Utility

		Decomposition of utility gains from trade	
	Utility gains from trade	**ACR formula**	**Skill acquisition**
Country	(1)	(2)	(3)=(1)-(2)
USA	4.58%	3.73%	0.84%
CHN	4.15%	3.99%	0.16%
JPN	2.83%	2.50%	0.33%
IND	5.27%	5.01%	0.26%
DEU	15.88%	14.13%	1.75%
FRA	9.42%	8.45%	0.97%
GBR	9.85%	8.71%	1.14%
RUS	10.41%	8.78%	1.64%
ITA	6.17%	5.66%	0.51%
BRA	4.64%	4.20%	0.44%
MEX	9.00%	8.00%	1.00%
KOR	6.68%	5.80%	0.88%
CAN	17.94%	14.96%	2.98%
ESP	8.32%	7.41%	0.91%
IDN	12.21%	11.74%	0.47%
TUR	5.73%	5.32%	0.42%
AUS	7.92%	6.96%	0.97%
NLD	45.95%	40.33%	5.62%
THA	16.88%	15.73%	1.15%
ARG	7.89%	7.32%	0.56%
Mean	10.59%	9.44%	1.15%

Table D.2: Gains from Trade: With and Without Learning Adjustments

Country	**Gains in trade (baseline, with adjustments)** (1)	**Gains in trade (w/o learning adjustments)** (2)	**Gains in skill acquisition** (3)=(1)-(2)
USA	5.46%	4.11%	1.35%
CHN	4.47%	4.05%	0.42%
JPN	3.15%	2.55%	0.60%
IND	5.60%	5.02%	0.58%
DEU	18.00%	14.57%	3.43%
FRA	10.76%	8.79%	1.97%
GBR	11.82%	9.38%	2.44%
RUS	11.30%	9.39%	1.91%
ITA	6.95%	5.78%	1.17%
BRA	4.52%	4.23%	0.29%
MEX	9.71%	8.39%	1.32%
KOR	7.50%	5.93%	1.57%
CAN	20.17%	16.05%	4.12%
ESP	9.41%	7.75%	1.66%
IDN	12.62%	11.92%	0.70%
TUR	6.04%	5.39%	0.65%
AUS	9.11%	7.45%	1.66%
NLD	53.80%	42.81%	10.99%
THA	18.36%	16.14%	2.22%
ARG	8.32%	7.34%	0.98%
Mean	11.85%	9.85%	2.00%