Trade, Inequality, and the Endogenous Sorting of Heterogeneous Workers*

Eunhee Lee†

Yale University

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Abstract

This paper presents a unified framework to investigate the effect of international trade on the increase of inequality in both high- and low-income countries. I embed workers' Roy-like occupational choice problem into a multi-country, multi-industry, and multi-factor trade model to study the distributional effect of trade at a disaggregate level. Workers are heterogeneous in their industry- and occupation-specific productivities, and they sort into the industry and occupation in which they have a comparative advantage. International trade impacts this sorting mechanism and, as a consequence, makes gains from trade different across workers. I quantify the model for 33 countries, 5 worker types defined by educational attainment, 4 industries, and 5 occupation categories to examine the distributional effect of changes in trade costs and changes in China's productivity between 2000 and 2010, using the microdata from household surveys of each country. I find that (1) trade increases between-educational-type inequality in both high- and low-income countries, which is a significant departure from the traditional Stolper-Samuelson prediction; (2) occupation-level labor reallocation is an important channel by which trade increases between-educational-type inequality in most countries; and (3) international trade contributes to the contraction of manufacturing employment and job polarization in high-income countries, and to the contraction of agricultural employment in low-income countries.

Keywords: trade, worker heterogeneity, inequality, occupational choice

JEL Codes: F16, F66, J24, C68, D33

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†Department of Economics, Yale University. Email: eunhee.lee@yale.edu

1 Introduction

This paper presents a unified framework to quantitatively investigate the effect of international trade on the increase of inequality in both high- and low-income countries. Although traditional trade theory predicts that trade increases inequality in high-income countries and decreases inequality in low-income countries, this prediction is at odds with empirical evidence.[1] To reconcile the empirical evidence on trade and inequality, I present a multi-country, multi-industry, and multi-factor general equilibrium trade model, focusing on worker-level comparative advantage within a country as the main channel by which trade increases inequality in both high- and low-income countries.

In this model, two distinct comparative advantage structures characterize the international trade environment and domestic labor markets, respectively. First, trade is driven by comparative advantage across countries based on productivity differences and relative factor endowments. Second, the effect of trade is disseminated differentially across workers within a country based on comparative advantage across workers for their industry and occupation choices. Workers draw industry- and occupation-specific productivities conditional on the exogenously endowed educational type. Then they endogenously sort into industry and occupation in order to maximize their incomes, as in the Roy (1951) model.[2] International trade impacts this sorting mechanism within each country and, as a consequence, gains from trade are different across workers. This mechanism is the *labor supply channel* by which trade impacts inequality through labor reallocation. This channel is a new mechanism explaining whether and why trade increases inequality in most countries regardless of country-level comparative advantage. Distribution of gains from trade within countries depends on worker-level comparative advantage in this model.

In addition, I extend the traditional *labor demand channel* through which trade impacts inequality by considering multiple occupations as complementary factors of production. Workers' occupation affiliation as well as their industry affiliation matters when investigating the effect of trade on inequality. The reason being that workers engage in different occupational tasks even within the same industry based on worker-level comparative advantage. As a result, they are differentially affected by trade through changes in relative demands for occupations.

I incorporate these labor supply and demand channels within a unified framework

[1] The actual pattern observed in the data is an increase of inequality in most countries concurrent with trade liberalization. Goldberg and Pavcnik (2003; 2004; 2007) provide empirical evidence on the relationship between trade liberalization and the increase of inequality in developing countries, where the prediction of the Stolper-Samuelson theorem (1941) in the Heckscher-Ohlin model is overall inconsistent.

[2] I consider efficiency units of labor supplied by each worker as labor productivity.

to explore how trade affects various measures of inequality. I first focus on how trade changes between-educational-type inequality measured by type-specific welfare gains from trade as well as the skill premium.[3] Second, I derive trade-induced changes in within-educational-type wage inequality and employment shifts across industries and occupations, given that workers sort their labor into industry and occupation conditional on their educational types. In this way, I demonstrate to what extent trade itself explains well-known stylized facts in the labor market, such as changes in the industry and occupational wage premium as well as the contraction of manufacturing employment and job polarization in high-income countries.[4] The ability to examine the distributional effect along disaggregate dimensions in an integrated framework is important, especially because within-educational-type inequality has increased significantly in recent years. The effect of trade on between-educational-type inequality, such as the skill premium, is thus only a partial explanation for the distributional effect of trade.[5]

I use this model to quantify the effects of changes in the trade environment between 2000 and 2010 on inequality across 5 worker types defined by educational attainment, 4 industries, and 5 occupation categories in 33 countries. This time period is particularly interesting, because international trade became an increasingly significant factor after China entered into the global market by joining the World Trade Organization (WTO) in 2001. I use international microdata gleaned from household surveys for each country to quantify workers' differential responses to trade shocks in different countries. This feature cannot be captured by existing multi-country trade models fit to aggregate-level data.

To take the model to the data, I estimate the key parameter, *labor supply elasticity*, for four different countries and five educational types of workers with individual worker's wage data. This parameter is directly related to the degree of worker heterogeneity and assumed to be country- and educational-type-specific, since the degree of worker heterogeneity is likely to vary by country and worker type. In this way, this paper departs from existing trade models that pre-commit to a specific assumption on the degree of worker

[3]I define the skill premium by the wage premium of college graduates over non-college graduates. In line with the international trade literature, welfare gains from trade are measured by changes in real income caused by changes in the trade environment assuming consumers have a homothetic preference.

[4]The polarization across skill levels of occupation is well-studied in the labor economics literature both theoretically and empirically. Built upon Baumol (1967)'s unbalanced technological growth, Acemoglu (1999) and Autor et al. (2003) formalize the skill content of occupation and the polarization phenomenon, primarily focusing on the skill-biased technical change. This theory is supported by much empirical evidence including Autor et al. (2008) for the U.S. and Goos and Manning (2007) for the U.K. How much the international trade contributes to this phenomenon is, on the other hand, not widely studied except in a recent empirical paper by Harrigan et al. (2015).

[5]Helpman et al. (2010; 2012) and Grossman et al. (2014) discuss the effect of trade on changes in the within-type inequality based on the search and matching framework. Grossman (2013) also points out the limitation of investigating the effect of trade only on the skill premium.

heterogeneity.[6] The model in this paper also nests existing trade models in a tractable way using different values of this key parameter.

Armed with the parameter estimates, I separately introduce two types of trade shocks between 2000 and 2010 to perform counterfactuals. To carry this procedure out, I first measure trade shocks by changes in bilateral trade costs between countries, which are calibrated to match changes in bilateral trade flows in the data. The calibration result shows that trade costs have decreased by 8.89% on average between 2000 and 2010. Next, I measure trade shocks by changes in China's industry-level labor productivity since China has recently been on the rise in the global market.[7] I calibrate productivity changes to match changes in the within-worker-type employment allocation in the microdata.

Counterfactual experiments with these two types of trade shocks, as well as parameter estimates, show that changes in the trade environment between 2000 and 2010 have raised between-educational-type inequality in both high- and low-income countries, which is a significant departure from the traditional Stolper-Samuelson prediction. For example, when combining the effects of two shocks, the welfare of high school dropouts increases by 4.43%, while that of college graduates increases by 6.43% on average across all countries. The discrepancy is larger in low-income countries. Trade shocks also increase the skill premium in most countries: 0.73% on average across OECD countries and 3.15% on average across non-OECD countries. For example, in the U.S., trade shocks increase the skill premium by 0.56%, which is more than 10% of the actual increase in the skill premium observed in the data. This paper quantitatively shows that trade increases between-type-inequality mostly through occupation-level labor reallocation rather than through industry-level reallocation within worker type.[8] Moreover, the result has an aggregate implication about trade-induced employment shifts across industries and occupations. For example, trade induces a significant contraction of manufacturing employment as well as a job polarization in high-income countries. On the other hand, it generates a contraction of agricultural employment in low-income countries.

This model provides a comprehensive framework which encompasses various channels by which international trade impacts domestic inequality: (1) worker-level comparative advantage based on heterogeneous productivities; (2) both industry- and occupation-level labor reallocation; and (3) non-linear production function with which country-level

[6]Workers are homogeneous in their productivities in most trade models, including the Ricardian and the Heckscher-Ohlin trade models. The specific factors model is the other extreme case, where workers are extremely heterogeneous and thus fixed at a certain industry.

[7]Many empirical works, such as Autor et al. (2013), connect the import competition from China in high-income countries to the increase of productivity in China, which eventually improves China's export supply capability mainly through their cost advantage.

[8]This is consistent with the data evidence in Kambourov and Manovskii (2008) and Groes et al. (2015).

comparative advantage may not be exactly transferred to domestic labor outcomes. By quantifying these channels within a unified framework, this paper not only uncovers the mechanism by which trade shocks are disseminated within countries, but also reconciles the empirical evidence on trade and inequality in the literature. The motivation of this paper stems from many previous empirical works that document the relationship between trade and the increase of inequality: e.g., Autor et al. (2013; 2015) and Ebenstein et al. (2014) for developed countries, Goldberg and Pavcnik (2003; 2005) and Topalova (2007) for developing countries. I provide a structural model that complements empirical findings in these previous works.

This paper is not the first to use a general equilibrium framework to examine the increase of trade-induced inequality in both developed and developing countries. Burstein and Vogel (2015) focus on the reallocation of factors across heterogeneous firms within a sector, and Parro (2013) focuses on the capital-skill complementarity. These works are in line with the literature about trade and the skill-biased technological change; e.g., Acemoglu (2003). Unlike these papers, I focus on workers' heterogeneous productivities and the endogenous labor sorting into industry and occupation as the key channel through which trade increases inequality in most countries.

Most importantly, this paper contributes to the fast-growing literature on the Roy-like assignment model with worker-level heterogeneity, such as Lagakos and Waugh (2013), Hsieh et al. (2013), and Burstein et al. (2015). To investigate the effect of trade on inequality, I embed the worker-level comparative advantage into the gravity structure of standard trade models based on the country-level comparative advantage.[9] This paper distinguishes itself from these existing papers in three important ways. First, workers have heterogeneous productivities across both industries and occupations. I quantitatively show that considering both industries and occupations as dimensions of worker heterogeneity and labor reallocation captures a novel mechanism by which trade increases inequality in most countries. Second, I quantify trade-induced changes of various inequality measures within a unified framework. Consequently, the model prediction has a close connection to changes in inequality measures observed in the actual data.[10] Lastly, this paper quantifies a high-dimensional model of trade, inequality, and worker heterogeneity with rich microdata from household surveys across a large number of countries instead of focusing on the outcome of a single country.

This paper also contributes to the literature by providing a quantitative strategy to

[9] Galle et al. (2015) follow a similar approach, but the worker heterogeneity is defined only across industries.

[10] Changes in inequality are quantified both conditional and unconditional on efficiency units of labor, which makes the connection to the data even stronger.

experiment with a wide range of trade liberalization episodes regarding changes in trade costs or changes in a partner country's productivity. While existing papers in the literature only consider restricted trade episodes such as moving to autarky or purely hypothetical changes in the trade environment, I present a calibration methodology to measure trade shocks from the data. Moreover, I estimate the key parameter – the labor supply elasticity, which is directly related to the degree of worker heterogeneity – in a more general setup. This parameter does not vary by country or worker type in existing papers. I relax this restrictive assumption to account for heterogeneous wage distributions between worker types and countries, which is easily evidenced in the data.

In the trade literature, worker heterogeneity has been studied in settings that differ from this paper. Ohnsorge and Trefler (2007) provide a theoretical foundation of worker-level comparative advantage in relation to international trade. Costinot and Vogel (2010) develop a general theory of country- and worker-level comparative advantage based on the continuum case and the assumption of log-supermodularity. I provide a quantitative framework for this theory by discretizing country- and worker-level characteristics and relaxing the linearity assumption for production. Grossman et al. (2014) focus on the search and matching in an open economy but with exogenously fixed occupations. Under a small open economy framework, comparative statics in these papers captures trade shocks with changes in price, which can be affected by many other concurrent shocks. This paper distinguishes itself from these existing studies by quantitatively isolating the effect of trade shocks from other effects. The setup of worker heterogeneity in this paper also differs from Artuç et al. (2010), Dix-Carneiro (2014), and Caliendo et al. (2015). While these papers focus on the transitional dynamics of industry-level labor adjustment based on heterogeneous preference shocks, they do not account for occupation-level reallocation which is the key channel in this paper.

The general framework of this paper nests many existing models about trade, welfare, and inequality. The model setup is based on the quantitative Ricardian trade model, as in Eaton and Kortum (2002). I generalize this model into a multi-industry and multi-factor setting with endogenously determined factor supply by heterogeneous workers.[11] The gravity structure is also embedded, and with several simplifying assumptions, the result shown in this paper follows the welfare formula derived in Arkolakis et al. (2012). Whereas Arkolakis and Esposito (2014) investigate the welfare effect of trade with an endogenous labor market participation, I focus on the distributional effect of trade with

[11] A multi-industry generalization of the Eaton and Kortum (2002) model is studied by Chor (2010), Costinot et al. (2011), Donaldson (2012), and Caliendo and Parro (2015). Building upon this literature, I generalize the model to a multi-factor setup as well in order to examine the distributional effect of trade.

workers' endogenous sorting into industry and occupation.

While this paper employs a high-dimensional general equilibrium model with a rich interrelation between trade, worker types, industries, and occupations, it still remains quantitatively tractable. I apply the technique of 'hat' algebra used by Dekle et al. (2008) to my model, which significantly relaxes the data requirement and reduces the number of parameters to be estimated. Quantitatively solving the model relies on Alvarez and Lucas (2007) and Caliendo and Parro (2015), but with multiple production factors–occupations.

The structure of this paper is as follows. In Section 2, I develop a general equilibrium trade model with endogenous sorting of heterogeneous workers. Welfare effect and distributional effect of trade are analytically derived. Section 3 discusses the strategy to quantify the model, including the estimation of parameters and the calibration of trade shocks. In Section 4, I present counterfactual results to discuss the distributional effect of trade. Section 5 presents a number of sensitivity analyses. Section 6 concludes.

2 Model

In this section, I construct a general equilibrium trade model that connects workers' occupational choice problem within a country to the trade environment. Two independent comparative advantage structures characterize the model: one, across countries and the other, across workers within each country. I formulate the Roy (1951)-like occupational choice problem based on the comparative advantage across workers. Workers choose an industry and an occupation to work in based on their heterogeneous productivities. The parametrization of worker heterogeneity is closely related to Hsieh et al. (2013) and Burstein et al. (2015). The model uncovers the general equilibrium mechanism by which changes in the trade environment affect the workers' sorting mechanism and, as a consequence, inequality.

2.1 Environment

Consider an economy with N countries indexed by $i \in \{1, \ldots, N\}$. Countries differ in factor endowments and factor neutral productivities. Thus, both the Heckscher-Ohlin and Ricardian forces of trade exist in the model. Each country has J industries indexed by $j \in \{1, \ldots, J\}$ and a continuum of products $e^j \in [0, 1]$ within each industry j. The trade environment of each industry follows Eaton and Kortum (2002) (EK, hereafter). [12]

[12] A Ricardo-Roy model combines the assignment-based Roy model and the Ricardian trade environment. Costinot and Vogel (2010) provide a theoretical foundation in a two-country setting based on the

Preferences Individuals have a nested CES utility over J industries and within-industry product varieties,

$$\begin{aligned} U_i &= (\sum_j (C_i^j)^{\frac{\eta_1-1}{\eta_1}})^{\frac{\eta_1}{\eta_1-1}} \\ \text{and } C_i^j &= (\int_0^1 C_i(e^j)^{\frac{\eta_2-1}{\eta_2}} de^j)^{\frac{\eta_2}{\eta_2-1}}, \end{aligned}$$

where C_i^j is a CES aggregate consumption bundle for industry j, and $\eta_1, \eta_2 > 0$ are elasticities of substitution across industries and across within-industry product varieties, respectively. All consumers have the same preference.

Workers Workers with the CES preference work and earn labor income to pay for consumption. Workers are classified by their types, which are mutually exclusive and exhaustive groups empirically defined by observable worker characteristics. These include educational attainment, age, gender, and race. Types are indexed by $\tau \in \{1, \dots, T\}$. Every worker is exogenously assigned to a type before entering the labor market. The total number of type τ workers in country i is exogenously given by $L_{i,\tau}$, and all workers inelastically supply one unit of time to work. These assumptions help to focus on the industry- and occupation-level labor allocation within a type.

Each worker solves an occupational choice problem by choosing the industry and occupation affiliation generating the highest labor income, as in the Roy (1951) model. The industry- and occupation-level labor supply is thus endogenous, whereas the type-level labor supply is exogenous. This model can be interpreted as a medium-run model, where workers are not allowed to switch their observable characteristics. There are O occupations indexed by $o \in \{1, \dots, O\}$. Each industry j employs a different amount of each occupation, resulting in any industry-level shocks being disseminated differentially across occupations.

The labor market is perfectly competitive, so that workers earn their marginal product. The workers' occupational choice problem depends on workers' productivity, which in turn determines the level of marginal product. Workers are heterogeneous in their industry- and occupation-specific productivities. Two workers of the same type in the same industry with the same occupation, for example, may have different productivities.

An individual worker ω of type τ has an idiosyncratic productivity $\epsilon_\omega^{j,o}$ for industry j

notion of log-supermodularity. Costinot and Vogel (2015) provide an authoritative overview of both theory and empirics in this literature.

and occupation o, where $\epsilon_{\omega}^{j,o}$ is randomly drawn from a Fréchet distribution as below.

$$F_{i,\tau}^{j,o}(\epsilon) = \exp(-T_{i,\tau}^{j,o}\epsilon^{-\theta_{i,\tau}})$$

This idiosyncratic productivity is interpreted as efficiency units of labor that worker ω is able to provide to industry j as occupation o. Each worker's productivity draw is an $(J \times O)$-dimensional vector of industry- and occupation-specific productivities. For simplicity, it is assumed that there is no correlation between draws, but this assumption can be easily generalized to allow correlations.[13] This parametrization is analogous to the Ricardian trade literature with a probabilistic assumption on the country-level productivity pioneered by Eaton and Kortum (2002). This parametrization of worker heterogeneity has several advantages. First, the Fréchet distribution is a type II extreme value distribution, and thus the maximum of independently drawn Fréchet random variables again follows another Fréchet distribution. This feature lends a great tractability to derive simple analytic solutions for equilibrium outcomes. Second, the interpretation of a random variable with an extreme value distribution is also consistent with the intuition that a worker's actual productivity is the maximum of all of his or her potential productivities.

