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

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Abstract

This paper studies how trade openness affects welfare through changes in workers' skill acquisition. We first document that on-the-job training participation varies largely across sectors and that schooling investments are complementary to on-the-job learning. Thus, trade openness impacts on-the-job skill formation through sector reallocation and trade-induced changes in schooling investments. Motivated by the empirical evidence, we develop a multisector Eaton–Kortum model, in which skill intensities and on-the-job learning opportunities are heterogeneous across sectors. Workers decide whether to become skilled before entering the labor market, and accumulate human capital on the job. Through the lens of our model, trade-induced sector reallocation changes the returns of becoming skilled and on-the-job learning opportunities. Our calibrated model suggests that the gains from trade due to changes in skill acquisition are vastly different across countries and that richer countries tend to enjoy better on-the-job learning opportunities after trade openness.

JEL Codes: F1; J2

Key Words: gains from trade; education; on-the-job learning

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1 Introduction

By shifting composition of economic activities, freer trade alters returns and opportunities for schooling and on-the-job learning. Despite rich empirical evidence on how trade affects schooling (e.g., Edmonds et al. 2010, Atkin 2016, Blanchard and Olney 2016, Li 2018, Ferriere et al. 2019), little quantitative evidence describes how educational choices affect welfare gains from trade in a large set of countries. More importantly, the role of on-the-job learning, which has long been recognized as essential in fostering human capital (Becker 1964) and drawn much attention recently due to richer micro-level data (Islam et al. 2018, Lagakos et al. 2018), has rarely been linked with trade openness.

In this paper, we fill this gap in the literature. Motivated by empirical evidence on how trade-induced sector reallocation affects on-the-job training investments and schooling, we develop a multisector Eaton–Kortum model with workers' education choices and sectoral heterogeneity in skill intensities and on-the-job learning. The quantitative model, which is calibrated to match cross-country trade, production, and education data, sheds light on how trade affects skill acquisition and welfare in a large set of countries.

We begin our analysis by documenting empirical evidence on how exporting alters on-the-job learning opportunities. We draw on representative firm-level and worker-level surveys from more than 20 countries with detailed information on on-the-job training investments. We find large variation in training investments across sectors, suggesting that trade-induced sector reallocation may change on-the-job learning. Linking training data with global trade data, we find that across broad sectors (agriculture, industry, services), poor countries tend to shift employment toward sectors with higher training investments through exporting. However, within manufacturing, rich countries specialize in sectors with faster on-the-job learning.

We then present reduced-form evidence on the relationship between trade and schooling. Using export and education data over time, we construct a Bartik-type instrument for export growth and demonstrate that growth in exports from relatively less skill-intensive sectors led to a reduction in the share of college graduates in the population. Whereas this relationship has been similarly established in the aforementioned empirical studies, we use this evidence to discipline the key model parameter that governs education responses through indirect inference. Finally, relying on worker-level surveys, we show that schooling and on-the-job training are complementary, as workers with better education levels tend to enjoy larger training investments on the job. Thus, studying schooling and on-the-job learning collectively is necessary for uncovering the impact of trade openness on workers' skill acquisition.

Whereas the evidence suggests the potential impact of trade on skill acquisition, it also indicates that the impact can vary in countries with different comparative advantages and levels of trade openness. Thus, a quantitative analysis is necessary for uncovering the overall impact. To do this, we develop a multisector Eaton–Kortum model with sectoral heterogeneity in skill intensities and on-the-job learning opportunities. On the worker side, we embed an OLG model, in which workers first decide whether to become skilled through schooling choices before entering the labor market. Then workers look for jobs by random search and accumulate human capital on the job. Through the lens of the model, trade-induced sector reallocation changes the demand for skills, as well as average on-the-job learning opportunities for workers. This model yields the same gravity equation as in Eaton and Kortum (2002). Most notably, this model allows for an analytical solution to the gains from trade, measured by changes in real consumption from autarky to the observed economy. Our formula incorporates Arkolakis et al. (2012) (ACR) formula, augmented by the gains due to changes in skill acquisition.

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 vastly different across countries and possibly negative. The United States and the United Kingdom gain from trade-induced shifts in skill acquisition, with an increase of 0.40% and 0.81% in real consumption respectively, because of their comparative advantages in high-skill services. The biggest losses due to trade-induced skill acquisition occur in Germany and Netherlands among high-income countries (with a reduction of 0.69% and 0.70% in real consumption respectively), and Argentina and Brazil among non-high-income countries (with a reduction of 0.60% and 0.56% respectively). The losses reflect these countries' comparative advantages in manufacturing or agriculture. Finally, we find that richer countries tend to enjoy better on-the-job learning opportunities after trade openness.

We then rely on the model to understand the impact of a reduction in bilateral trade costs between each country and its trade partners. Because a country' comparative advantages vary across trade partners, changes in skill acquisition after partner-specific trade liberalization will also vary. For example, as Brazil exhibits comparative advantages in high-skill sectors compared with non-high-income countries but exhibits comparative disadvantages in these sectors relative to high-income countries, it will enjoy gains of skill acquisition after liberalizing trade with non-high-income countries but losses after liberalization with high-income countries.

This paper relates to several strands of the literature. The first strand is the vast literature on the gains from trade. Extant studies emphasize the importance of several factors in accounting for the gains from trade, such as multiple 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, Lind and Ramondo 2017, Baqaee and Farhi 2019). Complementing these earlier contributions, we explore the effect of two other factors—education choices and on-the-job learning—on the gains from trade. We show how the basic ACR formula is modified to account for these two factors while still remaining parsimonious. Moreover, workers' on-the-job learning provides an extra channel through which trade can affect wage inequality, in addition to firm revenues commonly studied in the literature (e.g., Helpman et al. 2017). Finally, 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). Our analysis indicates that workers' human capital indirectly depends on the trade partners, as the skill returns change with trading with countries of different comparative advantages.

Second, we relate to the literature on trade and workers' skill acquisition. Aside from the aforementioned empirical evidence, there are also many theoretical papers investigating the impact of trade on schooling. Findlay and Kierzkowski (1983) first incorporate education choices into a two-factor, two-good trade model, linking skill acquisition with the country's comparative advantages. Many follow-up papers further extend this framework with workers' heterogeneity (e.g., Borsook 1987, Das 2006, Falvey et al. 2010) and other production factors (e.g., Bond et al. 2003). Following this line of research, we also focus on endogenous formation of education levels and countries' comparative advantages. Differing from these studies, we also embed on-the-job learning into the model, drawing on the training literature (e.g., Becker 1964, Acemoglu 1997, Acemoglu and Pischke 1998). Thus, our model can uncover the impact of trade on the joint determination of schooling and on-the-job learning. Compared to this empirical and theoretical literature, there are relatively fewer quantitative studies, mostly focusing 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 studying a large set of countries and also by quantifying the understudied impact of trade on on-the-job learning.

Finally, we make contact with recent papers that highlight the importance of life-cycle human capital accumulation in development accounting. Manuelli and Seshadri (2014) develop a quantitative framework based on the Ben-Porath model. They find that on-the-job training accounts for almost half of human capital differences across countries. Using individual-level surveys from many countries and estimating returns to experience, Lagakos et al. (2018) and Islam et al. (2018) also highlight the potential importance of on-the-job human capital accumulation in triggering the cross-country gap in wage profiles. Our results imply that trade liberalization has differential impacts on on-the-job learning in countries of different development levels and may even widen the income gap.

This paper is organized as follows. Section 2 presents suggestive evidence on the impact of trade on on-the-job learning and schooling, leading to the model developed in Section 3. Section 4 provides the model calibration and quantitatively analyzes the impact of trade on workers' skill acquisition. Section 5 provides the robustness check in an extended model with rich labor market dynamics. Section 6 concludes.

2 Empirical Evidence

This section presents empirical evidence on the relationship between trade and skill acquisition. We start by describing the main data sources and then proceed to provide empirical evidence on how exporting may alter human capital formation.

2.1 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, with a detailed definition of key variables on training in Appendix Section A.

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.

Training Returns. To translate training investments into human capital, we measure returns to training investments by experience-wage profiles (Manuelli and Seshadri 2014). Following the literature (Islam et al. 2018, Lagakos et al. 2018), we apply Mincer regressions to estimate the returns using population census data from IPUMS.

Output, Trade, and Schooling Data. Moreover, to link on-the-job training with global trade patterns, we use output and export data from OECD Input–Output Tables, and employment data from the World Bank. 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.

2.2 The Impact of Trade on On-the-Job Training

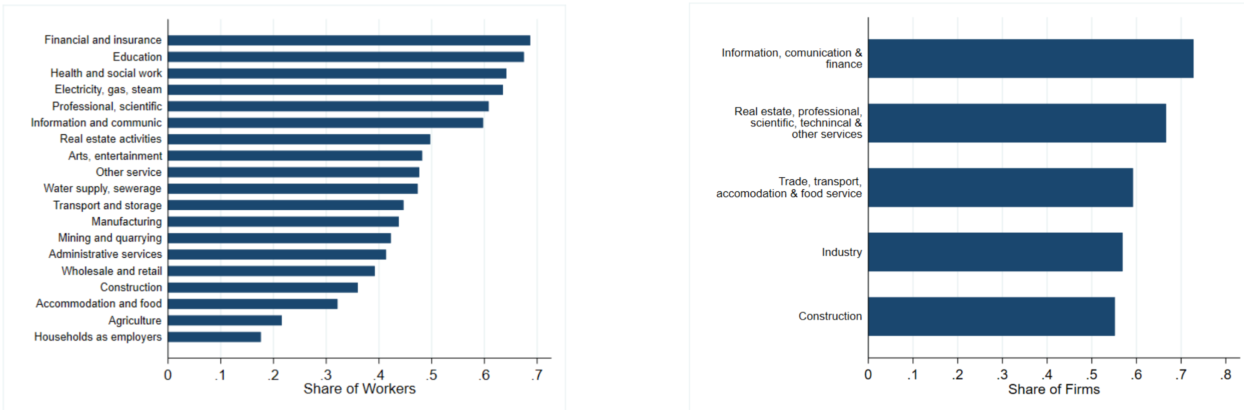
In this section, we provide suggestive evidence on the role of trade openness in affecting on-the-job learning. We show that on-the-job training levels vary across sectors, and thus trade-induced sector reallocation affects average levels of on-the-job learning.