The shape parameter of this distribution $\theta_{i,\tau}$ governs the within-type dispersion of productivity: a lower $\theta_{i,\tau}$ means that productivities are more dispersed across workers of type τ in country i. As shown in Section 2.5, this parameter is related to the elasticity of labor supply at the industry- and occupation-level. Hence, I will call it the "labor supply elasticity" parameter.[14] Worker types with higher $\theta_{i,\tau}$ have a more elastic labor supply at the industry and the occupation level. This is due to the fact that types with higher $\theta_{i,\tau}$ have fewer outliers in productivity, making it easier for them to adjust to shocks. This parameter can potentially differ across countries depending on the degree of worker heterogeneity within each country. This difference generates heterogeneous responses of

[13] If a correlation is allowed, the joint distribution function will be

$$F_{i,\tau}(\epsilon) = \exp[-\{\sum_{j,o}(T_{i,\tau}^{j,o}\epsilon^{-\theta_{i,\tau}})^{1/(1-\tilde{\rho})}\}^{1-\tilde{\rho}}]$$

where $\tilde{\rho}$ is a correlation parameter. With independence assumption ($\tilde{\rho} = 0$), the joint distribution of industry- and occupation-specific productivities used in this paper is

$$F_{i,\tau}(\epsilon) = \exp(-\sum_{j,o} T_{i,\tau}^{j,o}\epsilon^{-\theta_{i,\tau}})$$

[14] The exact derivation of labor supply elasticity will be discussed in section 2.5. The parameter $\theta_{i,\tau}$ is directly connected to the average responsiveness of type τ workers' labor allocation across industries and occupations with respect to price of labor.

workers to trade shocks across countries.

The other parameter of the distribution is the scale parameter $T_{i,\tau}^{j,o}$ which represents the level of workers' productivities. This parameter governs the absolute advantage of type τ workers in country i for (j,o). The worker-level comparative advantage structure is described by comparing ratios of this parameter: for example, type τ workers have a comparative advantage in (j,o) compared to type τ' workers and (j',o') if $\frac{T_{i,\tau}^{j,o}}{T_{i,\tau}^{j',o'}} > \frac{T_{i,\tau'}^{j,o}}{T_{i,\tau'}^{j',o'}}$.[15]

Production Workers engage in the production of final goods by choosing an industry and an occupation. Occupations are used as production factors within each industry. Production of a within-industry product variety e^j follows a nested CES production technology

$$Y_i(e^j) \quad = z_i(e^j) \quad (\sum_o \mu_i^{j,o} (y_i^{j,o})^{\frac{\gamma-1}{\gamma}})^{\frac{\gamma}{\gamma-1}}, \tag{1}$$

where $z_i(e^j)$ is a factor-neutral productivity of producing e^j in industry j in country i. The occupation-level labor input in industry j produced by all workers with occupation o is denoted by $y_i^{j,o}$. This variable depends on the number of workers in (j,o) and on the average productivity of workers employed for (j,o). Both quantities are endogenously determined from the worker's occupational choice problem. The occupation-intensity parameter is given by $\mu_i^{j,o}$ and summed to one for each industry.

The elasticity of substitution γ between occupations affects the channel by which international trade affects relative demands for occupations. In the quantitative analysis, I consider occupations as complementary production inputs, as evidenced by Goos et al. (2014), and compare the distributional effect of trade across different values of γ in robustness checks. If $\gamma \to \infty$, this production function becomes linear in occupational inputs analogous to Costinot and Vogel (2010). In this limit case, country-level comparative advantage is exactly transferred to worker-level comparative advantage within countries, and as a consequence, the model prediction becomes closer to the predictions of traditional trade theory: e.g., the Stolper-Samuelson theorem.

2.2 International Trade

There are N countries participating in international trade. Only final goods are traded i.e., there is no trade in occupational labor inputs. I assume that the final goods market

[15]This is a stochastic version of log-supermodularity as Costinot and Vogel (2015) point out.

is perfectly competitive, in which each country purchases each product from the lowest-cost supplier. The price of product e^j depends on the unit cost of the input bundle in industry j, c_i^j as well as on the product-specific factor-neutral productivity $z_i(e^j)$. The Heckscher-Ohlin force of trade is active mainly through c_i^j. Countries are exogenously endowed with different supplies of the type-level labor, and workers of different types have different patterns of endogenous occupational choices. This eventually generates differences in c_i^j across countries. The Ricardian force of trade, on the other hand, is active through productivity $z_i(e^j)$, which is different across countries.

The Ricardian trade environment for within-industry product varieties is characterized as described in the EK framework. The productivity $z_i(e^j)$ is drawn from the following Fréchet distribution independently for each product variety e^j in industry j

$$H_i(z) = \exp(-A_i^j z^{-\nu^j}), \tag{2}$$

where the scale parameter A_i^j is connected to the absolute advantage of each country i for industry j, and ν^j governs within-industry dispersion of productivity across countries. The degree of dispersion is different across industries, as ν^j depends on the industry. The heterogeneity in productivity across countries is inversely correlated with ν^j. This trade framework is built upon the literature of the multi-industry extension of the EK model by Chor (2010), Costinot et al. (2011), Donaldson (2012), and Caliendo and Parro (2015).[16]

A standard iceberg-type trade cost is applied: an additional cost $d_{in}^j \geq 1$ is multiplied by the price of any product in industry j produced in country i and shipped to country n. It is assumed that $d_{in}^j > 1$ for $i \neq n$, $d_{ii}^j = 1$ for every i, and $d_{in}^j = d_{ni}^j$. Trade cost is assumed to be different across industries. If $d_{in}^j \to \infty$ for a certain industry j, then this industry is considered a non-traded industry. This trade cost includes both tariff costs and non-tariff costs, which, for the sake of simplicity, are considered together in this paper. However, this model can easily be extended to consider two types of trade costs separately by assuming lump-sum transfer of tariff revenues to consumers, without much change to the main implication of the model on the distributional effect of trade.

[16] A parametrization of the productivity distribution in this paper is most closely related to Caliendo and Parro (2015) with industry-specific parameters. Costinot et al. (2011) consider one dispersion parameter that does not vary by industry. An input-output linkage across industries is a key subject in Caliendo and Parro (2015), as they consider intermediate inputs in production. In this paper, the production side is simpler in a sense that all production is for final consumption, but the labor supply side is generalized by considering workers' endogenous occupational choices.

2.3 Partial Equilibrium

Partial equilibrium results are derived separately for workers' occupational choices, equilibrium production of firms, and international trade flows between countries. Each partial equilibrium result is determined given the per-unit price $p_i^{j,o}$ of occupational input for each country, industry, and occupation.

Occupational choice problem A potential wage of individual worker ω in country i with an idiosyncratic productivity $\epsilon_\omega^{j,o}$ for (j, o) is given by $w_{i,\omega}^{j,o} = p_i^{j,o}\epsilon_\omega^{j,o}$, where $p_i^{j,o}$ is a price paid to per-unit occupational task o in industry j in country i.[17] In a perfectly competitive labor market, workers get paid their marginal product multiplied by the per-unit price of occupational input, where the per-unit price of occupational input is the key endogenous variable of the model.

The workers' occupational choice problem is to choose both industry and occupation that maximize the corresponding labor income $w_{i,\omega}^{j,o}$. Using the Fréchet distribution of workers' idiosyncratic productivity, the equilibrium probability that a worker ω of type τ works in industry j as occupation o is

$$\pi_{i,\tau}^{j,o} = \frac{T_{i,\tau}^{j,o}(p_i^{j,o})^{\theta_{i,\tau}}}{\sum_{j',o'} T_{i,\tau}^{j',o'}(p_i^{j',o'})^{\theta_{i,\tau}}}. \tag{3}$$

This is the equilibrium within-type employment allocation which endogenously determines the industry- and occupation-level labor supply. Worker-level comparative advantage affects this labor supply function: workers are more likely to supply their labor into the industry and the occupation where they have a comparative advantage. The same change in $p_i^{j,o}$ may induce differential labor reallocation patterns across different worker types because of worker-level comparative advantage. The direction of labor reallocation driven solely by country-level comparative advantage may be reversed within a specific country depending on this worker-level comparative advantage structure. A detailed derivation of (3) can be found in Appendix B.

Given workers' equilibrium choice of industry and occupation, the probability distri-

[17] The per-unit price for occupational input varies both by industry and by occupation, because the labor supply is upward-sloping. Workers are allowed to freely choose both industry and occupation, but the actual contribution of each occupation to production is different due to heterogeneous productivity. It also depends on the country, because labor demand and supply are different across countries. This variable is different from the actual wage observable in the data which includes unobservable efficiency units of labor.

bution of the equilibrium wage of type τ workers is derived by

$$G^*_{i,\tau}(w) = \exp[-(\sum_{j',o'} T^{j',o'}_{i,\tau}(p^{j',o'}_i)^{\theta_{i,\tau}})w^{-\theta_{i,\tau}}], \tag{4}$$

which does not depend on industry or occupation, as they are optimally chosen and thus integrated out. This is another Fréchet distribution with a scale parameter $\sum_{j',o'} T^{j',o'}_{i,\tau}(p^{j',o'}_i)^{\theta_{i,\tau}}$ and a shape parameter $\theta_{i,\tau}$. The equilibrium average wage for each type, given the equilibrium choice of industry and occupation, is derived by taking an expectation of (4):

$$w_{i,\tau} \;=\; (\sum_{j',o'} T^{j',o'}_{i,\tau}(p^{j',o'}_i)^{\theta_{i,\tau}})^{\frac{1}{\theta_{i,\tau}}}\Gamma(1-\frac{1}{\theta_{i,\tau}}), \tag{5}$$

where $\Gamma(\cdot)$ is a Gamma function. An assumption of $\theta_{i,\tau} > 1$ for all i and τ is required for the average wage to be well-defined. Worker-level comparative advantage also affects this equilibrium wage: if type τ workers have a comparative advantage in the high-paying industry and occupation, they have relatively higher wages on average.

The analytic distribution of equilibrium wage in (4) provides a rationale for having a type-specific and country-specific shape parameter $\theta_{i,\tau}$ in the distribution of workers' idiosyncratic productivity. This parameter governs the dispersion of (4), since it also follows a Fréchet distribution. In the data, it is evident that the degree of wage dispersion within worker types varies significantly by worker type. When worker type is defined by educational attainment, for example, the data clearly show that better-educated workers are more dispersed in earned wages within their type than are less-educated workers. The within-type dispersion of wages also varies by country considerably.[18] Thus, it is important to have a both type-specific and country-specific parameter $\theta_{i,\tau}$ in order to correctly capture any changes in the wage distribution caused by exogenous shocks.

Industry- and occupation-level average wages are derived from the type-level average wage in (5), within-type employment allocation (3), and type-level labor supply $L_{i,\tau}$, where the first two endogenous variables depend on $p^{j,o}_i$.[19] Since $p^{j,o}_i$ is linked to the price of final goods at a general equilibrium, trade shocks affect employment allocation and average wages at different levels of aggregation through changes in $p^{j,o}_i$.

Production Each firm solves a cost minimization problem by choosing $y^{j,o}_i$, demands

[18] A cross-country difference of within-type wage dispersion is more clearly shown when worker-level microdata are available. The evidence gleaned from the microdata for a variety of countries is discussed further in the data section.

[19] The average wage of industry j is $w^j_i = \sum_{\tau,o} w_{i,\tau}L_{i,\tau}\pi^{j,o}_{i,\tau} / \sum_{\tau,o} L_{i,\tau}\pi^{j,o}_{i,\tau}$ and that of occupation o is $w^o_i = \sum_{\tau,j}\sum_{\tau,o} w_{i,\tau}L_{i,\tau}\pi^{j,o}_{i,\tau} / \sum_{\tau,j} L_{i,\tau}\pi^{j,o}_{i,\tau}$.

for occupational inputs. The CES technology results in the following equilibrium unit cost function for each industry:

$$c_i^j = (\sum_o (\mu_i^{j,o})^\gamma (p_i^{j,o})^{1-\gamma})^{1/(1-\gamma)}. \tag{6}$$

Within-industry firms have the same unit cost function, since they have the same CES production function except for the product-specific factor-neutral productivity. With a heterogeneous productivity $z_i(e^j)$ for each within-industry product variety, the effective unit cost to produce a variety e^j in country i is $c_i^j/z_i(e^j)$. The heterogeneity across within-industry firms results solely from $z_i(e^j)$. This heterogeneity is the key source of the Ricardian comparative advantage which defines within-industry trade flows.

Trade The price of a product e^j in industry j produced in country i and sold in country n is

$$P_{in}(e^j) = (\frac{c_i^j}{z_i(e^j)})d_{in}^j.$$

The actual price of e^j in country n is given by $P_n(e^j) = \min_i P_{in}(e^j)$, since the final good market is perfectly competitive. Equilibrium price and trade flow are analogous to the results of the EK model. Details on the price distribution are provided in Appendix B.

Next, a gravity equation is formulated for each industry. Industry-level bilateral trade flows show patterns of within-industry specialization. A probability that a country n buys a good in industry j from a country i is

$$\lambda_{in}^j = \frac{A_i^j(c_i^j d_{in}^j)^{-\nu^j}}{\Phi_n^j} = \frac{X_{in}^j}{X_n^j}, \tag{7}$$

where $\Phi_n^j \equiv \sum_{i=1}^N A_i^j (c_i^j d_{in}^j)^{-\nu^j}$ is an effective price parameter in industry j in country n. This parameter depends on the state of technology, input costs, and geographic barriers in all partner countries, as in the EK model. Source countries' occupational choice patterns affect the equilibrium price of destination countries through industry-level unit costs. The model also shows that λ_{in}^j is equal to the ratio of bilateral trade flow in industry j from country i to country n (X_{in}^j) to the total expenditure for industry j in country n (X_n^j).

From this gravity equation, ν^j is the elasticity of imports with respect to trade costs, which is called trade elasticity in the international trade literature. An industry with less dispersion of productivity across countries has a higher trade elasticity, because trade flows respond more to changes in trade costs when countries are similar in productivity.

This model allows the trade elasticity to differ across industries.[20]

The exact price index P_i^j for industry j and country i is

$$P_i^j \quad = \quad (\Gamma(\frac{\nu^j + 1 - \eta_2}{\nu^j}))^{\frac{1}{1-\eta_2}}(\Phi_i^j)^{-\frac{1}{\nu^j}}, \tag{8}$$

where $\Gamma(\cdot)$ is a gamma function, and $\nu^j + 1 > \eta_2$ is required for all j for a well-defined gamma function. The industry-level exact price index can be further aggregated following the nested CES preference to derive a country-level exact price index, $P_i = [\sum_j (P_i^j)^{1-\eta_1}]^{\frac{1}{1-\eta_1}}$. The CES preference endogenously determines the aggregate expenditure share of industry j within each country i,

$$\lambda_i^j = \frac{(P_i^j)^{1-\eta_1}}{\sum_{j'} (P_i^{j'})^{1-\eta_1}}. \tag{9}$$

This expenditure share depends on both the productivity structure and the occupation-level employment structure of all countries. If $\eta_1 = 1$, then the result is in line with the Cobb-Douglas case discussed in Caliendo and Parro (2015) for the multi-industry EK model. All detailed derivations are described in Appendix B.

2.4 General Equilibrium

In general equilibrium, final goods markets and occupation markets should be cleared in all countries, and the trade balance condition should hold. Final goods markets are cleared when

$$E_i^j = \sum_{n=1}^{N} \lambda_{in}^j X_n^j \tag{10}$$

holds for each industry j and each country i, and $E_i^j = P_i^j Y_i^j$ is the total output in industry j in country i measured in price. The total expenditure is $X_i^j = \lambda_i^j I_i$, where I_i is the total spending in country i. Total spending is derived by $I_i = \sum_{j,o} \psi_i^{j,o} + D_i$, where D_i is an aggregate trade deficit of country i and

$$\psi_i^{j,o} = \sum_{\tau} w_{i,\tau} L_{i,\tau} \pi_{i,\tau}^{j,o} \tag{11}$$

is the total labor income earned by workers in industry j and occupation o. The final goods market clearing condition (10) thus holds when the total industry-level output is

[20] Since this model assumes a Ricardian trade environment where countries compete over the same set of products, trade elasticity is derived by ν^j without the elasticity of substitution in consumer preference, as in the standard Armington model. (Anderson (1979))

equalized to the total industry-level expenditure made by all countries in the world.

The occupation markets are cleared when the total income earned by workers with occupation o in industry j of country i is equal to the total cost paid for them by all firms in each industry j of country i. Since workers have heterogeneous productivities across industries and occupations, the occupation market clearing conditions are defined for each industry and occupation, making the total number of equations $(J \times O)$ for each country i,

$$(\mu_i^{j,o})^{\gamma}(\frac{p_i^{j,o}}{c_i^j})^{1-\gamma}E_i^j = \psi_i^{j,o}. \tag{12}$$

Lastly, the final goods market clearing condition and the occupation market clearing condition imply the trade balance condition for each country,

$$\sum_j \sum_{i=1}^{N} \lambda_{in}^j X_n^j - D_n = \sum_j \sum_{i=1}^{N} \lambda_{ni}^j X_i^j. \tag{13}$$

The equilibrium of this model is defined by the per-unit occupational price $p_i^{j,o}$ for each $i = 1, \ldots, N$, $j = 1, \ldots, J$, and $o = 1, \ldots, O$ that satisfies the equilibrium conditions (3), (5)-(13) with an appropriate normalization.[21]

Equilibrium in proportional changes Another way to characterize the equilibrium is to solve the model for proportional changes of equilibrium variables, so that the effect of changes in exogenous variables can be easily investigated in comparative statics. A proportional change of any variable x is denoted by $\hat{x} = x'/x$, where x' is a variable x at the counterfactual equilibrium. Following Dekle et al. (2008), the entire equilibrium conditions can be written in changes, using the so-called exact hat algebra. This approach has two important advantages. First, it reduces the number of parameters that need to be determined by pinning down parameters only for the base year and assuming time invariance. Second, this approach provides great tractability when introducing exogenous shocks to the model.

I introduce two exogenous shocks to the model in counterfactual analysis: changes in bilateral trade costs ($\hat{d}_{in}^j$) and changes in the labor productivity. To introduce changes in the labor productivity in a comparable way with respect to $\hat{d}_{in}^j$, I first decompose parameter $T_{i,\tau}^{j,o}$ by defining $T_{i,\tau}^{j,o} \equiv T_{\tau}^{j,o} T_i^j T_i^o$. The first component $T_{\tau}^{j,o}$ is about the fit of type-τ workers to industry j and occupation o, which is not necessarily country-specific.

[21] Allen et al. (2014) discuss possible normalizations to pin down the equilibrium. I keep the world total output constant as a normalization. The system then consists of $(N \times J \times O)$ independent equations and the same number of unknowns.

The remaining components are related to fundamentals in each country at industry- and occupation-level, respectively. Since trade costs are defined at the industry level, I only consider changes in the industry-specific component of productivity T_i^j time-varying, holding other components of $T_{i,\tau}^{j,o}$ fixed over time. Specifically, I consider $\hat{T}_{CHN}^j$ as trade shocks in the counterfactual analysis by assuming $\hat{T}_i^j = 1$ if $i \neq CHN$, given that changes in China's productivity are closely related to their exporting capability. Thus, the two exogenous shocks to consider are changes in trade costs ($\hat{d}_{in}^j$) and changes in industry-specific labor productivity in China ($\hat{T}_{CHN}^j$).[22] Aside from these two exogenous shocks, the remaining parameters are time-invariant. A counterfactual equilibrium in changes can be easily extended to incorporate the effect of changes in the other parameters such as $\mu_i^{j,o}$ and $L_{i,\tau}$. This extension is discussed in the online appendix.

All equilibrium conditions (3), (5)-(13) can be re-written in terms of proportional changes. The counterfactual equilibrium is defined by $\hat{p}_i^{j,o}$ for each $i = 1, \dots, N$, $j = 1, \dots, J$, and $o = 1, \dots, O$ that satisfies the following equilibrium conditions. The labor supply function for each industry and occupation in (3) becomes

$$\hat{\pi}_{i,\tau}^{j,o} = \frac{(\hat{p}_i^{j,o})^{\theta_{i,\tau}} \hat{T}_i^j}{\sum_{j',o'} (\hat{p}_i^{j',o'})^{\theta_{i,\tau}} \hat{T}_i^{j'} \pi_{i,\tau}^{j',o'}}, \tag{14}$$

and changes in the equilibrium type-level average wage is

$$\hat{w}_{i,\tau} = [\sum_{j,o} (\hat{p}_i^{j,o})^{\theta_{i,\tau}} \hat{T}_i^j \pi_{i,\tau}^{j,o}]^{\frac{1}{\theta_{i,\tau}}}. \tag{15}$$

Changes in partial equilibrium quantities of the occupational choice problem depend on exogenous shocks, before-change labor allocations across industries and occupations, labor supply elasticity $\theta_{i,\tau}$, and endogenous changes in per-unit price for occupational input which are solved in equilibrium. Assuming that the occupation intensity in production $\mu_i^{j,o}$ does not vary over time i.e., $\hat{\mu}_i^{j,o} = 1$ for every i,j,o, firms' equilibrium unit cost function (6) becomes

$$\hat{c}_i^j = [\sum_o \zeta_i^{j,o} (\hat{p}_i^{j,o})^{1-\gamma}]^{1/(1-\gamma)}, \tag{16}$$

[22] I consider the effect of changes in the factor-level productivity $\hat{T}_i^j$ as productivity shocks, instead of changes in the product-level productivity $\hat{A}_i^j$. As will be discussed in the quantitative section, $\hat{d}_{in}^j$ and $\hat{A}_i^j$ cannot be separately backed out from the model. This paper is able to examine the effect of both changes in trade costs and changes in productivities by considering the unobserved heterogeneity for workers separately from the heterogeneous productivity across products. More details to follow in the next section.

where $\zeta_i^{j,o} \equiv \frac{(\mu_i^{j,o})^\gamma (p_i^{j,o})^{1-\gamma}}{\sum_{o'} (\mu_i^{j,o'})^\gamma (p_i^{j',o'})^{1-\gamma}}$ is a cost share of occupation o in the unit cost of production in industry j. Further assuming $\hat{L}_{i,\tau} = 1$ for this specific counterfactual analysis, the occupation market clearing condition in the counterfactual equilibrium is

$$(\frac{\hat{p}_i^{j,o}}{\hat{c}_i^j})^{1-\gamma} \hat{E}_i^j = \sum_\tau (\frac{w_{i,\tau} L_{i,\tau} \pi_{i,\tau}^{j,o}}{\sum_{\tau'} w_{i,\tau'} L_{i,\tau'} \pi_{i,\tau'}^{j,o}}) \hat{w}_{i,\tau} \hat{\pi}_{i,\tau}^{j,o}. \tag{17}$$

Changes in labor income on the right-hand side in turn depends on both changes in the labor allocation and the type-level average wage derived in (14) and (15). Detailed derivations for proportional changes in the total industry-level output $\hat{E}_i^j$ and other equilibrium conditions including trade flows are described in Appendix B. The world total output is kept constant before and after shocks as a normalization: $\sum_{i,j} E_i^j = \sum_{i,j} E_i'^j = E$. I consider the aggregate trade deficit D_i as an exogenous policy variable, as in Dekle et al. (2008) and in Caliendo and Parro (2015).[23, 24]

2.5 Model Mechanism

This model clearly summarizes two channels through which worker-level comparative-advantage plays a role when trade shocks are disseminated within a country.[25] The first channel is the *labor demand channel*, which is the traditional channel by which trade shocks affect factor prices through factor demands. Differential response is first generated across industries along this channel, as the shock itself is of a different magnitude across industries with industry-specific trade elasticities ν^j. Together with the differential pattern of the initial labor allocation across industries and occupations for each type based on worker-level comparative advantage, this industry-specific trade elasticity parameter is the first key parameter that captures the differential impact of trade on labor market out-

[23] Caliendo and Parro (2015) deal with this time-invariant trade deficit in two ways. In the first approach, they set the trade deficit to zero and recalibrate the model as if there were no trade deficit in the world. Alternatively, the trade deficit is fixed as a ratio to the world GDP. I follow the latter approach, but get a very robust result with the first approach as well.

[24] Similarly to the equilibrium conditions in levels, the occupation market clearing condition together with $\hat{E}_i^j$ derived in the Appendix implies the trade balance condition at the counterfactual equilibrium.

$$\sum_j \sum_{i=1}^N \lambda_{in}'^j X_n'^j - D_n' = \sum_j \sum_{i=1}^N \lambda_{ni}'^j X_i'^j.$$

[25] In this model where tasks are not traded, domestic labor demands and supplies are both affected by trade shocks only indirectly. Both respond only through extensive margins, as workers choose industry and occupation and inelastically supply their entire labor for their choices of industry and occupation.

comes across workers.[26]

The labor demand channel departs from the Stolper-Samuelson prediction by considering multiple factors, namely endogenous relative factor employment within each industry and worker heterogeneity across factors. The elasticity of substitution γ between occupations in production carries weight in the labor demand channel, since demands for different occupational inputs are interrelated. This feature introduces a new margin in which the labor demand responds to trade shocks, and as such, departs from the Cobb-Douglas or the linearity assumption for production function. Even with the same industry-level trade shock, demands for different occupations may respond differentially within the industry. Since workers have comparative advantages not only across industries but also occupations, this channel engenders different gains from trade depending on workers' occupation affiliation.

The second channel through which trade impacts the labor supply decisions of heterogeneous workers is the *labor supply channel*. This is a new channel not widely studied within the general equilibrium trade framework. It is also based on workers' comparative advantages which generate a differential pattern of labor reallocation across industries and occupations within each type. The elasticity of industry- and occupation-level labor supply with respect to $p_i^{j,o}$ is $\theta_{i,\tau}(1-\pi_{i,\tau}^{j,o})$. While $(1-\pi_{i,\tau}^{j,o})$ depends on the (j,o) pair considered, $\theta_{i,\tau}$ governs type-τ workers' responsiveness to changes in $p_i^{j,o}$. This parameter is the key factor of the labor supply channel, as different worker types respond to exogenous shocks differentially in terms of labor reallocation. Self-selection of workers matters, because workers earn different wages across industries and occupations.

This model nests existing models by considering different values of $\theta_{i,\tau}$. The variation in equilibrium wages across industries and occupations is expected to vanish, when $\theta_{i,\tau}$ is large enough. In the extreme case when $\theta_{i,\tau} \to \infty$ and $T_{i,\tau}^{j,o} = 1$ for all (i,τ,j,o), workers are homogeneous in their productivities within a type and thus entirely substitutable. If there is only one occupation, then this case collapses to the multi-industry EK model that assumes homogeneity within each worker type.[27] If it is assumed that $\theta_{i,\tau} \to \infty$; $T_{i,\tau}^{j,o} = 1$ for all (i,τ,j,o); $\mu_i^{j,o} = \mu^{j,o}$ for all i; and that all within-industry product varieties have the same productivity across countries (i.e., $z_i(e^j) = z$ for all i and e^j), this model is then equivalent to the multi-industry Heckscher-Ohlin model with the CES production whose prediction on the distributional effect of trade is overall inconsistent with the empirical

[26]Ossa (2015) points out that industry-specific trade elasticities magnify the aggregate welfare effect of trade when compared to predictions of the model with a uniform trade elasticity across industries. I focus on the relationship between industry-specific trade elasticities and the distributional effect of trade.

[27]Between-type inequality depends on the difference in the type-level productivity which stays constant over time.

evidence. Another extreme case is the case where $\theta_{i,\tau}$ is equal to 1. In this case, workers are extremely heterogeneous in their industry- and occupation-specific productivities. This case corresponds with the intuition of the specific factors model. Instead of assigning a specific value for the parameter $\theta_{i,\tau}$ *ex ante*, I estimate this parameter in the next section in order to take the model most closely to the data. Changes in labor market outcomes caused by exogenous shocks will be quantified in Section 4 with different values of $\theta_{i,\tau}$ in order to show the role of worker heterogeneity and worker-level comparative advantage when investigating the distributional effect of trade.

2.6 Aggregate and Type-level Welfare Effect

The model derives the welfare effect of exogenous shocks both at a country level and a type level within a country. I define aggregate welfare in country i by total real income $W_i = I_i/P_i$ given that workers have the same homothetic preference. Thus, the proportional change in country i's welfare is

$$\hat{W}_i = \hat{I}_i/[\sum_j \lambda_i^j(\hat{c}_i^j(\hat{\lambda}_{ii}^j)^{\frac{1}{\nu^j}})^{1-\eta_1}]^{\frac{1}{1-\eta_1}}, \tag{18}$$

where $\hat{\lambda}_{ii}^j$ is the change in domestic absorption in industry j in country i, and $\hat{I}_i$ is the change in total spending of country i, as derived in Appendix B. Once the model is solved for the counterfactual equilibrium $\hat{p}_i^{j,o}$, welfare changes are calculated accordingly. Changes in welfare caused by trade shocks are each country's aggregate gains from trade.

This formula for welfare changes nests previous works with several simplifying restrictions to my model. If trade is balanced in all countries ($D_i = D_i' = 0$ for all i), and there is only one industry ($J = 1$) with a continuum of products, a single type of labor ($T = 1$) with a perfectly inelastic supply, and one occupation that becomes the only production factor, then equation (18) exactly matches the welfare formula derived by Arkolakis et al. (2012) (ACR, hereafter): it is $\hat{W}_i = \hat{\lambda}_{ii}^{-\frac{1}{\nu}}$ for the EK model with a trade elasticity ν. If we consider a multi-industry EK model with ACR restrictions as well as the Cobb-Douglas structure across industries, but without the endogenous labor allocation, equation (18) collapses to $\hat{W}_i = \prod_j (\hat{\lambda}_{ii}^j)^{-\frac{\lambda^j}{\nu^j}}$, where λ^j is a Cobb-Douglas share of industry j, and ν^j is the industry-specific trade elasticity.[28]

I also derive the welfare effect for each type of worker within a country in order to discuss the distribution of trade-induced welfare changes across different worker types, this

[28] Burstein et al. (2015) also derive changes in factor prices following the ACR approach.

being the main focus of this paper. Assuming that each worker type shares the aggregate trade deficit in their total income based on the ratio of their total labor income, the change in type-level welfare is

$$\hat{W}_{i,\tau} = \hat{I}_{i,\tau} / [\sum_j \lambda_i^j (\hat{c}_i^j (\hat{\lambda}_{ii}^j)^{\frac{1}{\nu^j}})^{1-\eta_1}]^{\frac{1}{1-\eta_1}}, \tag{19}$$

where $\hat{I}_{i,\tau}$ is the counterfactual change of the type-level spending $I_{i,\tau} = w_{i,\tau} L_{i,\tau} + D_{i,\tau}$, and $D_{i,\tau}$ is the type τ's share of the aggregate trade deficit.[29,30] By definition of $I_{i,\tau}$ and $D_{i,\tau}$, $\sum_\tau I_{i,\tau} = I_i$ holds for each country i. The change in aggregate welfare (18) is then a simple weighted average of the change in type-level welfare (19), where the weight is type-level income share in the base year. Changes in between-type-inequality are discussed by comparing this type-level welfare change across worker types in counterfactual analyses.

2.7 Changes in Real Wages and Employment Shifts

A standard measure of inequality between worker types is the skill premium defined by a wage premium of skilled workers over unskilled workers. I define the skill premium in this model by the wage premium of college graduates over non-college graduates, as such considering workers with college degrees as skilled workers. Proportional changes in type-level wages follow equation (15). This measure, as well as changes in type-level welfare (19), captures the model-predicted changes in between-type inequality induced by trade shocks.

Worker heterogeneity and the endogenous sorting into industry and occupation are key mechanisms behind unequal gains from trade across worker types, which work via both labor demand and labor supply channels. To study these channels, I focus on counterfactual changes in real wages as well as employment shares at the industry and the occupation level. Changes in industry- and occupation-level real wages are related to the labor demand channel, because different worker types in different countries are allocated differentially across industries and occupations before trade shocks. The labor supply channel is captured by the trade-induced employment shifts across industries and occupations within each worker type.

Changes in industry-level and occupation-level average real wages are defined by

[29] When I impose a balanced trade, then the expressions for $I_{i,\tau}$ and the corresponding $\hat{I}_{i,\tau}$ become simpler without a need to define D_i^τ.

[30] Galle et al. (2015) derive a similar formula for changes in type-level welfare. If I assume that there is only one occupation and that the preference follows a Cobb-Douglas, equation (19) matches their formula.

$\hat{w}_i^j/\hat{P}_i$ and $\hat{w}_i^o/\hat{P}_i$, respectively, where $\hat{P}_i$ is as derived in (29) in Appendix B, and

$$\hat{w}_i^j = [\sum_{\tau,o}(\frac{w_{i,\tau}L_{i,\tau}\pi_{i,\tau}^{j,o}}{\sum_{\tau',o'}w_{i,\tau'}L_{i,\tau'}\pi_{i,\tau'}^{j,o'}})\hat{w}_{i,\tau}\hat{\pi}_{i,\tau}^{j,o}]/[\sum_{\tau,o}(\frac{L_{i,\tau}\pi_{i,\tau}^{j,o}}{\sum_{\tau',o'}L_{i,\tau'}\pi_{i,\tau'}^{j,o'}})\hat{\pi}_{i,\tau}^{j,o}] \quad (20)$$

$$\hat{w}_i^o = [\sum_{\tau,j}(\frac{w_{i,\tau}L_{i,\tau}\pi_{i,\tau}^{j,o}}{\sum_{\tau',j'}w_{i,\tau'}L_{i,\tau'}\pi_{i,\tau'}^{j',o}})\hat{w}_{i,\tau}\hat{\pi}_{i,\tau}^{j,o}]/[\sum_{\tau,j}(\frac{L_{i,\tau}\pi_{i,\tau}^{j,o}}{\sum_{\tau',j'}L_{i,\tau'}\pi_{i,\tau'}^{j',o}})\hat{\pi}_{i,\tau}^{j,o}]. \quad (21)$$

By quantifying these industry-level real wages and comparing them across industries, I provide a structural counterpart to the trade-induced change in the industry wage premium captured in many reduced-form analyses. I also quantify the effect of trade on changes in the occupation-level wage gap by comparing $\hat{w}_i^o/\hat{P}_i$ across occupations.

For the labor supply channel through which trade impacts inequality, this model gives an analytic solution for the within-type labor reallocation, $\hat{\pi}_{i,\tau}^{j,o}$. Since $\pi_{i,\tau}^{j,o}$ is defined as a share which is summed to 1 for each type, a fair comparison of labor allocation before and after shocks should be based on $\Delta\pi_{i,\tau}^{j,o} \equiv \pi_{i,\tau}^{\prime j,o} - \pi_{i,\tau}^{j,o}$, rather than a proportional change $\hat{\pi}_{i,\tau}^{j,o}$. I first back out $\pi_{i,\tau}^{\prime j,o}$ with the model predicted $\hat{\pi}_{i,\tau}^{j,o}$ and the data for $\pi_{i,\tau}^{j,o}$. I then quantify $\Delta\pi_{i,\tau}^{j,o}$ to capture the employment shifts within a type. The employment shifts can be further aggregated across worker types up to the industry or the occupation level with the data on $L_{i,\tau}$ in order to quantify the patterns of labor reallocation across industries and across occupations, respectively. These measures quantify the actual effects of trade shocks on the industry- and occupation-level employment shift observed in the data.

3 Quantitative Analysis

The distributional effect of trade is quantitatively explored by solving this model for the counterfactual equilibrium when introducing exogenous trade shocks. In this section, I discuss the data, estimation of parameters, calibration of trade-related shocks, and the algorithm to solve the model.

3.1 Data

I study the distributional effects of changes in the trade environment between 2000 and 2010, 2000 being the base year of the counterfactual analysis. This time period is interesting from an international trade perspective, because China joined the WTO in 2001 and many bilateral free trade agreements were made.

In the quantitative analysis, I consider $N = 33$ countries which consist of 32 individual countries and a constructed rest of the world. These 32 countries account for 76.19% of the world total trade volumes and 68.27% of the world gross output in 2000. I empirically define $T = 5$ worker types, $J = 4$ industries, and $O = 5$ occupations. Worker types are defined by educational attainment: high school dropouts (HD), high school graduates (HG), workers with some college education (SC), college graduates (CG), and workers with advanced degrees (AD).[31] I assume that there are 4 industries: agriculture (AGR), mining (MIN), manufacturing (MFG), and non-traded (NTR) industries. As summarized in Table 1, occupation categories are defined by aggregating the occupation classification by Dorn (2009) and the International Standard Classification of Occupations (ISCO) classification up to five upper-level categories. Five categories are based both on the level of required skills and on the routineness of occupational task, as used in Autor and Dorn (2013).[32] More details about the model size are described in Appendix C.

Table 1: List of Occupation Categories

1. Low-skill Occupations (LSO)
2. Assemblers and Machine Operators (AMO)
3. Precision Production and Crafts Occupations (PPC)
4. Administrative, Clerical, and Sales Occupations (ACS)
5. Managers, Professionals, and Technicians (MPT)

The Integrated Public Use Microdata Series (IPUMS)-International database provides the detailed labor market information from the household survey data, including within-type labor allocation across industries and occupations, for the 22 countries in the sample.[33] As described in Figure A1, the household-level survey data show that patterns of labor allocation across industries and occupations vary significantly by worker type and country. The data also clearly show the importance of considering both industry

[31]The definition of educational attainment varies by household survey in different countries. As summarized in Appendix C, I make the definition consistent within each country.