2.2.1 Training Levels across Sectors

Using the EU-CVT survey and the EU-AES survey, Figure 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).[1] 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, as described below.

[1] Appendix table A.1 shows the shares of hours worked spent on training for different sectors. We still find large variation in training investments across sectors.

Figure 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.

In Appendix A, using the rich data on training participation, we show that variation of training across sectors is robust to using different on-the-job training measures.[2] We look into the share of firms providing training services in each type of training (Appendix Table A.2), as well as the share of workers participating in each training type from the enterprise and worker-level surveys (Appendix Tables A.3 and A.4 respectively). We find very similar differences in human capital investments across sectors for all training types. Finally, we show that our finding is not driven by specific countries. We find similar differences in training investments across sectors for all the EU countries in the sample (Appendix Table A.5).

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 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

[2] We construct measures of training including: (1) continuing vocational training, and seminars and conferences, which reflect more formal types of training; and (2) job rotation, guided on-the-job training, and self-learning, which reflect informal types of learning within the firm.

Table 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

remain vastly different training levels across sectors.

2.2.2 Linking On-the-Job Training with Trade Pattern

Due to the lack of well-estimated returns to training in the literature, we follow Manuelli and Seshadri (2014) to proxy on-the-job learning opportunities using returns to experience (RTE), which will allow us to have measures of human capital accumulation for many disaggregated sectors and to link them with export dynamics. This proxy is also motivated by the consistency between our ranking of sectors with higher training investments and the ranking of returns to experience estimated by Islam et al. (2018). In an extensive study, Islam et al. (2018) use 1,041 household surveys that include 23 million individuals from 145 countries (which account for 95% of the world population). They find population-weighted RTE for an extra year of experience is 2.6% (services), 2% (industry), and 1.3% (agriculture). These sectoral differences hold for developing and developed countries and are consistent with ranking of training investments in Figure 1.[3]

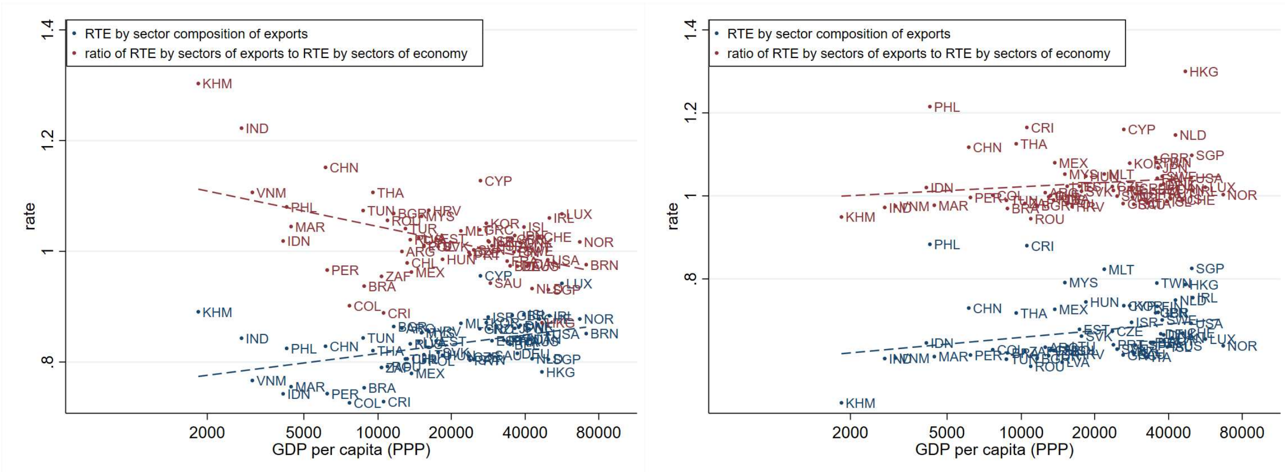
We document new evidence by connecting on-the-job learning with trade. To isolate the effects of trade-induced sector reallocation, we use the average RTE estimates for three broad sectors (agriculture, industry, and services) from Islam et al. (2018) and normalize the average RTE in services to be 1 for ease of description. For each country, we then compute: (1) an employment-weighted average RTE across three sectors' exports; and (2) an employment-weighted average RTE across three sectors' overall output.

Figure 2a presents the results. We highlight three findings. First, RTE by sectors of exports increases with GDP per capita, as richer countries tend to export more in services that embody the highest RTE among three sectors. Second, poor countries appear to shift employment toward sectors with higher RTE through exporting, as their RTE by sectors of exports tend to be higher than RTE by sectors of the overall economy. Third, the relative ratio of RTE by sectors of exports to RTE by sectors of the economy varies markedly across countries, suggesting large heterogeneity in countries' benefits from trade-induced changes in on-the-job learning.

Finally, using aggregate sectors may mask the vast amount of heterogeneity in RTE across detailed sectors, especially for manufacturing that is export-intensive. With this in mind, we use the U.S. Census and the American Community Survey (ACS) in the years

[3]See Table 1 in Islam et al. (2018). Herrendorf and Schoellman (2015) use the Current Population Survey and also document that in the United States, the wage-experience profile for nonagricultural workers is two times as steep as for agricultural workers.

Figure 2: Weighted Average RTE across Sectors



(a) Agriculture, Industry, and Services

(b) 2-digit Manufacturing Sectors

1980–2017 to estimate RTE after 35–40 years of experience for 16 2-digit ISIC manufacturing sectors[4] in the United States, by applying Mincer regressions and the Heckman–Locker–Taber method (Lagakos et al. 2018) detailed in Appendix Section D.4.

We use the RTE estimates from U.S. manufacturing sectors to compute an export-weighted average RTE and an output-weighted average RTE for each country in 2005.[5] Figure 2b presents the results.[6] The results show that even though rich countries already produce more in manufacturing sectors with higher RTE, they shift employment toward manufacturing sectors with even higher RTE through exporting. This result suggests that accounting for detailed manufacturing sectors can increase the gains in human capital from trade for richer countries. Due to different implications of Figures 2a and 2b about which countries gain more RTE after trade openness, we will use a quantitative analysis to understand how trade openness affects on-the-job learning opportunities through differences in countries' comparative advantages.

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

[5]Employment shares for detailed manufacturing sectors are not available in our dataset.

[6]We normalize the U.S.'s export-weighted average RTE for manufacturing sectors to be 0.75, to be consistent with Figure 2a, which normalizes RTE in industry to be 0.75.

2.3 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 following regression,

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

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 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 workers in employment for each sector in the Unite 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 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.[7]

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,

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

Table 2: The Impact of Exports on Education Choices

	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 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%.

we construct Bartik-type instruments as follows:

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

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 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 (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 noiser 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.[8]

2.4 Complementarity between On-the-Job Learning and Schooling

Finally, we show that schooling choices interact with on-the-job training participation. Figure 3 shows that on-the-job training participation sharply increases with workers' schooling levels. Moreover, in Appendix Table A.7, we show that after controlling for sector, occupation, socio-demographic characteristics, and country and year fixed effects, formal schooling is still positively associated with on-the-job training. Interestingly, this correlation does not depend on specific training types. In Appendix Table A.6, we show the positive association between schooling and on-the-job training investments holds for all formal and informal types of training. Thus, jointly studying schooling and on-the-job learning is necessary for uncovering the role of trade in skill acquisition.

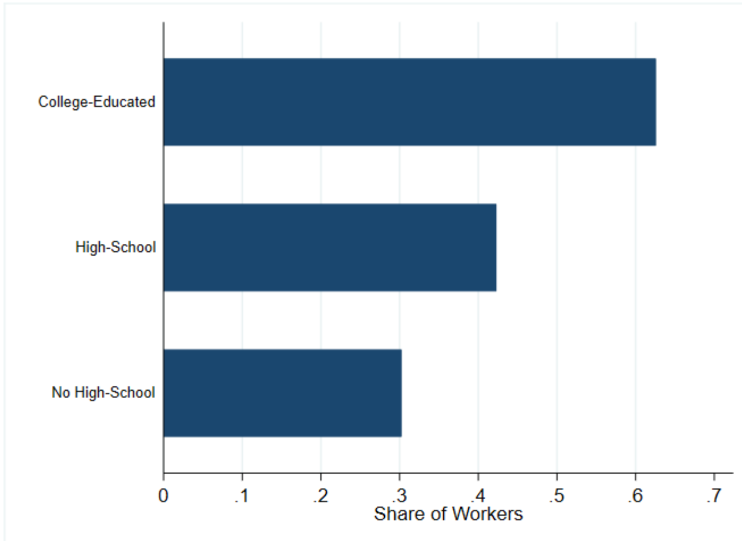
2.5 Summary

In summary, we show: (1) training investments differ across sectors, and thus trade-induced sector reallocation affects average training investments; (2) changes in sector composition of trade flows also affect schooling choices; and (3) schooling choices and on-the-job learning levels are complementary.

Whereas the evidence suggests the potential impact of trade on skill acquisition, it also indicates that the impact can vary across countries with different comparative advantages and levels of trade openness. Therefore, we need a quantitative analysis to uncover the overall impact of trade openness and perform the policy analysis. With this in mind, we proceed to present a model and perform a quantitative analysis in the next sections.

[8]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. It is worth noting that because we only focus on two education levels, comparison of our reduced-form estimates and the reduced-form evidence on how trade affects years of schooling in the literature is imperfect.

Figure 3: Training by Workers' Education Levels



Notes: These figures show employees' training participation rates by education. Data comes from the EU-AES. Results are simple averages of respective proportions from two different 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.

3 Model

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

3.1 Production

The world contains I countries and S sectors, and we index country by i and sector by s respectively. There is a non-storable final good in each country $Q_i = \prod_s Q_{is}^{\beta_{is}}$, where β_{is} is the expenditure share on intermediate goods from sector s with $\sum_s \beta_{is} = 1$. Denote P_i as the final-good price. Intermediate goods are produced by a unit measure of varieties $[0, 1]$ competitively:

$$Q_{is} = \left(\int_0^1 q_{is}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{\sigma_s}{\sigma_s - 1}}. \tag{3}$$

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

$$p_{is}(\omega) = \min_j p_{jis}(\omega), \tag{4}$$

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

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

$$y = z \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1-\alpha_s)\psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}}, \tag{5}$$

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

3.2 Workers

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

$$w_i^m + \frac{(1+\tau_{is}^m)w_i^m}{1+r_i} = c^Y + \frac{c^O}{1+r_i},\ m \in \{h, l\}, \tag{6}$$

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

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

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

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

Thus, in Appendix Section B.1, we show that the share of workers who decide to become skilled in country i is:

$$\Lambda_i^h = \frac{\exp(\kappa \mathbb{E}U(\mathbf{c_i^h}))(1-e_i)^\kappa}{\exp(\kappa \mathbb{E}U(\mathbf{c_i^h}))(1-e_i)^\kappa + \exp(\kappa \mathbb{E}U(\mathbf{c_i^l}))}. \tag{7}$$

Define $H_i = \Lambda_i^h N_i$ and $L_i = (1-\Lambda_i^h)N_i$ as the efficiency units of skilled and unskilled young workers, respectively. The parameter κ determines the magnitude of the response of education choices to changes in wage returns, which will be disciplined by our reduced-form evidence in Section 2.3 in the calibration.

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

3.3 Labor Market

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

We make several simplifying assumptions on labor market dynamics in order to derive an analytical solution for the gains from trade, and we relax these assumptions in Section 5 showing that these simplifications have modest effects on the quantitative results. Specifically, we assume that there is one national labor market for each skill type of worker. The amount of vacancies for each type of worker is aggregated across all firms and sectors. We abstract from job destruction, and therefore all searchers are young workers. We also abstract from unemployment by assuming that the matching function is $M(U,V) = min\{U,V\}$, and that vacancy posting costs (f^l and f^h) are small enough such that there is full employment. Denote by $\theta_i^h = \frac{V_i^h}{H_i}$ and $\theta_i^l = \frac{V_i^l}{L_i}$ the market tightness for skilled and unskilled workers, where V_i^h and V_i^l are the total number of vacancies for recruiting skilled and unskilled workers, respectively.

After searching and matching, workers and firms engage in wage bargaining as in Stole and Zwiebel (1996),[9] and workers capture a portion $0 < \beta < 1$ of marginal output.

3.4 Trade Shares

Taking market prices as given, a firm producing variety ω chooses vacancies v_i^h and v_i^l to maximize profits for different markets. Under perfect competition, foreign prices are proportional to domestic prices $p_{ijs}(\omega) = d_{ijs}p_{iis}(\omega)$ by the same proportion as transportation losses in output due to iceberg costs. For analytical tractability, we assume that firms are myopic in the sense that they only maximize one-period profits when posting vacancies and therefore ignore future profits from hiring young workers (when they turn old). This assumption will be relaxed in Section 5. We can write a firm's profit maximization

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

problem as:

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

where $(1+\tau_{is}^l)l^O$ and $(1+\tau_{is}^h)h^O$ denote the efficiency units of unskilled and skilled old workers that were hired in the last period.[10] Moreover, $\frac{v_i^h}{\theta_i^h}$ and $\frac{v_i^l}{\theta_i^l}$ specify the amount of new hires from posted vacancies for skilled and unskilled workers, respectively. Firms spend profits from hiring the remaining old workers on final goods.

In the equilibrium, free entry of vacancies implies that:

$$\begin{aligned} f^l \theta_i^l P_i &= (1-\beta) z_{is}(\omega) p_{iis}(\omega) \alpha_s \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1-\alpha_s)\psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{1}{\phi-1}} l^{\frac{-1}{\phi}}, \\ f^h \theta_i^h P_i &= (1-\beta) z_{is}(\omega) p_{iis}(\omega) (1-\alpha_s)\psi_i \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1-\alpha_s)\psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{1}{\phi-1}} h^{\frac{-1}{\phi}}. \end{aligned} \tag{8}$$

The left-hand side is the average vacancy costs to hire one unit of labor, whereas the right-hand side is the one-period profit from hiring that worker. By using the assumption that workers capture a portion $0 < \beta < 1$ of the marginal output and equation (8), we obtain wages for unskilled and skilled workers:

$$\begin{aligned} w_i^l &= \beta z_{is}(\omega) p_{iis}(\omega) \alpha_s \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1-\alpha_s)\psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{1}{\phi-1}} l^{\frac{-1}{\phi}} = \frac{\beta f^l \theta_i^l P_i}{1-\beta}, \\ w_i^h &= \beta z_{is}(\omega) p_{iis}(\omega) (1-\alpha_s)\psi_i \left(\alpha_s l^{\frac{\phi-1}{\phi}} + (1-\alpha_s)\psi_i h^{\frac{\phi-1}{\phi}} \right)^{\frac{1}{\phi-1}} h^{\frac{-1}{\phi}} = \frac{\beta f^h \theta_i^h P_i}{1-\beta}. \end{aligned} \tag{9}$$

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

$$w_{is} = \left(\alpha_s^{\phi} (w_i^l)^{1-\phi} + (1-\alpha_s)^{\phi} \psi_i^{\phi} (w_i^h)^{1-\phi} \right)^{1/(1-\phi)}. \tag{10}$$

Combining the formula for w_{is} and equation (9), we obtain:

$$p_{iis}(\omega) = \frac{w_{is}}{\beta z_{is}(\omega)}. \tag{11}$$

We solve for the share of country j's expenses in sector s that source from country i

[10] The next-period old workers' amount is decided by this period's hires: $l^{O'} = \frac{v_i^l}{\theta_i^l}$ and $h^{O'} = \frac{v_i^h}{\theta_i^h}$.

(shown in Appendix Section B.2), which is written as:

$$\Pi_{ijs} = \frac{A_{is}\left(d_{ijs}w_{is}\right)^{-\vartheta_s}}{\sum_k A_{ks}\left(d_{kjs}w_{ks}\right)^{-\vartheta_s}}. \tag{12}$$

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

3.5 Equilibrium

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

$$H_i\Lambda_{is}^h(2+\tau_{is}^h) = \frac{(1-\alpha_s)^\phi \psi_i^\phi (w_i^h)^{-\phi}}{(w_{is})^{1-\phi}} \sum_j \Pi_{ijs}\beta_{js}\left(w_j^h H_j \sum_s \Lambda_{js}^h(2+\tau_{js}^h) + w_j^l L_j \sum_s \Lambda_{js}^l(2+\tau_{js}^l)\right), \tag{13}$$

$$L_i\Lambda_{is}^l(2+\tau_{is}^l) = \frac{\alpha_s^\phi (w_i^l)^{-\phi}}{(w_{is})^{1-\phi}} \sum_j \Pi_{ijs}\beta_{js}\left(w_j^h H_j \sum_s \Lambda_{js}^h(2+\tau_{js}^h) + w_j^l L_j \sum_s \Lambda_{js}^l(2+\tau_{js}^l)\right), \tag{14}$$

where the left-hand side is the supply of each type of worker to each sector, and the right-hand side is the demand for each type of worker, aggregated over destinations. Note that by equation (12), Π_{ijs} is also a function of $\{w_i^h, w_i^l\}$. Therefore, combining equations (7), (13), and (14) as well as $\sum_s \Lambda_{is}^l = 1$ and $\sum_s \Lambda_{is}^h = 1$, we can solve for each country's wages $\{w_i^h, w_i^l\}$, share of workers in each sector $\{\Lambda_{is}^l, \Lambda_{is}^h\}$ and the share of skilled workers $\Lambda_i^h = 1 - \Lambda_i^l$. With wages and the measure of workers, we can solve all other endogenous variables $\{\theta_i^l, \theta_i^h, P_{is}, P_i, p_{ijs}(\omega), \Pi_{ijs}\}$. The interest rate r_i is determined such that the aggregate saving is zero for each country in each period.

3.6 Gains from Trade

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

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

$$GT_i = \underbrace{\prod_s (\Pi_{iis})^{-\frac{\beta_{is}}{\vartheta_s}}}_{\textit{ACR formula}} \times \underbrace{\frac{\lambda_i^l L_i \sum_s \Lambda_{is}^l (1+\tau_{is}^l/2) + \lambda_i^h H_i \sum_s \Lambda_{is}^h (1+\tau_{is}^h/2)}{\lambda_i^{l,auc} L_i^{auc} \sum_s \Lambda_{is}^{l,auc}(1+\tau_{is}^l/2) + \lambda_i^{h,auc} H_i^{auc} \sum_s \Lambda_{is}^{h,auc}(1+\tau_{is}^h/2)}}_{\textit{Gains due to skill acquisition}}, \tag{15}$$

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

Proof: See Appendix Section B.3.