[32]In his most aggregate categorization, Dorn (2009) distinguishes between 'transportation, construction, and agricultural occupations' and 'low-skill service occupations.' This distinction is possible with the U.S. data based on the detailed Census occupation codes. For the other countries, however, only the ISCO codes are available, which include agricultural laborers in low-skill (elementary) occupations. I thus aggregate all agricultural occupations and low-skill service occupations into one category: low-skill occupations.

[33]For 2000, the IPUMS-International only has microdata from 22 countries available. For the other countries in the sample, I proxy their labor market allocation with the lagged data or the data from the other available countries and adjust them with the data from ILOSTAT and LABORSTA. I also use the Barro and Lee (2013) dataset to supplement the information on the labor supply by workers' educational type. Detailed strategy is summarized in Appendix C.

and occupation as dimensions along which workers allocate their labor in order to precisely investigate the effect of trade on between-worker-type inequality. Many existing works in the international trade literature focus only on how different worker types are allocated differentially across industries. However, this industry-level difference in labor allocation is only a partial channel through which trade affects inequality, because the industry-level pattern of labor allocation does not vary much by worker type. As a matter of fact, different worker types show very different patterns of the occupation-level labor allocation. This evidence is mainly because workers' skills have higher complementarity with occupation-specific tasks than with industry-specific tasks. This descriptive evidence from the household level microdata from many countries provide a rationale for considering both industries and occupations as choice variables in the workers' occupational choice problem in the model.

I obtain the trade data from the UN Commodity Trade (COMTRADE) database for each country pair. Trade flows in HS 6-digit codes are aggregated into three tradable industries: agriculture, mining, and manufacturing. Country- and industry-level macro data are obtained from various sources: UN Statistical Division (UNSD) database of national accounts by industry, OECD STructural ANalysis (STAN) database, World Input-Output Database (WIOD), KLEMS database, ILOSTAT and LABORSTA from the International Labor Organization (ILO), and the Occupational Wage around the World (OWW) database.[34] Detailed descriptions of each data source can be found in Appendix C.

3.2 Parameters

Parameters of the model are either estimated, calibrated to the base year, or assigned from previous works. The key parameter that governs the distribution of workers' idiosyncratic productivity–labor supply elasticity $\theta_{i,\tau}$–is estimated with the data of the base year 2000. The occupation intensity parameter $\mu_i^{j,o}$ is calibrated to match the share of each occupation category within each industry in the base year. The remaining parameters are assigned values from previous research, as discussed below.

Estimation of labor supply elasticity $\theta_{i,\tau}$ For notational simplicity, I denote $\bar{T}_{i,\tau}^{j,o} \equiv T_{i,\tau}^{j,o}(p_i^{j,o})^{\theta_{i,\tau}}$ for the estimation of parameters. The Fréchet scale parameter $\sum_{j',o'} \bar{T}_{i,\tau}^{j',o'}$ and the shape parameter $\theta_{i,\tau}$ of the analytic distribution of the equilibrium wage in (4) are jointly estimated using the maximum likelihood (ML) method.[35] Denote individual worker

[34]The basic methodology used to obtain the input-output table in the WIOD is summarized by Timmer (2012). The OWW database are made publicly available by Oostendorp (2012).

[35]This estimation method also relies on the assumption that there is no correlation between draws of

ω's equilibrium wage by w_ω conditional on the equilibrium choice of (j, o), then the log-likelihood function for worker type τ in country i is derived as follows:

$$\ln \mathcal{L}(\theta_{i,\tau}, \sum_{j',o'} \bar{T}_{i,\tau}^{j',o'} | w_1, \ldots w_L) = L(\ln \theta_{i,\tau} + \ln(\sum_{j',o'} \bar{T}_{i,\tau}^{j',o'})) - (\theta_{i,\tau} + 1) \sum_{\omega=1}^{L} \ln w_\omega - (\sum_{j',o'} \bar{T}_{i,\tau}^{j',o'}) \sum_{\omega=1}^{L} w_\omega^{-\theta_{i,\tau}},$$

where L is the number of workers in the sample out of the total $L_{i,\tau}$ workers with type τ in country i. Since the estimation procedure requires detailed wage profiles of individual workers as well as the information on educational attainment, the baseline estimation is done for countries where these data are available for the base year: Brazil, India, Mexico, and the U.S.

The estimation result is summarized in Table A1. The ML estimates of $\theta_{i,\tau}$ vary from 1.48 to 1.97 for the U.S., and better-educated workers have smaller estimates.[36] Since this parameter is inversely correlated with the dispersion, the estimation result implies that better-educated workers are more dispersed in their industry- and occupation-specific productivities as well as in wages within the type. This result is consistent with the evidence in the data. In relation to the interpretation of this parameter as the labor supply elasticity with respect to per-unit price of occupational input in the model, the result also shows that less skilled workers have a larger elasticity on average, which generates differential impacts of trade across worker types.

When comparing estimates across four countries, the estimation result from Table A1 finds that $\theta_{i,\tau}$ parameters are larger in the U.S. on average. Given that the other three countries are less developed than the U.S., this result supports the existing research indicating a lack of labor reallocation as one of the reasons why inequality increases in developing countries after trade liberalization: e.g., Goldberg and Pavcnik (2003; 2005) and Topalova (2007). The baseline counterfactual result in the next section is derived with the actual estimates of $\theta_{i,\tau}$ for the U.S., Brazil, India, and Mexico. For the other OECD member countries, the average of the estimates for the U.S. and Mexico is used, while the average of the estimates for Brazil and India is used for the other non-OECD countries.[37] The predicted wage distribution of each worker type in each country with parameter es-

idiosyncratic productivities. If correlation is allowed, then further normalization is required for the scale parameter.

[36]Using GMM, I get larger estimates of $\theta_{i,\tau}$ for all worker types and an average of approximately 2.5 for the U.S. There are alternative ways to pin down the labor supply elasticity parameter $\theta_{i,\tau}$ in recent works including Lagakos and Waugh (2013), Hsieh et al. (2013), and Burstein et al. (2015). I get similar or slightly lower estimates compared to the estimates in the earlier works. This is related to the definition of worker types and the independence assumption across productivity draws.

[37]For the other countries where the wage data are available in different years from the base year, I estimate this parameter for available years and confirm that the main counterfactual result is very robust.

timates fits the distribution of the actual wage data very well for all four countries, as described in Figure A2.

Assigned parameters Type-level labor supply $L_{i,\tau}$, as well as the occupation intensity parameter $\mu_i^{j,o}$, are acquired from the data for 2000. Trade elasticity ν^j, which governs the comparative advantage structure across countries based on the product-specific productivity, is acquired from the estimates in Caliendo and Parro (2015).[38] The elasticity of substitution γ across occupations in the CES production function is set to 0.90 from Goos et al. (2014), which allows complementarity between occupations in final good production. The elasticity of substitution η_1 across industries in the CES preference is set to 1.5 from Backus et al. (1994) and Chari et al. (2002).[39] Results with different values of ν^j, γ and η_1 are discussed in the robustness section.

3.3 Measuring Shocks

I examine the effect of two exogenous shocks in the model: changes in bilateral trade costs ($\hat{d}_{in}^j$) and changes in the industry-specific labor productivity in China ($\hat{T}_{CHN}^j$) between 2000 and 2010.[40] Both shocks are calibrated to match the data using the equilibrium results of the model on trade flows and the within-type employment allocation. In order to account for changes in productivity, I consider changes in China's industry-specific labor productivity T_{CHN}^j instead of changes in A_{CHN}^j. While $\hat{A}_i^j$ cannot be backed out from the model separately from $\hat{d}_{in}^j$ using changes in the trade volume in the data, $\hat{T}_i^j$ can be independently calibrated with the household-level data on the employment allocation. This is one advantage of considering the unobserved heterogeneity across countries and across workers in an independent way in the model.[41] Other components of $T_{i,\tau}^{j,o}$ are time-invariant.

[38] They estimate the sector-level trade elasticities for 20 tradable sectors including agriculture, mining, and 18 2-digit International Standard Industrial Classification (ISIC) manufacturing sectors. Since the manufacturing industry is considered as a whole in my paper, the trade elasticity in the manufacturing industry is obtained by taking an average of trade elasticities of 18 sub-manufacturing sectors in their work. The estimates for the agriculture, mining, and manufacturing industries are 9.59, 14.83, and 5.5, respectively.

[39] I take the value of the elasticity of substitution between home-produced goods and foreign goods in those papers, since the empirical definition of industries in this paper is at the aggregate level. This value is lower than 4, which Broda and Weinstein (2006) estimate with much more narrowly-defined industries. With 4 aggregate industries, this parameter should be significantly lower than 4. As will be discussed in the robustness section, the main quantitative result is robust with η_1.

[40] Although the baseline counterfactual scenario considers only the effect of changes in China's industry-specific productivity, I discuss how to calibrate $\hat{T}_i^j$ for all countries. This model can be further extended to assess the effect of each country's own productivity changes on inequality.

[41] If I use the calibrated $\hat{T}_i^j$ in this subsection as $\hat{A}_i^j$, then the counterfactual result with $\hat{A}_i^j$ holding $\hat{T}_i^j = 1$ is very similar to the counterfactual result with the calibrated $\hat{T}_i^j$ holding $\hat{A}_i^j = 1$ in terms of the direction of

Changes in bilateral trade costs I calibrate changes in bilateral trade costs between 2000 and 2010 to match changes in bilateral trade flows in the data. Two assumptions are required for identification. First, I assume that the iceberg-type bilateral trade cost is symmetric (i.e., $d^j_{in} = d^j_{ni}$ for all i and n.) Second, I assume that there is no trade cost for domestic absorptions (i.e., $d^j_{ii} = 1$ for all i and j.)[42] Based on these two identifying assumptions, I follow the Head and Ries (2001) approach to back out proportional changes in trade costs from bilateral trade flow data.[43] The gravity equation from the model results in the following relationship between trade flows and the bilateral trade costs:

$$\frac{\hat{\lambda}^j_{in}}{\hat{\lambda}^j_{ii}} \frac{\hat{\lambda}^j_{ni}}{\hat{\lambda}^j_{nn}} = (\hat{d}^j_{in})^{-2\nu^j}, \tag{22}$$

where the trade elasticity parameter ν^j is obtained from Caliendo and Parro (2015). The change in trade costs $\hat{d}^j_{in}$ is calibrated to exactly match equation (22) given the value of ν^j.

Calibrated changes in trade costs show that bilateral trade costs have decreased by 8.89% on average between 2000 and 2010.[44] Most decreases in trade costs are driven by the reduction of manufacturing trade costs, which is consistent with the increased trade flows in the manufacturing industry in recent years. Bilateral trade costs between China and partner countries, for example, have decreased by 11.99% on average, and more significantly, 12.89%, in the manufacturing industry. This result suggests that trade with China has significant effects. Table A2 and Figure A3 show detailed calibration results of changes in bilateral trade costs.

Changes in industry-specific labor productivities Changes in China's industry-specific labor productivities $\hat{T}^j_{CHN}$ are considered as another trade shock in the model. I provide a calibration strategy to back out $\hat{T}^j_i$ for all countries, so that this model can be further extended to account for the effect of changes in each country's own productivity.

By normalizing $\hat{\pi}^{j,o}_{i,\tau}$ with respect to type τ' and industry j', $\hat{T}^j_i$ can be calibrated without

effects. Thus, measuring productivity changes by $\hat{T}^j_i$ instead of $\hat{A}^j_i$ gives the identifiability of shocks with the data, while still consistent with the gravity interpretation. The magnitude of effects, however, is different, because $\hat{A}^j_i$ has first-order effects only on the labor demand channel, while $\hat{T}^j_i$ has first-order effects for both the labor supply and the labor demand channels.

[42] These two assumptions are standard ones that are imposed for iceberg-type trade cost in the literature.

[43] Parro (2013) also follows this approach to back out changes in the non-tariff part of trade costs.

[44] All summary statistics discussed here are weighted averages of calibrated $\hat{d}^j_{in}$ with a corresponding level of aggregation. Weights are total trade volumes between each bilateral pair in each industry.

solving for the endogenous variable $\hat{p}_i^{j,o}$,

$$[(\frac{\hat{\pi}_{i,\tau}^{j,o}}{\hat{\pi}_{i,\tau}^{j',o}})^{\frac{1}{\theta_{i,\tau}}}(\frac{\hat{\pi}_{i,\tau'}^{j',o}}{\hat{\pi}_{i,\tau'}^{j,o}})^{\frac{1}{\theta_{i,\tau'}}}]^{1/(\frac{1}{\theta_{i,\tau}}-\frac{1}{\theta_{i,\tau'}})} = \frac{\hat{T}_i^j}{\hat{T}_i^{j'}}, \tag{23}$$

given the estimates of $\theta_{i,\tau}$ calculated earlier. I use $j' = AGR$ as a normalization, and thus have $\hat{T}_i^{AGR} = 1$ for all countries. Equation (23) should hold for all triplets of type, industry, and occupation, which is not necessarily true in the data. As discussed in Burstein et al. (2015), $\hat{T}_i^j$ is thus calibrated to match the mean of the left-hand side of equation (23) across worker types and occupations.[45]

This calibration can be done for countries where the microdata on the within-type employment allocation are available for both 2000 and 2010. Since those data are not readily available for most countries in the sample for the recent year 2010, I propose an indirect way to measure $\hat{T}_i^j$. First, I calibrate $\hat{T}_i^j$ for 13 countries where the data on $\hat{\pi}_{i,\tau}^{j,o}$ are available for the lagged period between 1990 and 2000. For the other countries without available microdata for both periods, I take the OECD and non-OECD averages of the calibrated results from available countries. I then proxy changes in each country's industry-level labor productivity by changes in industry-level capital stocks between 2000 and 2010. This is related to the interpretation of labor productivity as resources available for workers to produce occupational inputs, such as equipment or machines.[46] This measure is, however, subject to the endogeneity issue. I thus instrument this measure with the model-calibrated $\hat{T}_i^j$ as well as lagged changes in capital between 1990 and 2000 in each country. Then I use the fitted value of this first-stage regression as a measure of $\hat{T}_i^j$ for each country, which is introduced as shocks in the counterfactual analysis. To match the normalization used to calibrate $\hat{T}_i^j$, the fitted value for $\hat{T}_i^j$ is also normalized to have $\hat{T}_i^{AGR} = 1$ for all countries.

Measured changes in industry-level labor productivities are summarized in Table A3. On average, the productivity in most countries during the period of interest has significantly increased in the manufacturing and non-traded industries relative to the agriculture industry. Moreover, this pattern is more pronounced in low-income countries.

[45] A rationale for using the first moment to calibrate $\hat{T}_i^j$ in Burstein et al. (2015) is related to the potential measurement error problem. This problem is further corrected in this paper by using the calibrated $\hat{T}_i^j$ as instruments for actual productivity shocks in all countries in the sample.

[46] Caselli (2005) documents that the amount of capital stock at the industry level is positively correlated with labor productivity, when assuming that returns to capital are equalized across industries at equilibrium.

3.4 Solving for the World Equilibrium

The advantage of formulating the model in proportional changes means I only need to obtain the data on E_i^j, λ_i^j, λ_{in}^j, D_i^j, and $\zeta_i^{j,o}$ for the base year 2000. This also significantly reduces the number of parameters to be pinned down. To take the model to the data, E_i^j is first measured by gross output by industry and country. Bilateral trade flows X_{in}^j from the data are then used to calculate the domestic absorption $X_{ii}^j = E_i^j - \sum_{n\neq i} X_{in}^j$, bilateral trade shares λ_{in}^j, and industry-level trade deficits D_i^j. After that, I compute the total expenditure by $X_i^j = \sum_{n\neq i} X_{ni}^j + X_{ii}^j$ to construct the industry expenditure share λ_i^j. Lastly, $\zeta_i^{j,o}$ is measured by the share of hourly wage paid to a certain occupation relative to the average hourly wage paid to all occupations in industry j.

The computation strategy to solve the model for the counterfactual world equilibrium $\hat{p}_i^{j,o}$ for $i = 1, \ldots, N$, $j = 1, \ldots, J$, and $o = 1, \ldots, O$ is based on Caliendo and Parro (2015). Similar to their approach, the step-wise method of Alvarez and Lucas (2007) is adapted to solve for the equilibrium changes in per-unit occupational prices.[47] The technical details of the solution strategy are described in Appendix D.

To quantitatively solve the model, I first guess the initial $\hat{p}_i^{j,o}$ and then solve for the change in the industry-level price $\hat{P}_i^j$. After that, I calculate corresponding equilibrium quantities from the equations derived in the model. The counterfactual equilibrium is the change in the per-unit occupational price that solves the set of equations (17). The equilibrium $\hat{p}_i^{j,o}$ eliminates excess demands for each occupation in each industry and each country. I repeat these steps with the updated initial guess of $\hat{p}_i^{j,o}$ until the system of equations (17) is satisfied.

4 Counterfactuals

The main advantage of this model is the ability to easily test any specific counterfactual scenario regarding trade shocks and productivity shocks. The focus of the counterfactual analysis is to quantify the effect of changes in the trade environment on welfare and inequality. Trade shocks are measured in two ways: changes in bilateral trade costs among all country pairs ($\hat{d}_{in}^j$) and changes in China's industry-specific labor productivity ($\hat{T}_{CHN}^j$).[48] Parameters outside these counterfactual changes are assumed to be time-

[47]This strategy is also related to Burstein and Vogel (2011) who discuss the general equilibrium channel by which trade liberalization affects factor contents of trade. I consider not only changes in factor contents of trade caused by changes in the trade environment, but also changes in workers' industry- and occupation-level labor supply.

[48]In this way, the result complements many existing works including Autor et al. (2013) who consider technology-driven changes in China's export capability as one of the most important mechanisms by which

invariant.

The baseline counterfactual results are derived with the previously estimated $\theta_{i,\tau}$, which is country- and type-specific. Since this model can nest different model specifications regarding the degree of worker heterogeneity, the importance of having a correct specification for the degree of worker heterogeneity can be argued by comparing counterfactual results with different values of $\theta_{i,\tau}$. The trade effects on welfare, inequality, and employment shifts are reassessed with different $\theta_{i,\tau}$ later in this section.

Given $\hat{p}_i^{j,o}$ solved at the counterfactual equilibrium, corresponding equilibrium quantities are derived to measure both the welfare effect and the distributional effect of trade shocks. Accordingly, outcomes of interest are changes in aggregate welfare, type-level welfare, skill premium, real wages, as well as employment shares across industries and occupations.

4.1 Effect of Changes in Bilateral Trade Costs

Calibrated changes of bilateral trade costs between 2000 and 2010 are first introduced to the model holding other parameters fixed. Since the calibration result shows a decrease in overall trade costs during this period, this counterfactual analysis introduces the reduction of trade costs to the model; these changes in trade costs are neither uniform across industries nor across country pairs. Figure A4 describes the counterfactual changes in aggregate welfare around the world. Countries with a larger decline in average bilateral trade costs achieve larger welfare gains. While the model predicts an increase in aggregate welfare in most countries, it also predicts an unequal distribution of welfare gains across worker types.