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

The key contribution of this paper is the second term that captures the gains from trade due to changes in skill acquisition and involves three forces. First, trade openness alters the skill premium, which affects the relative ratio of wages to prices faced by different workers, as shown by $\lambda_i^m, m \in \{h, l\}$. Second, trade openness changes the measure of unskilled and skilled workers through education choices in equation (7). This force is reflected by changes in the number of skilled and unskilled workers H_i and L_i. Third, trade openness also affects on-the-job learning, by shifting employment (Λ_{is}^l and Λ_{is}^h) across sectors with different learning opportunities (τ_{is}^l and τ_{is}^h) for each type of worker.

If there is only one type of worker, i.e. $\alpha_s = 1 \; \forall \; s$ or $\alpha_s = 0 \; \forall \; s$, then the formula in equation (15) can be further simplified as (omit the superscript for workers' types):

$$GT_i = \underbrace{\prod_s (\Pi_{iis})^{-\frac{\beta_{is}}{\vartheta_s}}}_{\text{ACR formula}} \times \underbrace{\frac{\sum_s \Lambda_{is}(1+\tau_{is}/2)}{\sum_s \Lambda_{is}^{auc}(1+\tau_{is}/2)}}_{\text{Gains due to on-the-job learning}} . \tag{16}$$

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

For analytical tractability, we abstracted from job turnover and workers' and firms' internalization of benefits from on-the-job learning. In Section 5, we study an extension of our model with rich labor market dynamics, in which workers search for jobs and firms post vacancies by considering sector-specific learning opportunities. We will show that this extended model leads to similar quantitative results as our baseline model.

4 Quantitative Analysis

In this section, we take the model to the data. Then, we present quantitative results on how trade affects workers' skill acquisition and the associated welfare implications.

4.1 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 D provides the details of countries and sectors.

The calibration must determine the following parameter values: discount rate ρ, labor share β, elasticity of substitution between skilled/unskilled labor ϕ, firm vacancy costs $\{f^m\}$, trade elasticities $\{\vartheta_s\}$, employment $\{N_i\}$, origin-destination-sector-specific trade costs $\{d_{ijs}\}$, spending shares $\{\beta_{is}\}$, on-the-job learning strength $\{\tau_{is}^m\}$, sectoral skill intensities $\{\alpha_s\}$, productivity of skilled labor $\{\psi_i\}$, time costs of being skilled $\{e_i\}$, productivity levels $\{A_{is}\}$, 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.

4.1.1 Externally Calibrated Parameters

We first draw some common parameters directly from the literature, as presented in Panel A of Table 3. We set the discount rate $\rho = (1 + 0.04)^{20} - 1$, as we consider 20 years to be one period with an annualized discount rate of 4%. We set the labor share to be $\beta = 2/3$ according to estimates in Gollin (2002), and the elasticity of substitution between skilled and unskilled labor to be $\phi = 1.5$, as commonly found in the labor literature (e.g., Katz and Murphy 1992). In the equilibrium, $P_i f^m \theta_i^m = \frac{(1-\beta) w_i^m}{\beta}$ $m \in \{l, h\}$, and vacancy costs f^m cannot be separated from market tightness θ_i^m without information on each country's labor market tightness. Because the separation of f^m from θ_i^m does not affect equilibrium production and trade flows, we normalize $f^m = 0.1$ $m \in \{l, h\}$.[11]

We use sector-specific trade elasticities ϑ_s from Caliendo and Parro (2015).[12] We ob-

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

[12]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

Table 3: Parameter Values and Sources

Parameters			Sources or Targeted Moments
Symbol	Value	Description	Description
Panel A: Externally Calibrated Parameters			
ρ	1.19	Discount rate (20 years)	Annualized discount rate of 4%
β	2/3	Labor share	Estimate in Gollin (2002)
ϕ	1.5	Elasticity of substitution btw skilled/unskilled	Estimate in Katz and Murphy (1992)
f^m	0.1	Vacancy costs by skill types	Normalization
ϑ_s	8.07 (10.86)	Sector-specific trade elasticity	Estimates in Caliendo and Parro (2015)
N_i	0.37 (1.01)	Country-specific employment ($N_{US} = 1$)	World Bank Database
d_{ijs}	23.85 (81.99)	Origin-destination-sector-specific trade costs	Imputed from trade shares
β_{is}	0.05 (0.09)	Country-sector-specific consumption shares	World I/O Table 2005
τ_s^m	0.73 (0.22)	On-the-job learning returns by sector/skill	RTE by sector/skill in the U.S.
Panel B: Internally Calibrated Parameters			
τ_i	1.32 (0.44)	Country-specific on-the-job learning returns	Country-specific RTE in Lagakos et al. (2018)
α_s	0.39 (0.09)	Parameters about sectoral skill intensities	Sectoral college employment share in the U.S.
ψ_i	0.36 (0.16)	Country-specific productivity of college workers	Country-specific college premium
e_i	0.73 (0.16)	Country-specific time costs of becoming skilled	Shares of college workers, Barro and Lee (2013)
A_{is}	1.80 (2.04)	Country-sector-specific productivity ($A_{US,s} = 1$)	Country-sector-specific output in 2005
κ	2.5	Shape parameter of dist of education preferences	Coefficient in Column (2) of Table 2

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

tain employment N_i for each country in 2005 from the World Bank Database. We follow Head and Ries (2001) to assume symmetric trade costs $d_{ijs} = d_{jis}$ and infer them from actual bilateral trade shares $d_{ijs} = \left(\frac{\Pi_{ijs}\Pi_{jis}}{\Pi_{iis}\Pi_{jjs}}\right)^{-1/2\vartheta_s}$.[13] We calibrate consumption share $\beta_{is} = \frac{Y_{is}+IM_{is}-EX_{is}}{\sum_s Y_{is}+IM_{is}-EX_{is}}$, where Y_{is}, EX_{is} and IM_{is} represent sector-specific output, exports, and imports, respectively.

Due to data availability, we assume that on-the-job learning parameters can be decomposed into $\tau_{is}^m = \tau_i \tau_s^m, m \in \{l, h\}$. We measure τ_s^m by estimating RTE of 40 years of experience separately for 20 sectors and two education groups using the U.S. Census and ACS in the years 1980–2017, and the estimation method is discussed in detail in Appendix Section D.4. We will calibrate country-specific learning opportunities τ_i jointly with other parameters using the method of moments, as described below.

literature (Simonovska and Waugh 2014).

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

4.1.2 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 country-specific learning opportunities $\{\tau_i\}$, country-sector-specific productivity levels $\{A_{is}\}$, sector-specific skill intensities $\{\alpha_s\}$, country-specific productivity levels of college workers $\{\psi_i\}$, and country-specific education costs $\{e_i\}$ to match the targeted data moments. We iterate on the parameter values to minimize the sum of squared differences between the data moments and the model moments.

Specifically, we target the following moments in the data: (1) country-sector-specific output, drawn from OECD Input–Output Tables in 2005;[14] (2) the share of college workers in employment for each sector in the U.S., computed from the ACS data in 2005; (3) country-specific college premium, collected from multiple data sources summarized in Appendix Section D; and (4) the country-specific share of college graduates in 2005 from Barro and Lee (2013). 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):

$$\underbrace{\frac{L_i w_i^l \sum_s \Lambda_{is}^l (1+\frac{\tau_i \tau_s^l}{2}) + H_i w_i^h \sum_s \Lambda_{is}^h (1+\frac{\tau_i \tau_s^h}{2})}{L_i w_i^l + H_i w_i^h}}_{\text{model: avg wage relative to avg wage of young cohort}} = \underbrace{\sum_{x\in X} \Lambda_{x,i} \left(1 + \frac{\phi_{x,i}}{\phi_{20-24,i}} \times \phi_{20-24,i}\right)}_{\text{data: avg wage relative to avg wage of young cohort}}, \tag{17}$$

where the left-hand side represents the overall average wage relative to the average wage of the young cohort in the model. The right-hand side specifies the data counterpart, where $\phi_{x,i}$ and $\Lambda_{x,i}$ denote the RTE and the employment share for experience group $x \in X$ ={0–4,...,35–39}, with the youngest cohort's RTE $\phi_{0-4,i} = 0$. To calculate the data moment in equation (17), 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 $\Lambda_{x,i}$.

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

Outer Loop. We use our reduced-form estimate in Table 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 $\beta_{is}^{\epsilon} = \beta_{is}\exp(\epsilon_s)$, in line with our regression results about the effects of skill demand on education choices. Exogenous shock ϵ_s is independent across sectors and distributed according to $\epsilon_s \sim \mathcal{N}(-\frac{\nu_s^2}{2}, \nu_s^2)$, where ν_s is chosen to be the actual standard deviation of 10-year export growth in sector s between 1965 and 2010. For each value of parameter κ, we simulate the model for 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 OLS regression as in Column (2) of Table 2.

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 $[0, 4]$,[15] 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 education 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 $\beta_1 = -0.025$ in Column (2) of Table 2, and choose the value of κ that minimizes the absolute distance between the model moment and the data moment.

4.2 Calibration Results

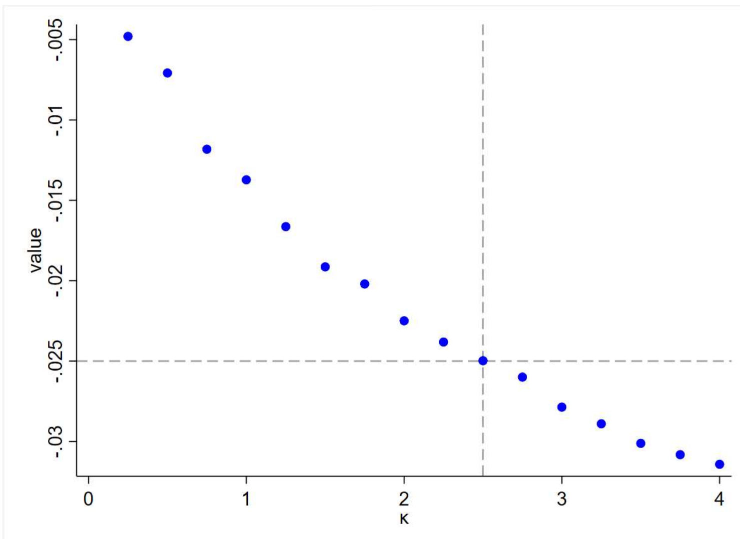
Panel B of Table 3 presents the internally calibrated parameter values. We find that with the calibrated parameters, our model matches the targeted data moments in the inner loop very well, as shown in Table 4. In Appendix Figure D.1, we further compare the country-sector output (targeted using A_{is}) and the origin-destination-sector trade shares (untargeted though the symmetric trade costs are inferred from actual trade shares) between the model and the data. We find that our model does a pretty good job with the regression coefficient of the data moments on the model moments being almost unity.

Table 4: Targeted Moments in the Model vs Data

Moments	Data	Model
1. Country-specific ratio of average wage to average wages of young cohort	1.51 (0.18)	1.51 (0.18)
2. Country-sector-specific output (relative to US)	0.11 (0.24)	0.11 (0.24)
3. Sector-specific college employment share in the U.S.	0.43 (0.14)	0.43 (0.14)
4. Country-specific college premium	2.06 (0.73)	2.03 (0.72)
5. Country-specific college employment share	0.21 (0.12)	0.21 (0.12)

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

Figure 4: 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 $\kappa = 2.5$, when the estimate from the model-generated data (-0.025) matches the estimate produced by the actual data (Column (2) of Table 2).

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 4 confirms this monotonic relationship between parameter value κ and the reduced-form estimate from the model-generated data. The value $\kappa = 2.5$ minimizes the absolute difference between the model-generated estimate and its counterpart in the data (Column (2) of Table 2).

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

4.3 Gains from Trade

Armed with our calibrated model, we perform the counterfactual exercise of the autarkic economy, by setting bilateral trade costs to be infinite $d_{ijs} \to \infty \; \forall \; i \neq j$. We then compute the proportional change in real consumption from the autarkic economy to the observed equilibrium to derive the gains from trade. To understand how education choices and on-the-job learning shape the gains, we compute proportional changes in the number of college workers and workers' lifetime wage growth from autarky to the observed equilibrium.[16]

Table 5 reports the results for the largest 20 economies in our calibrated model. Column (1) of Table 5 reports the overall gains from trade. Columns (2) and (3) further decompose the overall gains from trade into the ACR formula and the gains due to changes in skill acquisition according to Proposition 1. Consistent with the trade literature (e.g., Ramondo and Rodríguez-Clare 2013, Costinot and Rodríguez-Clare 2014), we find that the overall gains from trade are larger for small open economies, such as Canada and Netherlands. In particular, the values in terms of the ACR formula in Column (2) are similar to the results in Costinot and Rodríguez-Clare (2014) who study the gains from trade in a multisector model.[17] This result indicates that our quantitative results are reasonable.

Column (3) exhibits the gains from trade due to changes in skill acquisition, which are vastly different across countries. The United States and the United Kingdom are the two largest winners from trade-induced shifts in skill acquisition. The United States' gains from trade due to skill acquisition are 0.40%, accounting for 9.7% of the overall gains from trade. Its share of employment in high-skill services increases from 41.1% in autarky to 42.5% with trade openness. As a result, the United States enjoys higher aggregate human capital from trade openness, with a 0.55% growth in the number of college workers and a 0.58% increase in workers' lifetime wage growth, as shown in Columns (4) and (5). Similarly, the United Kingdom's gains from trade due to skill acquisition are 0.81%, accounting for 8.5% of the overall gains from trade. This gain is also largely accounted for by the increase in the employment share in high-skill services, from 34.8% in autarky to 37.2% with trade openness.

[16] Consistent with the calibration procedure, we compute lifetime wage growth as the percent increase in the overall average wage relative to the young cohort's average wage, measuring the RTE in the model.

[17] For example, in our calibrated model, the gains from trade computed 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) tend to find larger gains from trade than ours, because their calibrated model considers more

Table 5: Gains from Trade

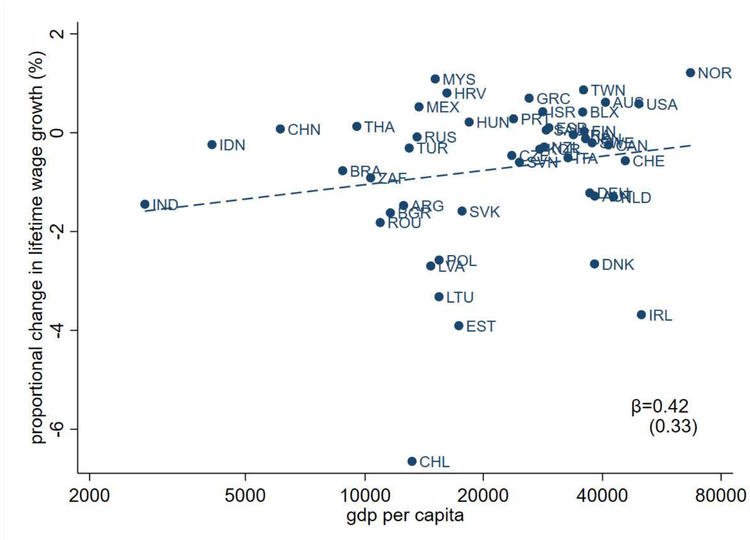
		Decomposition of gains from trade		Measures of skill acquisition	
	Gains from trade	**ACR formula**	**Skill acquisition**	**# college workers**	**Lifetime wage growth**
Country	(1)	(2)	(3)=(1)-(2)	(4)	(5)
USA	4.11%	3.71%	0.40%	0.55%	0.58%
CHN	3.97%	3.98%	-0.01%	-0.40%	0.08%
JPN	2.42%	2.50%	-0.08%	-0.25%	-0.12%
IND	5.08%	5.03%	0.05%	1.21%	-1.45%
DEU	13.46%	14.15%	-0.69%	-0.75%	-1.22%
FRA	8.38%	8.41%	-0.03%	0.18%	-0.04%
GBR	9.50%	8.69%	0.81%	1.91%	1.37%
RUS	8.75%	8.83%	-0.08%	-1.32%	-0.09%
ITA	5.37%	5.65%	-0.28%	-1.06%	-0.51%
BRA	3.65%	4.21%	-0.56%	-1.70%	-0.77%
MEX	7.84%	7.98%	-0.14%	-1.01%	0.52%
KOR	5.68%	5.78%	-0.10%	0.53%	-0.33%
CAN	14.68%	14.95%	-0.27%	-1.28%	-0.25%
ESP	7.41%	7.40%	0.01%	-0.19%	0.10%
IDN	11.44%	11.77%	-0.33%	-3.36%	-0.24%
TUR	5.04%	5.32%	-0.28%	-1.74%	-0.31%
AUS	7.18%	6.96%	0.22%	-0.71%	0.62%
NLD	39.63%	40.33%	-0.70%	1.51%	-1.30%
THA	15.64%	15.75%	-0.11%	-0.98%	0.13%
ARG	6.74%	7.34%	-0.60%	-2.06%	-1.47%

Among non-high-income countries, India is a marginal winner of trade-induced shifts in skill acquisition with a slight increase of 0.05% in real consumption. Most notably, the number of college workers increases by 1.21% if India moves from autarky to an open economy, which is partly induced by India's comparative advantage in services. However, Indian workers' lifetime wage growth tends to be lower after trade openness, because trade openness also induces reallocation of employment toward agriculture, which is associated with low on-the-job learning opportunities. Overall, the positive effect of its comparative advantage in services on skill acquisition slightly outweighs the negative effect of its comparative advantage in agriculture.

Many countries experience losses from trade due to skill acquisition. Among the high-income countries reported in Table 5, Germany and Netherlands lose most with a decrease of 0.69% and 0.70% in real consumption respectively, because of trade-induced shifts in skill acquisition. This is because after trade openness, these two countries shift employment from services to manufacturing sectors that tend to incur relatively lower

sectors.

Figure 5: Changes in Lifetime Wage Growth after Trade Openness



Note: For ease of describing graphs, we truncate the upper and lower 5% percentile of proportional changes. The regression coefficient barely changes with inclusion of these extreme values.

skill requirements and on-the-job learning compared with services. Among the non-high-income countries presented in Table 5, Argentina and Brazil experience the most losses with a reduction of 0.60% and 0.56% in real consumption respectively, mainly because these two countries enjoy comparative advantages in agriculture that entails low skill requirements and few on-the-job learning opportunities.

Finally, Figure 5 plots proportional changes in workers' lifetime wage growth from autarky to the observed equilibrium against log GDP per capita in 2005, for the set of countries in our quantitative analysis. We highlight two findings. First, we find that richer countries tend to enjoy better on-the-job learning opportunities after trade openness. This is because after trade openness, richer countries specialize in manufacturing or service sectors with higher RTE. Second, there is large variation in the changes of lifetime wage growth across countries, mostly due to different comparative advantages across countries. This highlights the importance of trade openness in shaping skill acquisition.