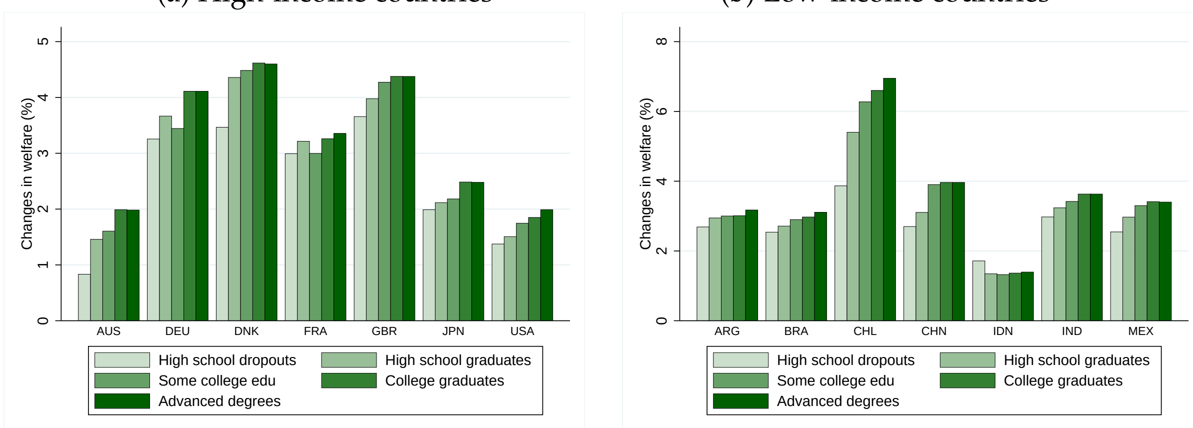
Changes in between-type inequality Between-type inequality measured by relative changes in the type-level welfare is predicted to increase due to changes in trade costs in both high- and low-income countries. Figure 1 shows counterfactual changes in the type-level welfare for some of the high- and low-income countries in the sample. Although traditional trade theory, such as the Stolper-Samuelson theorem within the Heckscher-Ohlin framework, predicts that trade decreases inequality in low-income countries with more relative endowments of unskilled types of workers, this model shows that between-type inequality in fact increases in most countries when there is a reduction of bilateral trade costs. This finding is consistent with the empirical evidence of large increases in inequality in developing countries during the same time period of dramatic trade liberalization episodes. Results for all countries in the sample are summarized in Table A4.

China affects the global market.

In addition to the relative changes in the type-level welfare, a trade-induced increase in between-type inequality is also captured by counterfactual changes in the skill premium. Figure A5 shows that changes in trade costs increase the skill premium in most countries. Moreover, it shows a greater increase of skill premium in countries with a larger decline in trade costs.

Figure 1: Changes in the Type-level Welfare Resulting from Changes in Trade Costs (%)

(a) High-income countries (b) Low-income countries



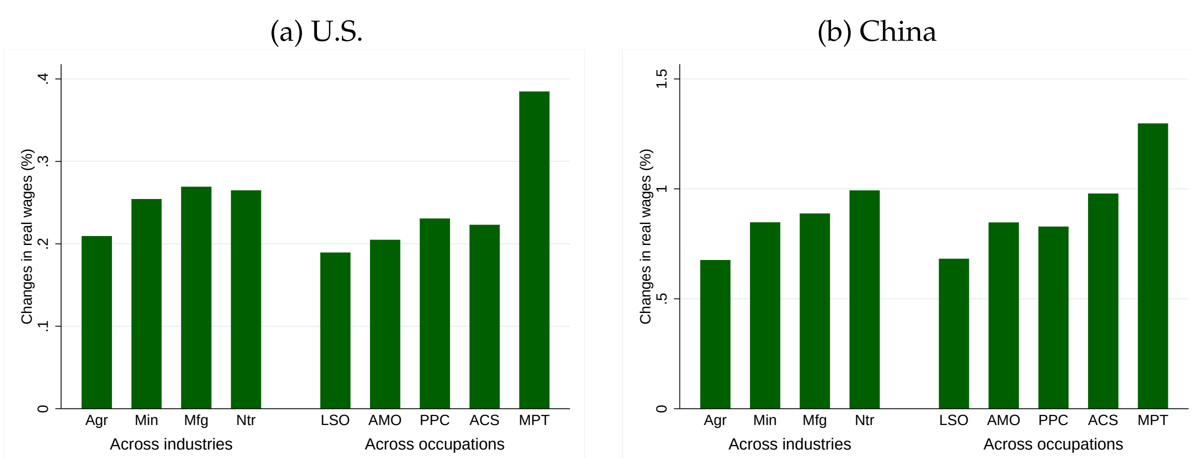
Labor demand channel Changes in between-type inequality engendered by changes in trade costs happen through both the labor demand and labor supply channels in relation to worker-level comparative advantages. The response of real wages and employment at industry- and occupation-level to changes in trade costs clearly uncovers these two channels behind the unequal gains from trade across worker types. The response of the labor demand side to trade shocks is documented by changes of real wages at industry- and occupation-level.[49] Better-educated workers are more frequently employed in high-skilled occupations in the non-traded industry as described in Figure A1. This is a result of their comparative advantages based on heterogeneous productivities. Consequently, a trade-induced increase of real wages in those industries and occupations aggravates between-type inequality. Figure 2 clearly shows this pattern for the U.S. and China. While a reduction of trade costs leads to an expansion of the manufacturing industry in China, it is well documented that domestic demands for the non-traded industry also augment significantly. As a consequence, labor demands in the non-traded industry in China also rise, which boosts real wages there.

[49] Conditional on the predicted aggregate employment shifts in Figure 3, counterfactual changes in industry- and occupation-level average wages can be interpreted as corresponding labor demand shifts.

On account of changes in trade costs, the occupation-level wage gap widens even more than the industry-level wage gap does. This result indicates the importance of considering what workers actually do within an industry. At the occupation level, the model predicts a reduction in trade costs leading to an increase in the real wages of high-skilled occupations compared to routine or low-skilled occupations in both high- and low-income countries. A relatively larger increase in the real wages of high-skilled occupations in low-income countries is related to the complementarity of occupations in production. Although the reduction of trade costs first intensifies the relative demand for low- and middle-skilled occupations in low-income countries such as China, complementarity in production eventually raises the demand for high-skilled occupations as well. Since productivities of high-skilled occupations are higher, the real wages of those occupations increase even more.

The model demonstrates another interesting prediction, namely the significant increase in manufacturing real wages due to trade shocks in the U.S. This prediction is connected to the existing reduced-form works that find no significant or significantly positive effects of import competition on the manufacturing wage in the U.S. These works include a regional level study by Autor et al. (2013) and an industry-level study by Ebenstein et al. (2014). They explain the wage effect they find in connection with worker heterogeneity: only productive and thus well-paid workers will remain in the manufacturing industry. This model confirms this conjecture with workers' occupational choices based on their productivities. Detailed results for other countries are summarized in Table A5.

Figure 2: Changes in Real Wages Resulting from Changes in Trade Costs (%)



Labor supply channel This paper focuses on the labor supply side's endogenous employment reallocation as a new channel through which welfare gains from trade are distributed unequally across worker types. This is equivalent to answering: "who goes where?" For a clear comparison, Table A6 shows patterns of the within-type labor reallocation in the U.S. and China.

The labor reallocation result from Table A6 first shows the importance of investigating the occupation-level labor reallocation of workers when connecting between-type inequality to trade shocks. Since the pattern of labor reallocation across industries is very similar between worker types, it only captures a negligible effect of trade on between-type inequality through the labor supply channel. On the other hand, the model shows that the within-type labor reallocation across occupations varies significantly by worker type. In high-income countries including the U.S., it is more likely that changes in trade costs force less-educated worker types to switch from routine and middle-skilled occupations to low-skill service occupations, and better-educated worker types are more likely to reallocate themselves into high-paying managerial or administrative occupations in a response to trade shocks. This aggravates between-type inequality in high-income countries. On the other hand, in low-income countries, workers with less education are likely to switch from low-paying and low-skilled occupations to middle-skilled occupations, while high-skilled workers in those countries mirror the reallocation pattern of those in high-income countries. Since it is well-evidenced in the data that the wage gap between high-skilled and middle-skilled occupations is much larger than the wage gap between middle-skilled and low-skilled occupations in developing countries, between-type-inequality increases due to this labor reallocation pattern.

This result is largely due to the different comparative advantage structures across worker types, as explicitly captured by this model. Workers also have clearer comparative advantage structures across occupations due to higher complementarity between their skills and occupation-specific tasks, as I discussed with the descriptive evidence from the household-level data. In summary, trade-induced labor reallocation favors better-educated workers in both high- and low-income countries. By looking at the occupation-level labor reallocation, this model is able to predict trade-induced increases in between-type inequality in both high- and low-income countries through the labor supply channel.

The importance of occupation-level analysis can be also explained in relation to the assumption on production function. If production structure is assumed to be linear, i.e., $\gamma \rightarrow \infty$, then the model prediction on the trade-induced inequality should be much closer to the Stolper-Samuelson effect.[50] The complementarity between workers' skills

[50] However, the model prediction does not necessarily replicate the predictions of traditional trade theory exactly, because the assumption on the ordering of country-level characteristics based on the notion of log-

and occupation-specific tasks is exactly paired with country-level comparative advantage, and as a consequence, the Stolper-Samuelson prediction holds in a generalized setting as described in Costinot and Vogel (2010). If production structure is non-linear as in this model, on the other hand, this link does not necessarily hold, because country-level ordering may be reversed through the non-linear production structure.[51]

In addition, the result finds that workers in the U.S. are more likely to switch their industry and occupation affiliations after changes in trade costs, when compared to Chinese workers. High-income countries in the sample mirror the U.S. in general, while low-income countries mirror China. As estimated earlier, this is related to the relatively lower labor supply elasticity $\theta_{i,\tau}$ in low-income countries. Although the trade shock itself favors middle- or low-skilled occupations in low-income countries due to the country-level comparative advantage as well as the differential occupation intensity across industries, an influx into these occupations is limited as a result of the inelastic labor market in low-income countries. This finding is consistent with the empirical evidence discussed by Goldberg and Pavcnik (2007).

Upon aggregating the predicted within-type labor reallocation caused by trade shocks across worker types up to industry- and occupation-levels, the model predicts interesting patterns of trade-induced employment shifts. Figure 3 compares the industry- and occupation-level employment shifts in the U.S. and China caused by changes in trade costs. The result from Figure 3 clearly shows that changes in trade costs significantly reduce the manufacturing employment in the U.S. The model also predicts that trade shocks induce job polarization across occupations in the U.S., which is one of the most well-known stylized facts in labor markets of many high-income countries in recent years.[52] In low-income countries such as China, on the other hand, employment shifts happen mainly from the agriculture industry to the manufacturing or non-traded industry at the industry level. The patterns of occupation-level employment shifts in developing countries including China are exactly reversed compared to the polarized patterns in high-income countries: the employment of routine and middle-skilled occupations increases

supermodularity may not hold for some country pairs in the data.

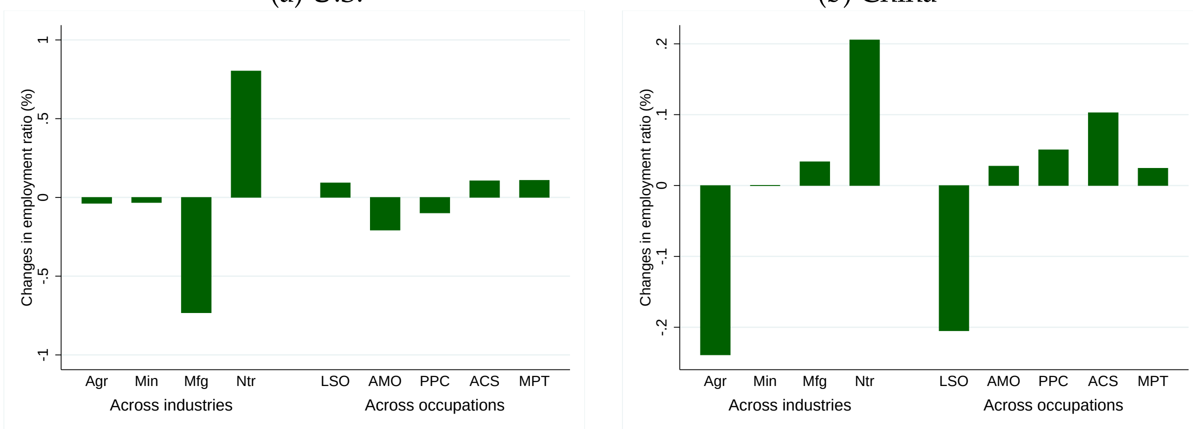
[51]If I run the same counterfactual analysis with a large enough value of γ, e.g., $\gamma = 200$, the effect of changes in trade costs on between-type-inequality becomes significantly smaller in both high- and low-income countries than the baseline counterfactual experiment predicts. Moreover, with $\gamma = 200$, changes in trade costs increase between-type-inequality much less in low-income countries compared to the baseline predictions. In some low-income countries, the direction of predicted changes is reversed, which brings the model prediction much closer to the Stolper-Samuelson prediction. For example, in Brazil, changes in trade costs *increase* the skill premium by 0.38% in the baseline result with $\gamma = 0.9$ but *decrease* the skill premium by 0.1% with a near-linear production function.

[52]In this paper, job polarization is defined as a relative contraction of employment in routine and middle-skilled occupations.

more. This finding suggests that large migrations to urban regions in those low-income countries are partly due to trade shocks making those countries more export-oriented in the manufacturing industry.

Figure 3: Changes in Employment Shares Resulting from Changes in Trade Costs (%)

(a) U.S. (b) China



In summary, this model predicts that the reduction of bilateral trade costs between 2000 and 2010 results in the unequal gains from trade across different worker types in most countries. I show that the worker heterogeneity and the endogenous sorting of workers into industry and occupation based on worker-level comparative advantage are the key factors that generate this increase of trade-induced inequality through the labor demand and supply channels in both high- and low-income countries. The result also shows that changes in trade costs contribute to explaining many well-known labor market outcomes, such as contractions of manufacturing employment and job polarization in high-income countries, as well as a large employment reallocation from the agriculture industry to the manufacturing and non-traded industry in low-income countries.

4.2 Effect of Changes in China's Productivity

The effect of trading partners' export capabilities on inequality is another important channel by which trade affects domestic inequality. In a simple trade model setup, Autor et al. (2013) show that import competition from China is connected to changes of productivity in China. I clearly document this relationship in this paper. Changes in China's industry-specific labor productivity affect its cost advantage in the global market. As a result, within-industry trade flows with all their partner countries are affected. Each country's domestic demand for labor is affected accordingly, with workers' endogenous sorting into industry and occupation being the labor supply side's reaction.

To isolate the effect of changes in China's productivity from each country's own productivity effect, I assume $\hat{T}_i^j = 1$ for all $i \neq CHN$. It is reasonable to choose China especially because of the time period considered in this paper, from 2000 and 2010, because China joined the WTO in 2001.[53] The shock of interest is, therefore, $\hat{T}_{CHN}^j$ which is calibrated as discussed in the previous section. Calibrated $\hat{T}_{CHN}^j$ shows that industry-level productivities have increased by 72.70% on average in non-agricultural industries relative to the agriculture industry in China. Figure A6 shows that aggregate welfare is predicted to increase due to changes in China's productivity in most countries. It is also evident that welfare gains are greater in countries with a larger increase in imports from China between 2000 and 2010. The magnitude is comparable to, but slightly smaller than, welfare gains from changes in bilateral trade costs.

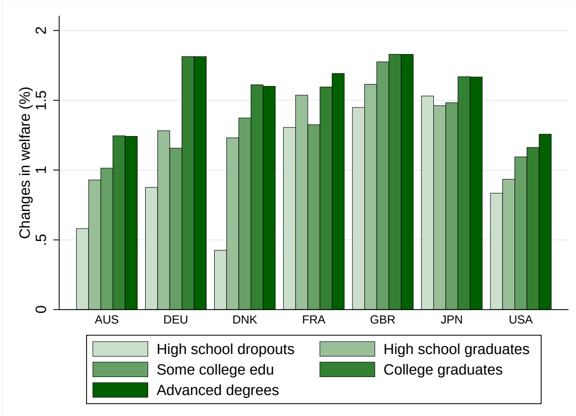
Similarly, welfare gains from China's productivity change are distributed unequally across worker types in most countries. Workers with more education gain more from changes in China's productivity than workers with less education do. As described in Figure 4, the difference in welfare gains across types due to China's productivity change is in fact larger than the distributional effect of changes in trade costs (Figure 1) for both high- and low-income countries. This finding is related to the fact that changes in trade costs between all bilateral country pairs have mixed effects across worker types depending on the country-level comparative advantage position within each country pair. Conversely, the increase in China's productivity in non-agricultural industries has a definitive effect in the form of import competition from China to partner countries. Detailed results for all the other countries in the sample are in Table A7. As described in Figure A7, between-type inequality measured by the skill premium also increases due to China's productivity improvement in non-agricultural industries. The increase is greater in countries with a larger increase in import volumes from China between 2000 and 2010.

Two channels by which trade increases inequality also operate in a similar way to the case of changes in trade costs. Changes in China's industry-specific labor productivities increase inequality first through the labor demand channel. The calibrated model predicts

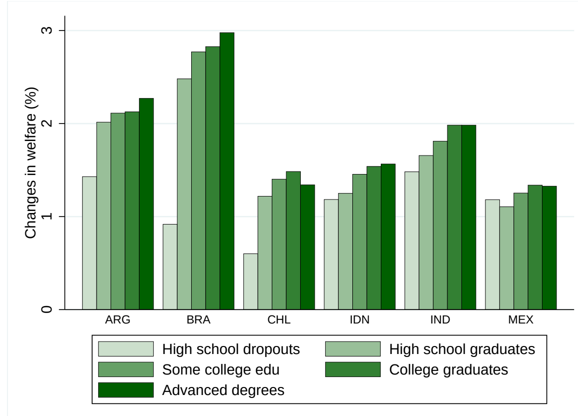
[53]The importance of China in terms of trade can also be argued based on the effect of changes in bilateral trade costs with China compared to the effect of changes in the entire bilateral trade costs discussed in the previous subsection. The result shows that changes in bilateral trade costs with China explain a large share of the distributional effect of changes in the entire trade costs, especially in high-income countries where imports from China have increased significantly between 2000 and 2010. Detailed results are described in the online appendix.

Figure 4: Changes in Type-level Welfare Resulting from Changes in China's Productivity (%)

(a) High-income countries



(b) Low-income countries



that real wages increase relatively more in the industry and occupation where better-educated workers have a comparative advantage. In this way, this trade shock increases between-type inequality due to worker-level comparative advantage even without labor reallocation.

The labor supply channel additionally enhances inequality in most countries after China's productivity changes. In order to uncover this channel, I examine the within-type endogenous labor reallocation across industries and occupations due to changes in China's productivity between 2000 and 2010. The labor reallocation result again confirms that the endogenous sorting of heterogeneous workers is another key channel that generates unequal gains from trade in both high- and low-income countries. The predicted pattern of changes in the within-type labor allocation resulting from changes in China's productivity is similar to the predicted effect of changes in bilateral trade costs. The predicted labor reallocation across industries and occupations also shows that the occupation-level labor reallocation is a much more significant channel.

In summary, the counterfactual result discussed in this subsection shows the importance of considering the effect of both China's productivity changes and changes in bilateral trade costs on inequality in order to correctly capture how much trade affects inequality in each country. Adding these two effects provides a more precise prediction for the distributional effect of trade. The model predicts that in the U.S., for example, these two types of trade shocks increase the skill premium by 0.56%, which is more than 10% of actual changes in the skill premium observed in the data.

4.3 Effect of Worker Heterogeneity on Counterfactual Outcomes

A key difference between my model and standard trade models is that this model allows workers to endogenously choose both industry and occupation based on their heterogeneous productivities. This feature is clearly different from two extreme cases–the specific factors model and the model with homogeneous workers–that traditional trade theory assumes. As discussed in Section 2.5, different values of $\theta_{i,\tau}$–the labor supply elasticity which governs the degree of within-type worker heterogeneity–are expected to generate different patterns of welfare effects and distributional effects.

Instead of pre-committing to a specific assumption regarding the degree of worker heterogeneity, all counterfactual results discussed earlier are derived with the estimates of $\theta_{i,\tau}$ from the actual data in different countries.[54] In this section, the earlier counterfactual results about the distributional effect of trade are reassessed with different values of $\theta_{i,\tau}$ in order to discuss the importance of endogenizing the sorting of heterogeneous workers with a correct degree of worker-level comparative advantage. For a clear comparison, I consider only changes in bilateral trade costs as trade shocks, as in Section 4.1. The baseline counterfactual result in Section 4.1 is compared to the results with five alternative specifications of $\theta_{i,\tau}$. Case 0 assumes $\theta_{i,\tau} = 1$ for all i and τ in order to consider the case where workers are extremely heterogeneous in their industry- and occupation-specific productivities, which is in line with the intuition of the specific factors model. Case 1 takes an average of the estimated $\theta_{i,\tau}$ across countries. Case 2 also eliminates the type-level difference in $\theta_{i,\tau}$ by taking another average across types. Case 3 and 4 take large values of parameters for all types and countries, which are 10 and 50, respectively, in order to consider the cases with extremely homogeneous workers assumed by traditional trade models. As a limit case, I also consider a multi-country, multi-industry, and multi-factor Heckscher-Ohlin model where $\theta_{i,\tau} \to \infty$ for all i and τ; $T^{j,o}_{i,\tau} = 1$ for all (i, τ, j, o); $\mu^{j,o}_i = \mu^{j,o}$ for all i; and $z_i(e^j) = z$ for all i and e^j. This limit case captures the Stolper-Samuelson effect in a generalized Heckscher-Ohlin setting with CES production function.[55]

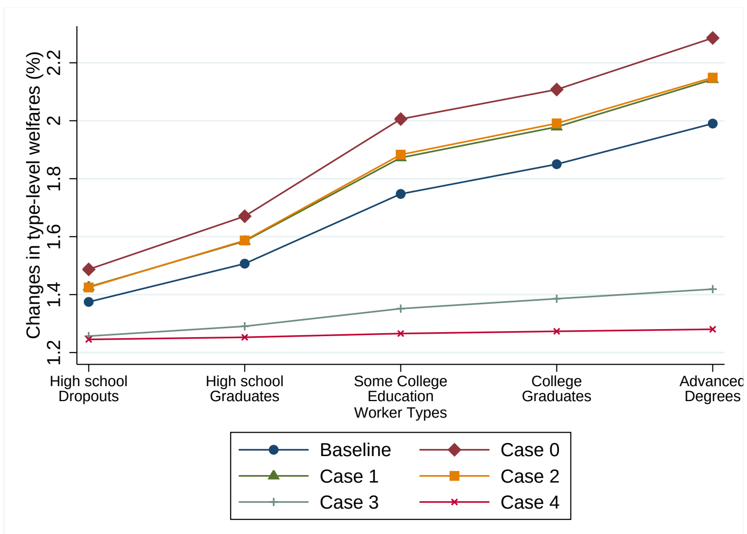
Counterfactual changes in the type-level welfare vary significantly depending on the labor supply elasticity $\theta_{i,\tau}$. Figure 5 shows that the baseline result for the effect of changes in trade costs on changes in type-level welfares is significantly different from the result

[54] Although the parameters are estimated for only four countries and proxied for the other countries due to limited availability of data, the counterfactual result shows that the estimates effectively generate both cross-country and within-country variation in welfare effects and in distributional effects of trade shocks.

[55] Since workers do not choose occupations in the Heckscher-Ohlin model, I assume that worker types are considered as production inputs. This assumption changes the implication for type-level welfare effects. Thus, I compare the result from this limit case to the results from the other alternative cases only in terms of counterfactual changes in the skill premium.

with alternative specifications of $\theta_{i,\tau}$. Case 0, as expected, predicts larger differences in changes in welfare across types, demonstrating that trade induces larger increases in inequality with a higher degree of worker heterogeneity. When workers are homogeneous as in Case 3 and 4 where I have unrealistically large values for $\theta_{i,\tau}$, the prediction departs further from the baseline. Cases with homogeneous workers predict almost no effect of trade on the increase in inequality, holding true for the U.S. and most of the countries in the sample, as described in Figure 5 for the U.S. The figure clearly supports the importance of having the endogenous sorting of heterogeneous workers with correct estimates of $\theta_{i,\tau}$, rather than committing to a specific model *ex ante*.

Figure 5: Changes in the Type-level Welfare in the U.S. by Different $\theta_{i,\tau}$



Skill premium, another measure of between-type inequality, also varies by specification of $\theta_{i,\tau}$. The baseline result in Section 4.1 shows that the amount of increase in the skill premium due to changes in trade costs vary considerably by country, although the model predicts increases in the skill premium in most countries. As described in Figure A8, this cross-country variation of a trade-induced increase in the skill premium vanishes as we move from the baseline specification of $\theta_{i,\tau}$ to the cases with homogeneous workers: Cases 3 and 4. Figure A8 also exemplifies the variations in the relationship between the reduction of trade costs and changes in the skill premium across specifications of $\theta_{i,\tau}$. Trade enhances the increase in the skill premium when the model assumes more heterogeneous workers and has almost no effect when workers are homogeneous within their type.

When I consider the limit case where workers are perfectly homogeneous within types, the effect of changes in trade costs on inequality is even smaller, as described in Figure A8. This result is consistent with the predictions of existing quantitative trade models which find almost negligible Stolper-Samuelson effects: e.g., Parro (2013). In addition, direction of changes follows the prediction of the Stolper-Samuelson theorem on average, which is largely inconsistent with the reduced-form evidence especially in developing countries.[56]

The labor demand and the labor supply channels behind the unequal gains from trade also depend on the specification of $\theta_{i,\tau}$. Figure A9, for example, summarizes the effect of having different $\theta_{i,\tau}$ on the real wage gaps across industries and occupations in the U.S. Higher values of $\theta_{i,\tau}$, as predicted, eliminate the predicted real wage gaps across industries and occupations, showing almost no effect of trade on inequality. This result explains why many existing works based on the framework of traditional trade theories with homogeneous workers predict only a negligible effect of trade on inequality. These results all support the importance of having precise country- and type-specific estimates of $\theta_{i,\tau}$, especially when the main focus is on the effect of trade shocks on inequality at a disaggregate level across worker types, industries, and occupations.

5 Robustness Check

In this section, I again derive counterfactual results with different parameter values of the elasticity of substitution between occupations in production (γ), the elasticity of substitution across industries in preference (η_1), and the trade elasticity (ν^j). The effect of changes in bilateral trade costs ($\hat{d}^j_{in}$) is examined with different parameter values here. Additionally, the same sensitivity analysis for the effect of changes in China's industry-specific labor productivity ($\hat{T}^j_{CHN}$) is presented in the online appendix. These parameters are closely connected to the labor demand channel by which trade impacts inequality within a country. The main findings in the counterfactual analysis are robust across different values of labor demand channel parameters: changes in the trade environment between 2000 and 2010 increase inequality in both high- and low-income countries.

5.1 Elasticity of Substitution between Occupations in Production

In the baseline specification, I assign $\gamma = 0.90$ following Goos et al. (2014) to account for the complementarity between occupations in production. As discussed earlier, this

[56] Predictions for some countries are not in line with the Stolper-Samuelson theorem, because the limit case is still more general than the Heckscher-Ohlin model.

complementarity influences the labor demand channel by which trade shocks are disseminated differentially across different worker types, especially in low-income countries. I consider alternative values of $\gamma = 0.1$, 1, 3, and 10.[57]

Changes in the type-level welfare show similar patterns to the baseline result as γ takes different values: gains from trade are distributed unequally across different worker types. The gains for better-educated workers are higher than for less-educated workers. Figure A10 shows that all specifications with different γ predict an increase of type-level inequality in the U.S. and China, when inequality is measured by differential changes in the type-specific welfare. This finding is consistent in most countries in the sample. Since lower values of γ correspond to higher complementarity between occupations in production, the labor demand channel of the distributional effect of trade becomes more important with lower γ, especially in developing countries where the Stolper-Samuelson prediction does not hold in the data. Figures exhibit exactly this pattern, with a larger predicted inequality given lower γ.

Furthermore, the predicted effect of γ on the labor demand channel is clearly documented in counterfactual changes in real wages described in Figure A11 and A12. While the predicted patterns of changes in industry- and occupation-level real wages caused by changes in trade costs are all similar across different values of γ, the relative magnitude of changes in real wages reveals that a higher complementarity across occupations in production favors industries and occupations where better-educated workers have comparative advantages.

5.2 Elasticity of Substitution between Industries in Preference

The elasticity of substitution in preference between within-industry product varieties (η_2) does not affect equilibrium outcomes in this model, except that $\nu^j + 1 > \eta_2$ is required for the price to be well-defined. On the other hand, the elasticity of substitution for the upper nest of the utility function across industries (η_1) affects the equilibrium, since the expenditure share of industry λ_i^j changes endogenously. As the definition of industry in this paper is more aggregate than the SIC 2-digit level, I use $\eta_1 = 1.5$ from Backus et al. (1994) and Chari et al. (2002) for the baseline results. They assume that consumers have a preference for home-produced and foreign goods and have 1.5 as the elasticity of substitution between these two types of goods. I consider alternative values of $\eta_1 = 1$, 3, and 4 in this section, where the alternative value 4 comes from Broda and Weinstein

[57]These alternative values include moderate variations in the parameter γ. In the near-limit case where γ is large enough, the production structure becomes much more linear in occupational inputs, as discussed in the previous section.

(2006) with much more narrowly defined industries at a product level.

The main finding remains unchanged. Changes in bilateral trade costs between 2000 and 2010 increase between-type inequality in terms of both type-specific welfares and the skill premium with alternative values of η_1. Figure A13 displays that the Cobb-Douglas specification ($\eta_1 = 1$), which is the most common framework in the literature, predicts larger increases in inequality. Predicted change is smaller with a larger elasticity of substitution in preference across industries. The intuition behind this finding is the following: if goods from different industries are more substitutable, then the relative demand for goods in the importing industry increases even more due to the decreased price following the reduction of trade costs. This increases labor demands in those industries and for occupations that are more employed there, which offsets the negative effect on the labor in import-competing industries. Higher η_1 thus decreases the negative effect of trade shocks on the manufacturing industry and middle-skill occupations in high-income countries as well as on the agriculture industry and low-skill occupations in low-income countries. Counterfactual changes in industry- and occupation-level real wages in Figure A14 and A15 support this intuition. The effects of changes in trade costs on the industry-level and occupation-level real wage gaps are smoothed out with higher η_1 in most countries, which in turn leads to less of an increase of trade-induced between-type inequality.

5.3 Trade Elasticity

There are a number of previous works estimating the trade elasticity in different frameworks using different estimation methods. Among those works, the trade environment in this paper is most closely related to Caliendo and Parro (2015). They consider a multi-industry EK model with industry-specific trade elasticities. As discussed earlier, I derive baseline results with their industry-specific estimates of trade elasticities. I consider $\nu = 6.53$ (Costinot et al. (2011)), 6.9 (intermediate value of Head and Ries (2001)'s estimates that Anderson and van Wincoop (2004) consider in their survey), 8.28 (EK), and 10.4 (the largest estimate in Head and Ries (2001) based on the pooled OLS specification) as alternative values of trade elasticity and assume that these alternative values do not vary by industry.[58] Compared to the estimates of Caliendo and Parro (2015), the first three alternative specifications assume relatively lower trade elasticities in agriculture and the

[58] Head and Ries (2001)'s estimates are based on the Armington model with the CES preference for source-specific varieties. Trade elasticity is $1 - \sigma$, where σ is the elasticity of substitution in preference between source-specific varieties, as Arkolakis et al. (2012) note. There are many other existing papers that estimate trade elasticity with different methods. Most results find trade elasticities overall ranging from 5 to 20: e.g., Broda and Weinstein (2006), Head and Mayer (2014), Bergstrand et al. (2013), Hertel et al. (2007), and Romalis (2007).

mining industry.

The main finding is robust across different values of trade elasticities. As documented in Figure A16, the type-level inequality increases due to trade shocks with all alternative values of ν^j. In high-income countries, the predicted changes in the type-level inequality is nearly equal across different values of trade elasticities. This result is related to the fact that agriculture and the mining industry, whose trade elasticities in the baseline specification differ more from the alternative values of ν^j that I consider, account for only a small fraction of the entire economy in high-income countries. Figure A17 shows that the model with alternative values of ν^j provides a different prediction on changes in relative real wages in the agriculture and mining industries compared to the baseline prediction. However, due to their relatively small shares in the total economy and the trade-induced contraction of employment in those industries, the alternative values of ν^j do not affect the overall prediction on the type-level inequality much.

Having industry-specific trade elasticities is much more important to correctly capture the distributional effect of trade in low-income countries, where the relative share of the agriculture industry is high before the reduction of trade costs. Caliendo and Parro (2015)'s estimates of the trade elasticity used in the baseline results are much higher in the agriculture industry than in other tradable industries, and the reduction of trade costs is more concentrated in the manufacturing industry. As a result, the shift of labor demand favors the manufacturing and non-traded industries as well as high-skilled occupations in low-income countries. Changes in industry- and occupation-level real wages in Figure A17 and A18 demonstrate that real wages move exactly toward the predicted direction, while the main findings of the model remain unchanged across different values of ν^j. With alternative trade elasticities assumed to be uniform across industries, the model predicts that changes in occupation-level real wages still vary significantly by occupation.

6 Conclusion

In this paper, I present a general equilibrium trade model with worker heterogeneity and endogenous sorting of workers based on worker-level comparative advantage in order to explore the distributional effect of trade in many countries. The model shows the mechanism by which international trade increases between-educational-type inequality in most countries. Worker heterogeneity and endogenous sorting of heterogeneous workers into industry and occupation play a key role when changes in the trade environment shift both labor demand and labor supply in favor of better-educated workers in both high- and low-income countries.

I quantify the model to examine the effect of changes in the trade environment on inequality between 2000 and 2010, where these changes are captured by the reduction of bilateral trade costs as well as the change in China's labor productivity. In order to take the model to the data, I use the household-level survey data for a large number of countries that encompass the information on detailed patterns of labor allocation across workers' educational attainment, industries, and occupations. The quantitative result shows that between-educational-type inequality increases due to trade shocks in both high- and low-income countries between 2000 and 2010. I also quantify both labor demand and labor supply channels behind these unequal gains from trade across workers. I show that workers' differential patterns of self-selection into industries and occupations generate an increase in inequality in many countries. The occupation-level labor reallocation, however, has much more significant effects. The model is also able to show that international trade helps explain many stylized facts in labor markets, such as industry and occupation wage premia, employment shifts across industries, and job polarization in high-income countries.

The general, but still tractable model of this paper can easily nest many existing trade models, depending on the different values of the labor supply elasticity parameter. Instead of pre-committing to a specific model framework, I estimate the labor supply elasticity, which brings the model most closely to the data. Comparing the distributional effect of trade predicted in this paper to the predictions of many existing models shows the importance of correctly introducing worker heterogeneity and worker-level comparative advantage to explain the increase of trade-induced inequality in many countries.

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A Tables and Figures

Table A1: Maximum Likelihood Estimates of $\theta_{i,\tau}$

Worker type	High school Dropouts	High school Graduates	Some College Education	College Graduates	Advanced Degrees
U.S.	1.97	1.86	1.74	1.61	1.48
(2000)	(0.033)	(0.042)	(0.043)	(0.049)	(0.055)
Brazil	1.09	1.24	1.17	1.05	1.04
(2000)	(0.093)	(0.129)	(0.158)	(0.231)	(0.362)
India	1.26	1.09	1.00	1.03	1.05
(1999)	(0.172)	(0.180)	(0.259)	(0.346)	(0.335)
Mexico	1.18	1.28	1.23	1.19	1.19
(2000)	(0.225)	(0.372)	(0.409)	(0.510)	(0.545)

Notes: For the U.S., N=10,000 for each type. For the other three countries, N=5000 for each type. Standard errors are displayed in parentheses.

Table A2: Summary of Calibrated Changes in Bilateral Trade Costs $\hat{d}^{j}_{in}$ (%)

	All industries	Agriculture	Mining	Manufacturing
		I. Aggregate country groups		
All countries	-8.89	-4.47	-0.05	-9.74
OECD	-7.76	-3.74	0.03	-8.44
Non-OECD	-8.05	-6.38	-0.26	-9.25
		II. Individual countries		
Argentina	-4.87	4.92	3.90	-7.04
Australia	-0.20	3.52	4.60	-1.74
Austria	-1.27	-1.41	-5.72	-1.17
Brazil	-11.36	-5.27	0.39	-13.04
Canada	5.63	-14.70	-1.02	6.82
China	-11.99	-2.74	2.56	-12.89
Chile	-9.28	-1.11	2.75	-12.46
Denmark	-8.71	-3.36	13.70	-10.24
Finland	-5.03	-3.65	4.77	-5.65
France	-10.72	-3.71	1.46	-11.53
Germany	-9.89	-5.92	-11.15	-9.92
Greece	-5.16	-1.73	2.40	-6.23
Hungary	-4.42	-5.81	-2.20	-4.44
Iceland	-8.68	-5.45	-2.61	-8.88
India	-11.90	-4.57	-1.92	-15.71
Indonesia	-0.01	-0.05	4.08	-1.03
Ireland	-0.10	1.19	-10.07	0.00
Israel	-4.39	0.56	3.06	-5.73
Italy	-7.21	-3.75	-2.36	-7.55
Japan	-5.98	-1.19	-0.91	-6.57
Republic of Korea	-8.26	-3.63	0.22	-9.30
Mexico	-5.15	-5.31	2.18	-5.58
Netherlands	-19.88	-6.75	-0.07	-21.72
New Zealand	-9.89	-2.82	3.17	-11.25
Poland	-14.63	-9.51	0.01	-16.00
Portugal	24.74	-7.03	-3.21	26.86
Spain	-7.80	-5.87	-1.88	-8.40
Sweden	-9.34	-8.74	0.42	-9.79
Switzerland	-7.47	-0.87	19.82	-8.84
Turkey	-25.74	-1.62	-0.75	-29.28
United Kingdom	-22.76	-3.80	11.67	-25.80
United States	-5.79	-0.57	0.91	-6.37
ROW	-7.21	-8.34	-1.42	-8.30

Notes: Numbers are in %. Changes in trade costs are weighted by the volume of trade, when being aggregated up to industry, country, country group, and the world level.