4.4 Impact of Trade Liberalization

For main winners and losers due to trade-induced skill acquisition from Table 5, we now perform the counterfactual experiments to understand how these gains from trade would change after trade liberalization. In Table 6, for each country in our consideration, we

Table 6: 10% Reductions in Bilateral Trade Costs

	High-income destinations			Non-high-income destinations		
		Decomposition			Decomposition	
	Δ%real income	ACR	Skill	Δ%real income	ACR	Skill
USA	0.99%	0.87%	0.12%	0.34%	0.28%	0.06%
GBR	2.61%	2.50%	0.11%	0.61%	0.61%	0%
DEU	2.94%	3.04%	-0.10%	0.61%	0.57%	0.04%
NLD	5.56%	6.14%	-0.58%	1.59%	1.84%	-0.25%
IND	1.57%	1.54%	0.03%	1.85%	1.73%	0.12%
ARG	1.92%	2.04%	-0.12%	1.31%	1.36%	-0.05%
BRA	1.17%	1.32%	-0.15%	0.65%	0.63%	0.02%

Notes: This table presents the effect on real consumption and its decomposition after a 10% reduction in bilateral trade costs between the country in consideration and its trade partners. We divide countries into high-income and non-high-income countries according to the World Bank's definition in 2005. The high-income countries are countries with GNI per capita higher than $10,725 in 2005.

report changes in real income after a 10% decline in bilateral trade costs with high-income and non-high-income trade partners, respectively. We highlight two findings. First, in line with Table 5, the United States, the United Kingdom, and India have additional gains of skill acquisition from trade liberalization, largely thanks to their comparative advantages in the services sectors. In contrast, because of comparative advantages in manufacturing or agriculture, Germany, Netherlands, Argentina, and Brazil mostly suffer losses in skill acquisition after trade liberalization.

Second, because a country's comparative advantages vary with trade partners, the changes in skill acquisition are different after trade liberalization with different countries. For example, as Brazil exhibits comparative advantages in high-skill sectors compared with non-high-income countries but exhibits comparative disadvantages in these sectors relative to high-income countries, it will enjoy gains of skill acquisition after liberalizing trade with non-high-income countries but losses after liberalization with high-income countries. In the trade literature, there is much evidence on direct knowledge diffusion associated with different trade partners (e.g., Coe and Helpman 1995, Eaton and Kortum 1999), as reviewed by Keller (2021). Our analysis indicates that workers' human capital indirectly depends on the trade partners, because the skill returns change with trading with countries of different comparative advantages.

5 Model Extension

Our baseline model abstracts from job turnover and workers' and firms' internalization of benefits from human capital accumulation. To understand whether our quantitative results are robust to these simplifications, this section studies a more realistic extension of our model with rich labor market dynamics. We first present the model extension in Section 5.1 and then report quantitative findings of the extended model in Section 5.2.

5.1 Incorporating Labor Market Dynamics

We now discuss how we extend the model from Section 3. We add the following features:

Labor Market. We consider that labor markets are separate by sectors and worker types in each country. The matching function is $M(U_{is}^m, V_{is}^m) = \min\{U_{is}^m, V_{is}^m\}$. U_{is}^m and V_{is}^m are the total amount of searchers and vacancies, respectively, for workers of type $m \in \{l, h\}$ in country i and sector s. We still abstract from unemployment by assuming that vacancy costs are small enough, which eases comparing our results with the trade literature that usually considers full employment (e.g., Eaton and Kortum 2002, Melitz 2003).

Workers. We now assume that workers can live for potentially many periods. For convenience, we adopt a Blanchard-Yaari "perpetual youth" structure, in which workers die with a probability δ_d in each period after production and consumption. Workers enjoy utility from consumption $\sum_{\tau=0}^{\infty} (1+\rho)^{-\tau} \log(c_\tau)$. The capital market is complete to avoid precautionary saving.[18] In the beginning of each period, old workers who died in the last period are replaced by the same number of new entrants, who determine whether to become skilled and then start to search for jobs. To model that college education leads to less production time in addition to education costs in the pre-period, we assume that new skilled workers spend the first four years not working. Alive employed workers are exogenously separated from their employers with a possibility δ_p and become unemployed.

New entrants and laid-off workers choose the sector to look for jobs. To generate upward-sloping labor supply curves on the sector level, we follow Hsieh et al. (2019) to assume that workers maximize cash flow from the job, facing idiosyncratic taste shocks y

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

that are i.i.d. across sectors and individuals, according to a *Fréchet* distribution $\exp(-y^{-\chi})$. The parameter $\chi > 0$ captures the dispersion of idiosyncratic tastes and therefore the elasticity of labor supply to wage rates. One-period working in sector s generates a proportional increase of τ_{is}^{m} in human capital. Therefore, for workers of type $m \in \{l, h\}$ in country i, the probability to look for jobs in sector s is:

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

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

Firms. Firms post vacancies each period to attract job searchers. Instead of assuming that firms are myopic as in Section 3, we now assume that firms post vacancies by considering the present value of workers' future benefits to the firm. This means that firms internalize the benefits from workers' on-the-job human capital accumulation, adjusted for workers' potential death and exogenous separations.

5.2 Quantitative Results

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

Due to the lack of an analytical solution for the gains from trade, we perform two counterfactual exercises to obtain the gains from trade due to changes in skill acquisition. In the first exercise, we set bilateral trade costs to be infinite $d_{ijs} \to \infty \; \forall \; i \neq j$. With this

Table 7: Gains from Trade (Extended Model)

		Decomposition of gains from trade		Measures of skill acquisition	
	Gains from trade	**Without changes in skill acquisition**	**Skill acquisition**	**# college workers**	**Lifetime wage growth**
Country	(1)	(2)	(3)=(1)-(2)	(4)	(5)
USA	5.18%	4.71%	0.47%	0.27%	1.01%
CHN	3.94%	3.94%	0.00%	-0.26%	0.05%
JPN	2.78%	2.88%	-0.10%	-0.12%	-0.24%
IND	6.74%	6.78%	-0.04%	0.91%	-1.65%
DEU	12.50%	13.44%	-0.94%	-0.11%	-1.96%
FRA	9.10%	9.17%	-0.07%	-0.08%	-0.14%
GBR	10.70%	9.77%	0.93%	1.05%	2.32%
RUS	9.26%	9.11%	0.15%	-1.21%	-0.16%
ITA	5.74%	6.15%	-0.41%	-0.63%	-0.99%
BRA	3.08%	3.44%	-0.36%	-0.89%	-1.02%
MEX	7.34%	7.20%	0.14%	-0.58%	0.77%
KOR	5.42%	5.70%	-0.28%	0.61%	-0.61%
CAN	14.72%	14.76%	-0.04%	-0.87%	-0.44%
ESP	8.76%	8.73%	0.03%	-0.35%	0.00%
IDN	11.88%	12.07%	-0.19%	-2.36%	-0.40%
TUR	5.20%	5.42%	-0.22%	-1.39%	-0.56%
AUS	9.30%	8.61%	0.69%	-0.87%	1.22%
NLD	38.23%	39.41%	-1.18%	0.96%	-1.66%
THA	15.10%	15.05%	0.05%	-0.51%	0.20%
ARG	6.05%	6.55%	-0.50%	-1.86%	-1.73%

exercise, we quantify the overall gains from trade. In the second exercise, we assume that for workers of type $m \in \{l, h\}$ in country i, on-the-job learning opportunities are identical across sectors by letting $\tau_{is}^m = \bar{\tau}_i^m \ \forall\ s$, where $\bar{\tau}_i^m$ is the employment-weighted average of τ_{is}^m across sectors. We also fix the share of college workers in each country. Under these restrictions, we recalibrate the model to match all the data moments specified earlier.[19] We then set bilateral trade costs to be infinite $d_{ijs} \to \infty \ \forall\ i \neq j$. With this exercise, we quantify the gains from trade without changes in skill acquisition. By deducting the gains from trade without changes in skill acquisition from the overall gains from trade, we obtain the gains from trade due to changes in skill acquisition. To understand how education levels and on-the-job learning change due to trade openness, for the first counterfactual exercise, we also measure changes in skill acquisition from autarky to the observed equilibrium in the same way as in Table 5.

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

Table 7 presents the results for the largest 20 economies in our calibrated model. Column (1) reports the overall gains from trade in our extended model, which are slightly larger than the gains from trade in our baseline model shown in Table 5, with a correlation coefficient of 0.99.[20] Column (3) of Table 7 reports the gains from trade due to changes in skill acquisition in the extended model, and they are quantitatively similar to our baseline results in Table 5, with a correlation coefficient of 0.92. Reassuringly, in Columns (4) and (5), trade-induced proportional changes in the number of college workers and lifetime wage growth are also analogous to the corresponding results for the baseline model, with correlation values of 0.98 and 0.97, respectively. These results suggest that our quantitative findings in the baseline model (with analytical solutions for the gains from trade) are robust to incorporating labor market dynamics.

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 document that on-the-job training participation varies largely across sectors and that schooling investments are complementary to on-the-job learning. Thus, trade openness impacts on-the-job skill formation through sector reallocation and trade-induced changes in schooling investments. Motivated by the empirical evidence, we develop a multisector Eaton–Kortum model with education choices and sectoral heterogeneity in skill intensities and on-the-job learning opportunities. The calibrated model reveals that the gains from trade due to changes in skill acquisition are not negligible and vastly different across countries. The primary driver for these countries' different outcomes is their different specialization patterns after trade openness.

Our paper has explored how trade-induced sector reallocation affects education choices and on-the-job learning. There are many other potential channels through which trade impacts human capital. For example, trade may reallocate workers toward firms with better learning opportunities or expose workers to diffusion of knowledge from suppliers and clients in other countries. A fruitful area for future study is whether these other

[20]The larger gains from trade in the extended model than those in the baseline model are partly driven by the upward-sloping sectoral labor supply curve as shown by Galle et al. (2017). In line with Galle et al. (2017), we find that as sectoral labor supply becomes more elastic ($\chi \to \infty$), the gains from trade tend to become smaller in the extended model.

channels are present in the data and quantitatively important.

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A Empirical Evidence on On-the-job training

We first provide definitions for the educational and training variables from the EU-CVT and the EU-AES. Then we provide further empirical evidence from these sources.

Schooling: According to ISCED 2011, formal education is defined as "education that is institutionalized, intentional and planned through public organizations and recognized private bodies and in their totality constitutes the formal education system of a country. Formal education programs are thus recognized as such by the relevant national education authorities or equivalent authorities, e.g. any other institution in cooperation with the national or sub-national education authorities. Formal education consists mostly of initial education. Vocational education, special needs education and some parts of adult education are often recognized as being part of the formal education system."

Training: According to ISCED 2011, non-formal education and training is defined as "any organized and sustained learning activities outside the formal education system. Non-formal education is an addition, alternative and/or complement to formal education. Non-formal education may therefore take place both within and outside educational institutions and cater to people of all ages. Depending on national contexts, it may cover educational programs to impart adult literacy, life-skills, work-skills, and general culture. Note that within non-formal education, we can have *formal training* or *informal training* depending on its level of organization."

We rely on the definitions for *formal training* and *informal training* from the EU-CVT survey manuals. Continuing vocational training (*formal training*) refers to education or training activities that are planned in advance, organized, or supported with the specific goal of learning and financed at least partially by the enterprise. These activities aim to generate "the acquisition of new competences or the development and improvement of existing ones" for firms' employees. Persons currently engaging in an apprenticeship or training contract should not be considered as taking part in CVT. Random learning and initial vocational training are explicitly excluded and measured separately. These courses are typically separated from the active workplace (for example, they take place in a classroom or at a training institution), show a high degree of organization by a trainer, and the content is designed for a group of learners (e.g., a curriculum exists).

As defined by the EU-CVT survey, "other forms of CVT" that we refer to as *informal training* are geared towards learning and are typically connected to the active work and the active workplace, but they can also include participation (instruction) in conferences, trade fairs, etc. These are often characterized by self-organization by the individual learner or by a group of learners and are typically tailored to the workers' needs. The following types of "other forms of CVT" are identified in the survey:

1. Guided on-the job training: "It is characterised by planned periods of training, instruction or practical experience in the workplace using the normal tools of work, either at the immediate place of work or in the work situation. The training is organised (or initiated) by the employer. A tutor or instructor is present. It is an individual-based activity, i.e. it takes place in small groups only (up to five partici-

pants)."

2. Job rotation, exchanges, secondments, or study visits: "Job rotation within the enterprise and exchanges with other enterprises as well as secondments and study visits are other forms of CVT only if these measures are planned in advance with the primary intention of developing the skills of the workers involved. Transfers of workers from one job to another which are not part of a planned developmental programme should be excluded."

3. Learning or quality circles: "Learning circles are groups of persons employed who come together on a regular basis with the primary aim of learning more about the requirements of the work organisation, work procedures and workplaces. Quality circles are working groups, having the objective of solving production and workplace-based problems through discussion. They are counted as other forms of CVT only if the primary aim of the persons employed who participate is learning."

4. Self-directed learning/e-learning: "An individual engages in a planned learning initiative where he or she manages the settings of the learning initiative/activity in terms of time schedule and location. Self-directed learning means planned individual learning activities using one or more learning media. Learning can take place in private, public or job-related settings. Self-directed learning might be arranged using open and distance learning methods, video/audio tapes, correspondence, computer based methods (including internet, e-learning) or by means of a Learning Resources Centre. It has to be part of a planned initiative. Simply surfing the internet in an unstructured way should be excluded. Self-directed learning in connection with CVT courses should not be included here."

5. Participation in conferences, workshops, trade fairs, and lectures: "Participation (instruction received) in conferences, workshops, trade fairs and lectures are considered as training actions only when they are planned in advance and if the primary intention of the person employed for participating is training/learning."

Table A.1: Proportion of Hours Worked Devoted to CVT (Enterprise Survey).

Activity	CVT
Information, communication and finance	0.011
Real estate, professional, and other services	0.008
Industry	0.007
Trade, transport, accommodation and food services	0.006
Construction	0.007
Total	0.007

Notes: This table shows, for each sector, the proportion of hours worked that is devoted to CVT courses. Sectors are ordered decreasingly by the relative importance in the sample. Results are simple averages of respective proportions from two different CVT survey waves: CVTS4 (2010) and CVTS5 (2015). Data from CVTS3 (2005) is not comparable due to different sector classifications. Weighting factors are used in order to calculate proportions for each wave.

Table A.2: Share of Firms Whose Workers Participate in Training (Enterprise Survey)

Activity	CVT Courses	Guided on the job training	Job rotation, exchanges, secondments, study visits	Conferences, workshops, trade fairs, lectures	Learning or quality circles	Any CVT activity
Information, communication and finance	0.727	0.502	0.157	0.577	0.149	0.831
Real estate, professional, and other service activities	0.666	0.463	0.122	0.480	0.136	0.769
Industry	0.568	0.399	0.132	0.329	0.101	0.669
Trade, transport, accommodation and food services	0.551	0.377	0.105	0.310	0.096	0.662
Construction	0.591	0.340	0.064	0.308	0.071	0.676
Total	0.609	0.417	0.151	0.385	0.120	0.696

Notes: This table shows, for each sector, the proportion of firms in Europe whose workers participate in each type of CVT activity. Sectors are ordered decreasingly by the relative importance in the sample. Results are simple averages of respective proportions from two different CVT survey waves: CVTS4 (2010) and CVTS5 (2015). Data from CVTS3 (2005) is not comparable due to different sector classifications. Weighting factors are used in order to calculate proportions for each wave.

Table A.3: Share of Workers Who Participate in Training (Enterprise Survey)

Activity	Guided on the job training	Job rotation, exchanges, secondments, study visits	Conferences, workshops, trade fairs, lectures	Learning or quality circles
Information, communication and finance	0.409	0.124	0.264	0.264
Real estate, professional, and other service activities	0.410	0.158	0.244	0.200
Industry	0.379	0.160	0.135	0.178
Trade, transport, accommodation and food services	0.409	0.184	0.193	0.255
Construction	0.396	0.252	0.182	0.201
Total	0.386	0.197	0.163	0.204

Notes: This table shows, for each sector, the proportion of workers in Europe who participate in each type of "other CVT activity" (not CVT courses). Sectors are ordered decreasingly by the relative importance in the sample. Results are from survey CVTS4 (2010). Data from CVTS3 (2005) is not comparable due to different sector classifications, whereas CVT5 (2015) presents uncomparable measures for worker shares (quantiles instead of shares). Weighting factors are used in order to calculate proportions for each wave. Note that the variable is only measured for “other CVT activities”, and data is not available for the proportion for “CVT courses”.

Table A.4: Share of Workers Participating in Training Activities (Worker Survey)

Activity	Courses and private lessons	Guided on the job training	Seminars and workshops	Training Total
Financial and insurance	0.457	0.288	0.273	0.687
Education	0.458	0.221	0.315	0.675
Health and social work	0.448	0.239	0.261	0.642
Electricity, gas, steam	0.428	0.267	0.225	0.635
Professional, scientific	0.417	0.187	0.272	0.608
Information and communication	0.396	0.229	0.251	0.597
Real estate activities	0.339	0.146	0.195	0.497
Arts, entertainment	0.325	0.124	0.177	0.482
Other service	0.326	0.139	0.211	0.476
Water supply, sewerage	0.314	0.187	0.119	0.473
Transport and storage	0.286	0.188	0.103	0.446
Manufacturing	0.278	0.190	0.119	0.438
Mining and quarrying	0.281	0.166	0.099	0.422
Administrative services	0.269	0.165	0.108	0.414
Wholesale and retail	0.242	0.158	0.111	0.392
Construction	0.237	0.124	0.088	0.360
Accommodation and food	0.197	0.114	0.083	0.321
Agriculture	0.148	0.051	0.067	0.216
Households as employers	0.098	0.047	0.058	0.176
Total	0.314	0.182	0.162	0.478

Notes: This table shows, for each sector, the proportion of workers in Europe taking part in each type of training activities, under AES classification. Sectors are ordered decreasingly by the relative training relevance in the sample. Results are simple averages of respective proportions from two different 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.

Table A.5: Share of Firms Whose Workers Participate in Any CVT (Enterprise Survey)

Country	Information, comunication and finance	Real estate, professional, and other services	Industry	Trade, transport, accomodation and food service	Construction
Germany	0.871	0.764	0.762	0.735	0.689
France	0.850	0.862	0.791	0.753	0.622
United Kingdom	0.880	0.845	0.814	0.795	0.844
Italy	0.789	0.626	0.570	0.497	0.706
Spain	0.865	0.810	0.805	0.771	0.848
Poland	0.548	0.422	0.347	0.284	0.287
Romania	0.375	0.284	0.243	0.193	0.227
Belgium	0.947	0.853	0.821	0.762	0.773
Portugal	0.881	0.770	0.649	0.705	0.652
Czech Republic	0.885	0.817	0.843	0.772	0.821
Hungary	0.688	0.431	0.491	0.418	0.471
Sweden	0.940	0.948	0.888	0.867	0.862
Bulgaria	0.541	0.427	0.365	0.302	0.422
Denmark	0.949	0.940	0.851	0.858	0.821
Slovak Republic	0.821	0.673	0.713	0.640	0.760
Finland	0.917	0.803	0.782	0.794	0.677
Norway	0.996	0.980	0.981	0.971	0.990
Lithuania	0.693	0.674	0.528	0.517	0.563
Estonia	0.818	0.804	0.722	0.760	0.763
Cyprus	0.889	0.792	0.666	0.653	0.679
Luxembourg	0.917	0.841	0.788	0.682	0.585
Malta	0.879	0.747	0.515	0.492	0.352
Total	0.831	0.769	0.669	0.662	0.676

Notes: This table shows, for each country and sector, the proportion of firms in which workers participate in CVT courses or any other CVT activity. Countries are ordered decreasingly by population size, and sectors are ordered decreasingly by the relative importance in the sample. Results are simple averages of respective proportions from two different CVT survey waves: CVTS4 (2010) and CVTS5 (2015). Data from CVTS3 (2005) is not comparable due to different sector classifications. Weighting factors are used in order to calculate proportions for each wave.