Table A3: Summary of Calibrated Changes in Industry-level Productivity $\hat{T}_i^j$ (%)

	Mining	Manufacturing	Non-traded
	I. Aggregate country groups		
All countries	7.59	30.16	37.99
OECD	-0.58	23.51	39.28
Non-OECD	33.13	50.94	33.95
	II. Individual countries		
Argentina	9.06	73.13	1.33
Australia	25.65	24.35	47.13
Austria	-37.35	-21.83	13.00
Brazil	35.30	55.53	35.20
Canada	30.19	22.62	30.02
China	69.98	66.88	81.23
Chile	35.30	55.53	35.20
Denmark	35.40	44.72	50.47
Finland	23.49	44.78	54.94
France	-28.41	-7.19	9.81
Germany	53.09	64.58	88.38
Greece	-1.12	15.16	33.81
Hungary	-16.80	33.08	23.37
Iceland	-0.27	22.62	39.44
India	28.94	17.11	19.88
Indonesia	35.30	55.53	35.20
Ireland	40.28	50.00	57.39
Israel	29.50	60.65	30.77
Italy	4.58	16.22	29.02
Japan	-14.92	18.87	24.18
Republic of Korea	-0.59	39.76	38.16
Mexico	-0.27	22.62	39.44
Netherlands	-8.39	4.29	30.90
New Zealand	-72.39	-4.19	0.37
Poland	-70.69	-2.48	60.21
Portugal	-0.27	22.62	39.44
Spain	0.54	30.45	52.64
Sweden	3.47	35.33	39.63
Switzerland	-0.94	34.36	43.64
Turkey	2.27	16.14	27.49
United Kingdom	22.32	42.60	68.51
United States	-3.37	18.17	40.73
ROW	21.67	23.20	32.81

Notes: Numbers are in %. Changes in the agriculture industry are normalized to 0% for all countries. Changes in productivity for all countries or for OECD/non-OECD country groups are calculated by a simple average of corresponding countries. This change is derived from the first-stage regression of IV specification for the proxy of productivity changes with model-calibrated changes in productivity for available countries as well as lagged proxy. Since the measure for industry-level capital stock is not available for all countries in the sample, the OECD/non-OECD average is imputed for those countires with the measure for industry-level capital missing, which results in the same predicted changes in industry-specific systematic productivity for some countries.

Table A4: Changes in the Type-level Welfare Resulting from Changes in Trade Costs (%)

	HD	HG	SC	CG	AD
Argentina	2.69	2.95	3.00	3.01	3.17
Australia	0.83	1.46	1.61	1.99	1.98
Austria	2.40	3.11	2.50	3.17	3.17
Brazil	2.54	2.71	2.90	2.97	3.11
Canada	3.00	1.76	1.48	1.45	1.44
China	2.70	3.10	3.90	3.96	3.96
Chile	3.87	5.40	6.27	6.60	6.95
Denmark	3.47	4.36	4.48	4.62	4.60
Finland	0.10	0.36	0.39	0.35	0.35
France	2.99	3.21	3.00	3.26	3.36
Germany	3.26	3.67	3.44	4.11	4.11
Greece	4.67	5.59	5.81	6.36	6.55
Hungary	6.57	6.20	6.20	6.29	6.29
Iceland	5.37	5.95	6.08	6.39	6.38
India	2.98	3.24	3.42	3.63	3.63
Indonesia	1.71	1.35	1.32	1.37	1.40
Ireland	-2.14	-2.17	-2.32	-2.56	-2.56
Israel	4.76	5.10	5.55	5.85	5.87
Italy	2.56	3.22	3.47	3.89	3.89
Japan	1.99	2.12	2.18	2.48	2.48
Republic of Korea	1.80	2.23	2.33	2.57	2.57
Mexico	2.55	2.97	3.30	3.41	3.40
Netherlands	9.46	9.38	9.68	9.73	9.74
New Zealand	3.85	3.89	3.93	4.15	4.14
Poland	6.45	7.12	7.26	7.60	7.59
Portugal	0.85	1.92	2.27	2.57	2.72
Spain	3.40	3.43	3.85	3.87	4.01
Sweden	2.94	4.54	4.83	5.34	5.33
Switzerland	3.00	3.17	3.18	3.52	3.52
Turkey	5.77	8.50	8.74	8.42	8.41
United Kingdom	3.66	3.98	4.27	4.38	4.38
United States	1.37	1.51	1.75	1.85	1.99
ROW	4.48	10.79	14.27	15.15	15.17

Notes: Numbers are in %.

Table A5: Changes in Real Wages and Employment Shares across Industries and Occupations Resulting from Changes in Trade Costs (%)

	A. Counterfactual change in real wage									B. Counterfactual change in employment share								
	I. By industries				II. By occupations					I. By industries				II. By occupations				
	Agr	Mining	Mfg	Non-tr	LSO	AMO	PPC	ACS	MPT	Agr	Mining	Mfg	Non-tr	LSO	AMO	PPC	ACS	MPT
Argentina	1.16	1.28	1.25	1.27	1.20	1.30	1.24	1.32	1.34	-0.10	-0.01	-0.40	0.51	0.09	-0.06	-0.16	0.07	0.05
Australia	-0.07	0.01	0.01	0.03	-0.08	-0.07	-0.05	0.00	0.24	-0.38	-0.02	-0.48	0.88	-0.29	-0.05	-0.07	0.31	0.10
Austria	0.69	0.89	0.84	0.97	0.67	0.71	0.68	0.93	1.12	-0.04	-0.03	-0.85	0.91	-0.07	-0.09	-0.12	0.17	0.11
Brazil	0.96	1.00	1.02	1.05	0.97	0.99	0.96	1.04	1.22	-0.05	-0.01	-0.42	0.49	-0.01	-0.12	-0.09	0.20	0.01
Canada	1.24	1.08	1.35	1.12	1.28	1.28	1.26	1.15	1.02	1.48	1.13	-2.66	0.04	1.49	-0.86	-0.30	-0.17	-0.16
China	0.68	0.85	0.89	0.99	0.68	0.85	0.83	0.98	1.30	-0.24	0.00	0.03	0.21	-0.20	0.03	0.05	0.10	0.02
Chile	0.63	1.45	1.26	1.47	0.76	1.15	0.98	1.45	2.45	-0.85	0.29	-0.96	1.52	-0.34	0.03	-0.09	0.29	0.11
Denmark	1.89	2.63	2.04	2.18	1.93	1.97	1.99	2.24	2.42	-1.18	-0.40	1.17	0.41	-1.00	0.22	0.37	0.30	0.10
Finland	0.24	0.23	0.27	0.32	0.25	0.25	0.27	0.34	0.36	-0.45	0.05	0.51	-0.11	-0.34	0.12	0.16	0.03	0.02
France	1.40	1.38	1.44	1.44	1.37	1.39	1.37	1.44	1.50	-0.02	0.00	-0.58	0.60	0.03	-0.18	-0.05	0.14	0.05
Germany	1.35	1.38	1.38	1.48	1.27	1.28	1.33	1.45	1.73	-0.18	-0.09	-0.40	0.67	-0.15	-0.04	-0.12	0.24	0.07
Greece	0.99	1.06	1.30	1.44	1.09	1.18	1.20	1.48	1.83	-0.32	0.05	-1.42	1.70	-0.23	-0.11	-0.41	0.54	0.20
Hungary	3.80	4.00	3.79	3.75	3.91	3.82	3.78	3.74	3.76	0.43	-0.02	-0.77	0.36	0.32	-0.06	-0.26	0.03	-0.03
Iceland	2.61	2.86	2.75	2.83	2.63	2.66	2.68	2.85	3.10	-0.57	-0.14	-0.11	0.83	-0.44	0.00	0.04	0.31	0.09
India	1.02	1.13	1.09	1.12	1.02	1.11	1.09	1.15	1.19	-0.13	-0.06	-0.14	0.34	-0.08	-0.01	-0.06	0.06	0.09
Indonesia	0.98	0.91	0.92	0.91	0.98	0.93	0.93	0.86	0.83	0.38	0.00	-0.45	0.07	0.33	-0.09	-0.22	-0.01	-0.01
Ireland	-0.41	-0.51	-0.49	-0.47	-0.41	-0.40	-0.41	-0.44	-0.60	-0.02	0.12	0.76	-0.86	-0.03	0.15	0.14	-0.21	-0.06
Israel	1.97	2.71	2.22	2.33	1.96	2.05	2.04	2.26	2.63	-0.23	-0.56	0.05	0.73	-0.17	-0.01	-0.12	0.19	0.10
Italy	0.34	0.61	0.57	0.63	0.43	0.51	0.48	0.70	0.83	-0.45	-0.04	-0.55	1.05	-0.36	-0.06	-0.04	0.37	0.08
Japan	0.45	0.56	0.54	0.54	0.45	0.48	0.48	0.52	0.71	0.07	-0.04	-0.80	0.77	0.06	-0.13	-0.17	0.19	0.05
Republic of Korea	0.67	0.72	0.77	0.81	0.68	0.71	0.73	0.81	0.96	-0.33	0.02	-0.27	0.58	-0.24	-0.02	-0.02	0.21	0.07
Mexico	0.77	0.93	0.96	1.00	0.82	0.94	0.89	1.03	1.40	-0.31	-0.01	-0.25	0.57	-0.20	-0.02	0.00	0.19	0.02
Netherlands	6.12	6.07	6.02	6.05	5.98	6.01	6.00	6.04	6.43	-0.68	0.00	0.43	0.24	-0.15	0.05	0.12	0.18	-0.21
New Zealand	1.92	1.98	2.00	1.99	1.93	1.95	1.95	1.97	2.10	0.11	-0.01	-0.63	0.54	0.09	-0.10	-0.14	0.11	0.03
Poland	3.32	3.47	3.47	3.53	3.36	3.40	3.42	3.57	3.73	-0.64	-0.06	-0.21	0.91	-0.49	0.00	0.03	0.37	0.10
Portugal	-1.58	-1.03	-1.42	-1.25	-1.53	-1.58	-1.59	-1.27	-0.74	-0.67	-0.02	-1.09	1.78	-0.29	-0.16	-0.14	0.46	0.14
Spain	1.45	1.50	1.50	1.53	1.45	1.45	1.43	1.49	1.69	0.01	-0.05	-0.66	0.70	0.07	-0.17	-0.13	0.17	0.06
Sweden	1.21	1.51	1.48	1.65	1.27	1.31	1.37	1.66	2.04	-1.49	-0.07	0.43	1.13	-1.15	0.14	0.24	0.58	0.20
Switzerland	1.16	1.17	1.17	1.18	1.07	1.14	1.15	1.14	1.30	-0.12	0.00	-0.63	0.75	-0.04	-0.06	-0.20	0.19	0.11
Turkey	3.65	4.42	4.37	4.78	3.78	4.49	4.29	4.82	5.13	-2.68	-0.05	2.83	-0.09	-2.59	0.33	1.98	0.17	0.12
United Kingdom	1.31	1.23	1.36	1.38	1.26	1.25	1.33	1.38	1.56	-0.13	0.07	-1.07	1.14	-0.05	-0.22	-0.10	0.30	0.07
United States	0.21	0.25	0.27	0.26	0.19	0.20	0.23	0.22	0.38	-0.04	-0.03	-0.73	0.80	0.09	-0.21	-0.10	0.11	0.11
ROW	-4.18	-2.26	-2.28	-1.79	-4.06	-2.76	-2.99	-1.15	0.84	-7.52	0.26	3.35	3.90	-5.96	1.03	2.27	2.01	0.65

Notes: Numbers are in %. Counterfactual changes in real wages are proportional changes, and changes in employment shares are in linear difference.

Table A6: Changes in Within-type Employment Allocations in the U.S. and China Resulting from Changes in Trade Costs(%)

		I. U.S.					II. China				
Type	Ind\Occ	LSO	AMO	PPC	ACS	MPT	LSO	AMO	PPC	ACS	MPT
HD	Agr	-0.1567	-0.0021	-0.0007	-0.0016	-0.0019	-0.1382	-0.0002	-0.0016	-0.0003	-0.0002
	Mining	-0.0338	-0.0023	-0.0011	-0.0011	-0.0019	0.0005	0.0002	0.0025	0.0003	0.0001
	Mfg	-0.2262	-0.4370	-0.1518	-0.0467	-0.0322	0.0049	0.0035	0.0240	0.0044	0.0013
	Non-tr	0.7358	0.0402	0.0208	0.1967	0.1034	0.0157	0.0130	0.0203	0.0436	0.0061
HG	Agr	-0.0372	-0.0006	-0.0009	-0.0028	-0.0021	-0.3173	-0.0018	-0.0080	-0.0029	-0.0019
	Mining	-0.0325	-0.0026	-0.0015	-0.0029	-0.0042	-0.0002	-0.0001	-0.0010	-0.0002	-0.0001
	Mfg	-0.1943	-0.3436	-0.1580	-0.1013	-0.0869	0.0035	0.0054	0.0238	0.0087	0.0026
	Non-tr	0.4245	0.0216	0.0198	0.2809	0.2245	0.0254	0.0348	0.0448	0.1507	0.0338
SC	Agr	-0.0205	-0.0003	-0.0017	-0.0037	-0.0038	-0.0201	-0.0003	-0.0007	-0.0181	-0.0126
	Mining	-0.0142	-0.0012	-0.0008	-0.0035	-0.0060	-0.0004	-0.0002	-0.0023	-0.0095	-0.0055
	Mfg	-0.1024	-0.1462	-0.0963	-0.1095	-0.1936	-0.0034	-0.0053	-0.0208	-0.0652	-0.0328
	Non-tr	0.1579	0.0072	0.0099	0.2014	0.3273	0.0017	0.0020	0.0034	0.0875	0.1025
CG	Agr	-0.0102	-0.0001	-0.0010	-0.0020	-0.0067	-0.0014	0.0000	-0.0001	-0.0097	-0.0071
	Mining	-0.0031	-0.0002	-0.0002	-0.0015	-0.0137	0.0000	-0.0001	-0.0007	-0.0070	-0.0043
	Mfg	-0.0186	-0.0312	-0.0321	-0.0794	-0.4011	-0.0007	-0.0005	-0.0054	-0.0851	-0.0400
	Non-tr	0.0312	0.0019	0.0023	0.0770	0.4886	0.0002	0.0002	0.0008	0.0429	0.1180
AD	Agr	-0.0034	0.0000	-0.0003	-0.0005	-0.0112	-0.0014	0.0000	-0.0001	-0.0097	-0.0071
	Mining	-0.0008	-0.0001	0.0000	-0.0003	-0.0106	0.0000	-0.0001	-0.0007	-0.0070	-0.0043
	Mfg	-0.0067	-0.0120	-0.0144	-0.0254	-0.3351	-0.0007	-0.0005	-0.0054	-0.0855	-0.0402
	Non-tr	0.0067	0.0005	0.0005	0.0144	0.3988	0.0002	0.0002	0.0008	0.0431	0.1190

Notes: Numbers are linear differences of employment shares in %.

Table A7: Changes in the Type-level Welfare Resulting from Changes in China's Productivity (%)

	HD	HG	SC	CG	AD
Argentina	1.43	2.02	2.11	2.13	2.27
Australia	0.58	0.93	1.01	1.25	1.24
Austria	1.15	1.60	1.21	1.63	1.63
Brazil	0.92	2.48	2.77	2.83	2.98
Canada	1.31	1.64	1.80	2.02	2.02
Chile	0.60	1.22	1.40	1.48	1.34
Denmark	0.43	1.23	1.37	1.61	1.60
Finland	0.09	0.22	0.25	0.31	0.30
France	1.31	1.54	1.32	1.60	1.69
Germany	0.88	1.28	1.16	1.81	1.81
Greece	1.78	2.77	2.98	3.37	3.48
Hungary	0.73	0.79	0.74	0.84	0.84
Iceland	1.47	1.76	1.85	2.17	2.17
India	1.48	1.66	1.81	1.98	1.98
Indonesia	1.18	1.25	1.46	1.54	1.57
Ireland	0.62	0.67	0.71	0.77	0.77
Israel	4.08	3.95	4.03	4.23	4.24
Italy	1.42	1.50	1.63	1.95	1.95
Japan	1.53	1.46	1.48	1.67	1.67
Republic of Korea	0.80	0.82	0.84	0.93	0.93
Mexico	1.18	1.11	1.25	1.34	1.33
Netherlands	0.74	0.82	0.77	0.81	0.75
New Zealand	1.39	1.46	1.51	1.73	1.73
Poland	2.00	2.22	2.29	2.56	2.55
Portugal	-0.03	-0.03	0.02	0.04	0.09
Spain	1.34	1.41	1.73	1.74	1.85
Sweden	1.14	1.26	1.31	1.50	1.49
Switzerland	1.29	1.47	1.47	1.81	1.81
Turkey	2.46	2.50	2.74	3.34	3.34
United Kingdom	1.45	1.61	1.78	1.83	1.83
United States	0.83	0.93	1.09	1.16	1.26
ROW	1.41	8.49	12.35	13.28	13.30

Notes: Numbers are in %. China is not included in this table, because the introduced shock includes both trade-related effect and the own-productivity effect for China.