Table A.6: Share of Workers Participating in Training Activities (Worker Survey)

Activity	Courses and private lessons	Guided on the job training	Seminars and workshops	Training Total
College-Educated	0.426	0.223	0.270	0.626
High-School	0.274	0.167	0.112	0.423
No High-School	0.180	0.131	0.059	0.302
Total	0.314	0.182	0.162	0.478

Notes: This table shows, for each schooling level, the proportion of workers in Europe taking part in each type of training activities, under AES classification. Schooling levels are ordered decreasingly by the relative training relevance in the sample. Results are simple averages of respective proportions from two different 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.

Table A.7: Workers' Participation in Training

	(1)	(2)	(3)
High School	0.025***	0.078***	0.071***
	(0.003)	(0.003)	(0.003)
More than high school	0.115***	0.166***	0.148***
	(0.003)	(0.003)	(0.004)
Professionals	0.245***	0.190***	0.150***
	(0.007)	(0.007)	(0.009)
Technicians and associate professionals	0.237***	0.154***	0.109***
	(0.007)	(0.007)	(0.008)
Managers	0.221***	0.145***	0.126***
	(0.008)	(0.007)	(0.009)
Clerical support workers	0.166***	0.092***	0.043***
	(0.007)	(0.007)	(0.009)
Service and sales workers	0.098***	0.050***	0.019**
	(0.007)	(0.007)	(0.008)
Assamblers, plant and machine operators	0.086***	0.050***	0.002
	(0.007)	(0.007)	(0.009)
Craft and related trades workers	0.049***	0.015**	-0.016*
	(0.007)	(0.007)	(0.009)
Elementary occupations	-0.013*	-0.038***	-0.085***
	(0.007)	(0.006)	(0.008)
Observations	247,380	247,380	206,364
R-squared	0.123	0.203	0.202
Sector 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 association between schooling (occupations) and the probability of taking part in training activities in the last 12 months. The following variables are regarded as socio-economic controls: log of per capita GDP (PPP), age, squared age, gender dummies, and firm size dummies. Individual-level data is from AES 2011 and 2016. Data from AES 2007 is not comparable due to different sector and training classifications. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B Proofs

B.1 Share of College Graduates

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

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

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

B.2 CES Trade Shares and Prices

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

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

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

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

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

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

By plugging $\int_{\Omega_{ijs}} p_{ijs}(\omega)^{1-\sigma}d\omega$ into equation (18), we obtain trade shares in equation (12). Also note that CES preferences imply:

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

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

B.3 The Gains from Trade

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

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

where C_i is some country-specific constant. The first equality uses the definition of real consumption. The second equality uses $P_i = \prod_s (P_{is}/\beta_{is})^{\beta_{is}}$ and price index in equation (20). The third equality uses the expression for trade shares in equation (12). The fourth equality divides the numerator and the denominator by $\prod_s w_{is}^{\beta_{is}}$.

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

C Extensions of the Model

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

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

A worker that maximizes lifetime income solves:

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

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

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

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

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

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

D Data Description and Robustness Checks

D.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.

D.2 Sector Decomposition

Table D.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 manufacturing sectors, and 16 service sectors. For precision of estimating RTE, we collapse 16 service sectors into high-skill and low-skill services, based on the share of college workers in employment in each service sector. Specially, we use the U.S. ACS 2005 data and classify a service sector to belong to high-skill services if its share of college workers in employment lies above the median among all service sectors.

Table D.1: Sector Decomposition

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

D.3 College Premium

We collect the college premium for each country in 2005 (or the nearest year when the data is available) from multiple data sources, as shown by Table D.2.

D.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 worked. We

Table D.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)

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):

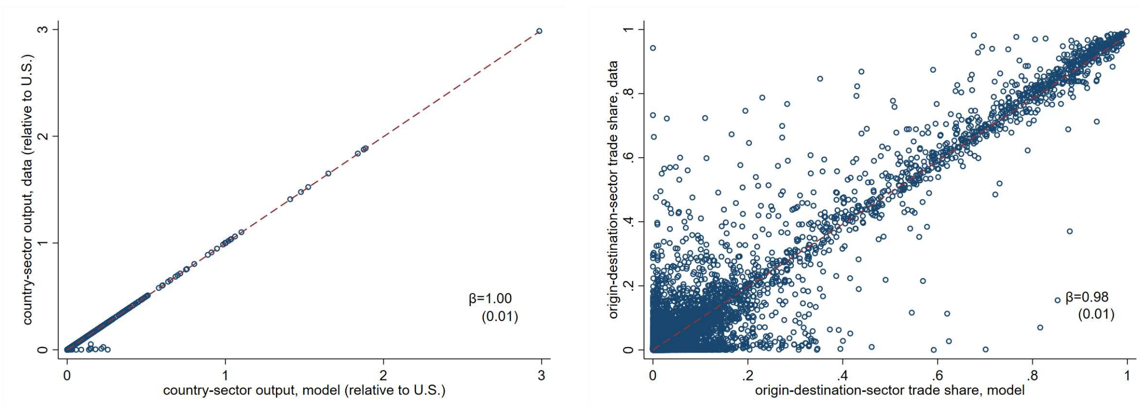
$$\log(w_{ict}) = \sum_{x \in X} \phi^x D^x_{ict} + \mathbf{b}\mathbf{X}_{ict} + \gamma_t + \gamma_c + \epsilon_{ict}, \tag{22}$$

where i and t represent individuals and years respectively. $\log(w_{ict})$ denotes the log hourly wage for an individual i. γ_t represents time fixed effects, and γ_c is cohort fixed effect. D^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:

$$\gamma_t = gt + e_t. \tag{23}$$

where g denotes aggregate time trends. Specially, we restrict the cyclical component e_t to average zero over the time period $\sum_t e_t = 0$ and to be orthogonal to the time trend $\sum_t e_t t = 0$. These assumptions are also made in Deaton (1997) and Aguiar and Hurst (2013) in estimating life-cycle profiles. To pin down the time trend g, we build on the assumptions from Heckman et al. (1998). The idea of this approach is to assume that there are no experience effects at the end of the working life of agents, and thus, all wage growth in this last period has to come from other sources which are assumed to be common across all cohorts. This approach requires two parameter values: the value for human capital depreciation rate and the amount of years at the end of the worker's life cycle 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 D.1 and each type of worker (skilled/unskilled), we separately estimate regression (22) by imposing $\gamma_t = gt + e_t$ such that there is no wage growth coming from experience in the last 10 years of individuals' working life in this sector. More details of this approach can be found in Lagakos et al. (2018).

Figure D.1: Comparison of Output and Trade Shares in the Model and in the Data



(a) Country-sector Output (b) Origin-destination-sector Trade Share

D.5 Parameter Values and Moments in the Extended Model

Table D.3 and D.4 present the parameter values and the targeted moments in the extended model. Overall, our model matches the data moments pretty well.

Table D.3: Parameter Values in the Extended Model

Parameters			Sources or Targeted Moments
Symbol	Value	Description	Description
Panel A: Externally Calibrated Parameters			
ρ	0.04	Discount rate	Annualized discount rate of 4%
β	2/3	Labor share	Estimate in Gollin (2002)
ϕ	1.5	Elasticity of substitution btw skilled/unskilled	Estimate in Katz and Murphy (1992)
f^m	0.1	Vacancy costs by skill types	Normalization
ϑ_s	8.07 (10.86)	Sector-specific trade elasticity	Estimates in Caliendo and Parro (2015)
N_i	0.37 (1.01)	Country-specific employment ($N_{US} = 1$)	World Bank Database
d_{ijs}	23.85 (81.99)	Origin-destination-sector-specific trade costs	Imputed from trade shares
β_{is}	0.05 (0.09)	Country-sector-specific consumption shares	World I/O Table 2005
τ_s^m	0.73 (0.22)	On-the-job learning returns by sector/skill	RTE by sector/skill in the U.S.
Panel B: Internally Calibrated Parameters			
τ_i	0.011 (0.003)	Country-specific on-the-job learning returns	Country-specific RTE in Lagakos et al. (2018)
α_s	0.45 (0.12)	Parameters about sectoral skill intensities	Sectoral college employment share in the U.S.
ψ_i	0.38 (0.16)	Country-specific productivity of college workers	Country-specific college premium
e_i	0.77 (0.24)	Country-specific time costs of becoming skilled	Shares of college workers, Barro and Lee (2013)
A_{is}	1.54 (1.93)	Country-sector-specific productivity ($A_{US,s} = 1$)	Country-sector-specific output in 2005
κ	1	Shape parameter of dist of education preferences	Coefficient in Column (2) of Table 2
χ	5.3	Shape parameter of dist of sector preferences	Between-sector dispersion of average wages

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

Table D.4: Targeted Moments in the Extended Model vs Data

Moments	Data	Model
1. Country-specific ratio of average wage to average wages of young cohort	1.51 (0.18)	1.51 (0.18)
2. Country-sector-specific output (relative to US)	0.11 (0.24)	0.11 (0.24)
3. Sector-specific college employment share in the U.S.	0.43 (0.14)	0.44 (0.14)
4. Country-specific college premium	2.06 (0.73)	2.01 (0.72)
5. Country-specific college employment share	0.21 (0.12)	0.21 (0.10)
6. Coefficient in Column (2) of Table 2	-0.025	-0.025
7. Between-sector dispersion of log average wage in the U.S.	0.20	0.20

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