Table A8: Changes in Real Wages and Employment Shares across Industries and Occupations Resulting from Changes in China's Productivity (%)

	A. Counterfactual change in real wage									B. Counterfactual change in employment share								
	I. By industries				II. By occupations					I. By industries				II. By occupations				
	Agr	Mining	Mfg	Non-tr	LSO	AMO	PPC	ACS	MPT	Agr	Mining	Mfg	Non-tr	LSO	AMO	PPC	ACS	MPT
Argentina	0.15	0.35	0.34	0.38	0.25	0.42	0.31	0.49	0.52	-0.36	0.01	-0.29	0.65	0.00	-0.05	-0.11	0.11	0.06
Australia	-0.02	0.03	0.03	0.04	-0.02	-0.01	-0.01	0.02	0.17	-0.20	-0.01	-0.32	0.54	-0.15	-0.04	-0.05	0.18	0.06
Austria	0.16	0.26	0.26	0.34	0.15	0.18	0.15	0.31	0.43	0.02	-0.01	-0.61	0.60	-0.02	-0.07	-0.09	0.11	0.06
Brazil	-1.06	-0.70	-0.51	-0.39	-0.95	-0.65	-0.79	-0.31	0.29	-0.92	-0.02	-0.08	1.02	-0.77	0.05	0.16	0.52	0.04
Canada	0.25	0.29	0.31	0.34	0.26	0.26	0.27	0.31	0.46	-0.11	-0.07	-0.50	0.68	-0.19	-0.14	-0.01	0.23	0.11
Chile	-0.17	0.16	0.06	0.13	-0.11	0.03	-0.03	0.15	0.39	-0.39	-0.09	0.03	0.45	-0.18	0.01	0.04	0.10	0.03
Denmark	-0.47	-0.12	-0.31	-0.20	-0.43	-0.40	-0.37	-0.15	0.08	-1.00	-0.22	0.56	0.66	-0.80	0.13	0.23	0.33	0.11
Finland	-0.11	-0.08	-0.08	-0.06	-0.11	-0.10	-0.09	-0.06	-0.01	-0.15	-0.01	0.01	0.15	-0.11	0.01	0.02	0.06	0.02
France	0.28	0.29	0.32	0.32	0.25	0.27	0.25	0.32	0.38	-0.06	-0.01	-0.53	0.60	0.00	-0.16	-0.04	0.14	0.06
Germany	-0.42	-0.42	-0.37	-0.27	-0.45	-0.48	-0.43	-0.31	0.03	-0.05	-0.01	-0.74	0.80	-0.06	-0.04	-0.21	0.23	0.07
Greece	-0.33	-0.16	-0.04	0.13	-0.20	-0.12	-0.13	0.20	0.48	-0.66	-0.03	-0.52	1.21	-0.53	0.00	-0.06	0.41	0.17
Hungary	0.32	0.31	0.33	0.33	0.30	0.32	0.32	0.33	0.35	-0.02	0.00	-0.15	0.17	-0.01	-0.01	-0.04	0.05	0.01
Iceland	-0.05	0.02	0.05	0.08	-0.04	-0.01	0.00	0.08	0.30	-0.14	-0.01	-0.68	0.84	-0.08	-0.11	-0.12	0.24	0.07
India	0.17	0.21	0.23	0.24	0.17	0.23	0.22	0.26	0.30	-0.07	-0.01	-0.21	0.29	-0.02	-0.01	-0.08	0.05	0.07
Indonesia	0.09	0.11	0.11	0.11	0.09	0.10	0.09	0.11	0.20	-0.06	0.02	-0.26	0.30	-0.01	-0.02	-0.07	0.09	0.01
Ireland	0.15	0.17	0.19	0.18	0.15	0.15	0.16	0.17	0.22	-0.04	-0.02	-0.18	0.23	-0.03	-0.03	-0.03	0.06	0.02
Israel	2.01	2.49	2.01	2.03	2.00	1.97	1.98	1.96	2.11	0.10	-0.56	0.04	0.41	0.09	-0.04	-0.17	0.07	0.05
Italy	0.06	0.10	0.10	0.12	0.06	0.07	0.07	0.11	0.25	0.03	0.00	-0.68	0.65	-0.02	-0.09	-0.14	0.21	0.03
Japan	0.41	0.43	0.45	0.43	0.41	0.42	0.42	0.41	0.51	0.21	0.00	-0.71	0.50	0.17	-0.12	-0.17	0.09	0.02
Republic of Korea	0.24	0.22	0.27	0.26	0.25	0.25	0.25	0.26	0.31	0.04	0.03	-0.32	0.25	0.04	-0.04	-0.07	0.06	0.01
Mexico	0.32	0.32	0.30	0.32	0.31	0.29	0.30	0.30	0.42	0.05	-0.03	-0.31	0.29	0.06	-0.07	-0.09	0.08	0.01
Netherlands	0.35		0.38	0.37	0.37	0.36	0.38	0.37	0.31	0.16	0.00	-0.31	0.15	0.04	-0.04	-0.06	0.01	0.05
New Zealand	0.25	0.31	0.33	0.33	0.26	0.28	0.28	0.31	0.45	0.09	-0.01	-0.65	0.57	0.08	-0.10	-0.14	0.12	0.04
Poland	0.47	0.52	0.54	0.55	0.48	0.50	0.51	0.56	0.67	-0.07	-0.01	-0.65	0.73	-0.04	-0.10	-0.13	0.22	0.05
Portugal	-0.16	-0.20	-0.16	-0.16	-0.17	-0.17	-0.16	-0.16	-0.13	0.10	0.01	-0.23	0.12	0.07	-0.03	-0.06	0.02	0.00
Spain	0.27	0.31	0.33	0.35	0.28	0.29	0.27	0.32	0.48	-0.04	-0.01	-0.48	0.53	0.02	-0.12	-0.08	0.13	0.05
Sweden	0.22	0.35	0.27	0.27	0.22	0.24	0.24	0.27	0.37	0.00	-0.07	-0.42	0.49	-0.01	-0.07	-0.09	0.14	0.04
Switzerland	-0.01		0.01	0.02	-0.05	-0.02	0.00	-0.02	0.15	0.02	0.00	-0.79	0.77	0.07	-0.08	-0.26	0.19	0.09
Turkey	0.13	0.17	0.19	0.23	0.14	0.13	0.13	0.19	0.64	0.12	0.00	-0.73	0.60	0.15	0.01	-0.39	0.21	0.03
United Kingdom	0.25	0.32	0.30	0.31	0.25	0.24	0.28	0.31	0.41	0.03	-0.02	-0.69	0.69	0.04	-0.17	-0.07	0.17	0.03
United States	0.08	0.06	0.12	0.12	0.06	0.08	0.09	0.09	0.20	-0.03	0.01	-0.53	0.55	0.08	-0.15	-0.07	0.07	0.07
ROW	-6.91	-4.82	-4.78	-4.24	-6.77	-5.31	-5.57	-3.51	-1.30	-8.47	0.57	3.60	4.29	-6.70	1.16	2.60	2.23	0.71

Notes: Numbers are in %. Counterfactual changes in real wages are proportional changes, and changes in employment shares are in linear difference. China is not included in this table, because the introduced shock includes both trade-related effect and the own-productivity effect for China.

Figure A1: Within-type Labor Allocation across Industries and Occupations in 2000 by Country Group

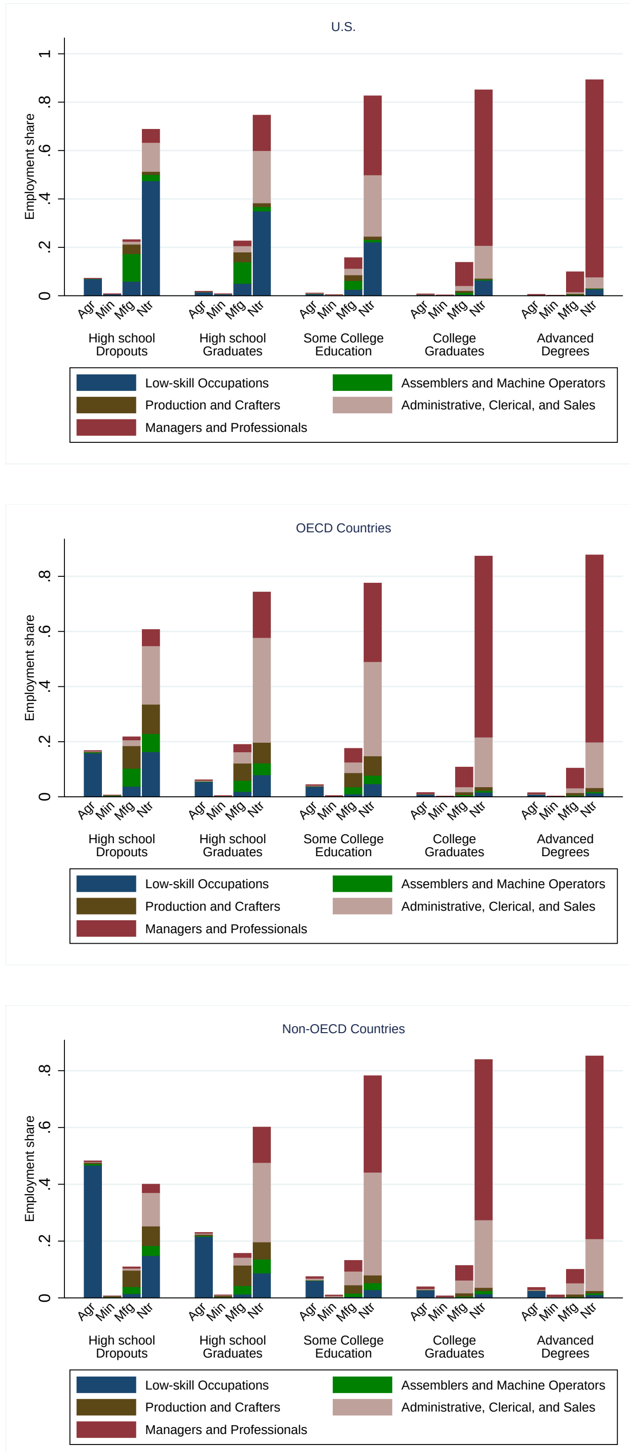
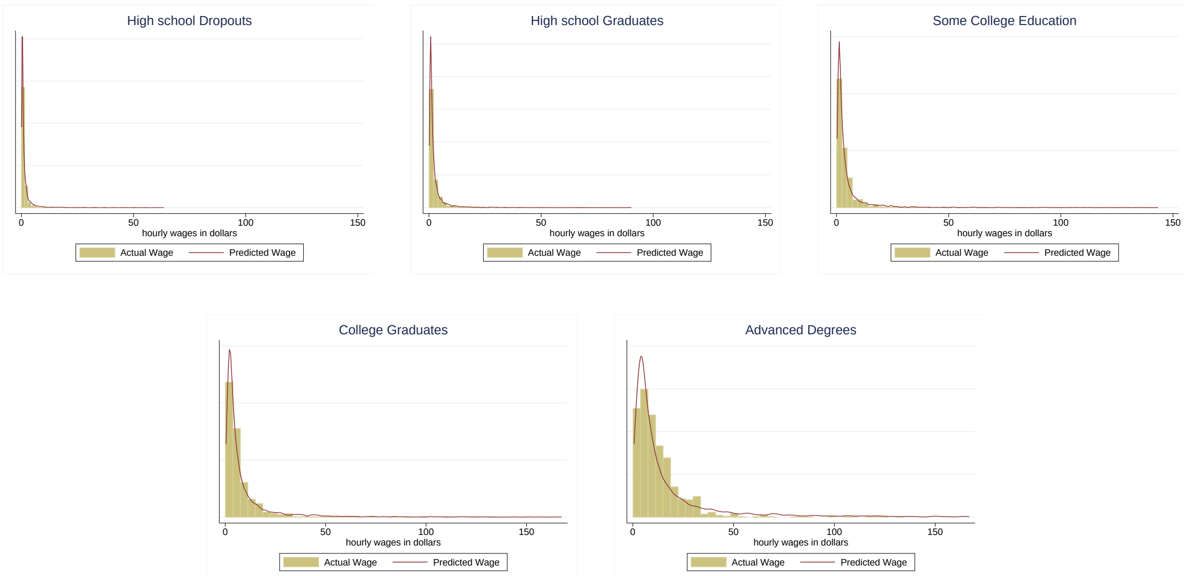


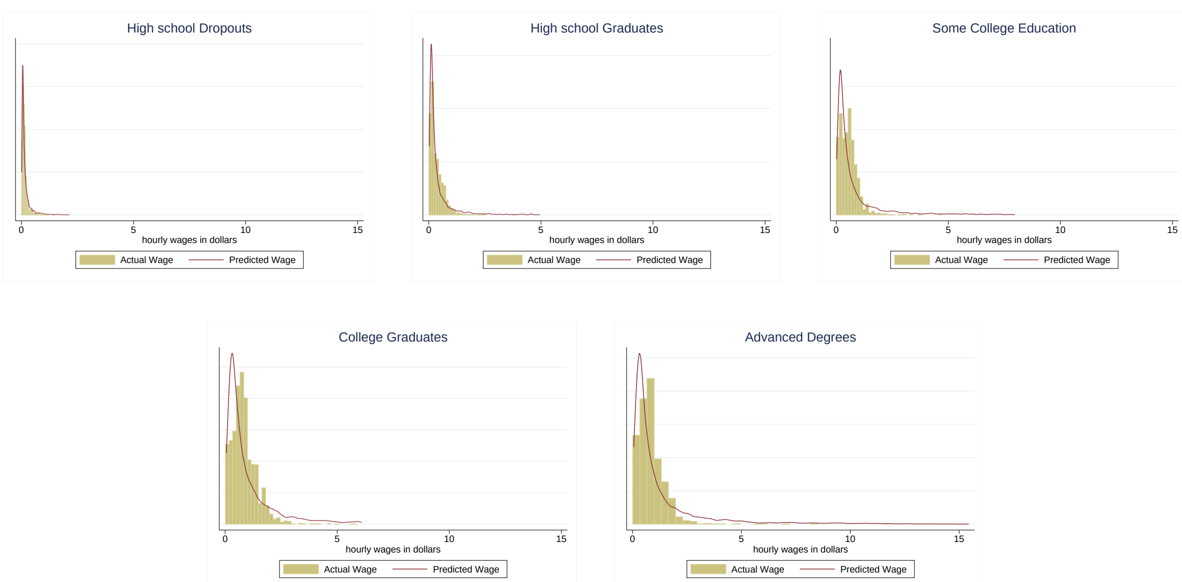
Figure A2: Model Fit with the ML Estimates of $\theta_{i,\tau}$ for Within-type Wage Distribution

(a) Brazil (2000)

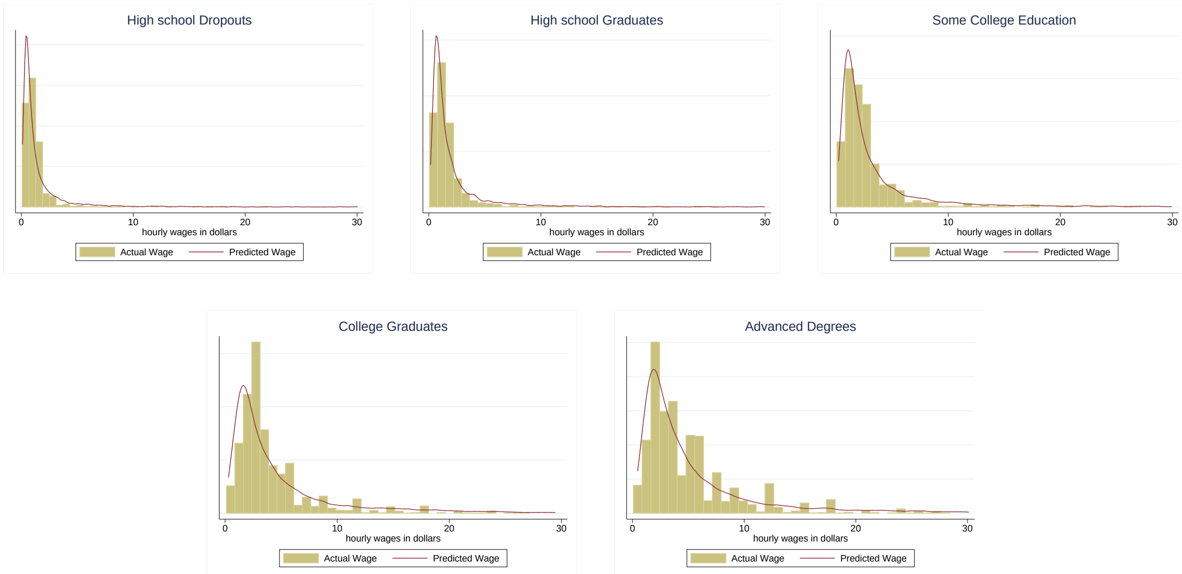


Notes: The estimation for non-U.S. countries is with the local currency. Fits are drawn in terms of U.S. dollar converted with the exchange rates of the corresponding year for expositional purposes.

(b) India (1999)



(c) Mexico (2000)



(d) U.S. (2000)

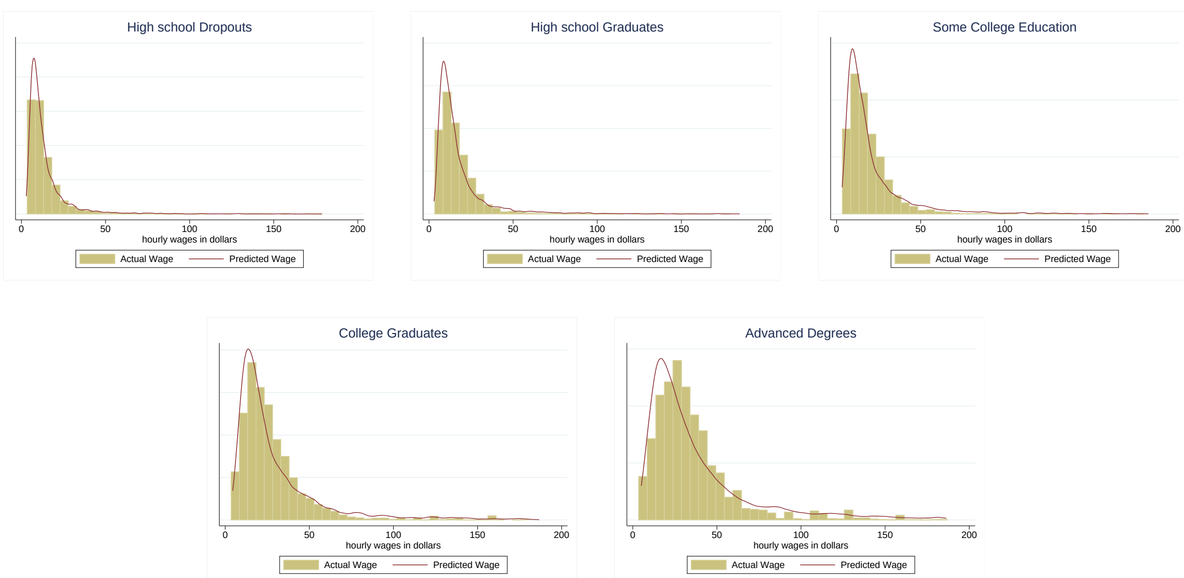


Figure A3: Calibrated Changes in Bilateral Trade Costs by Industry

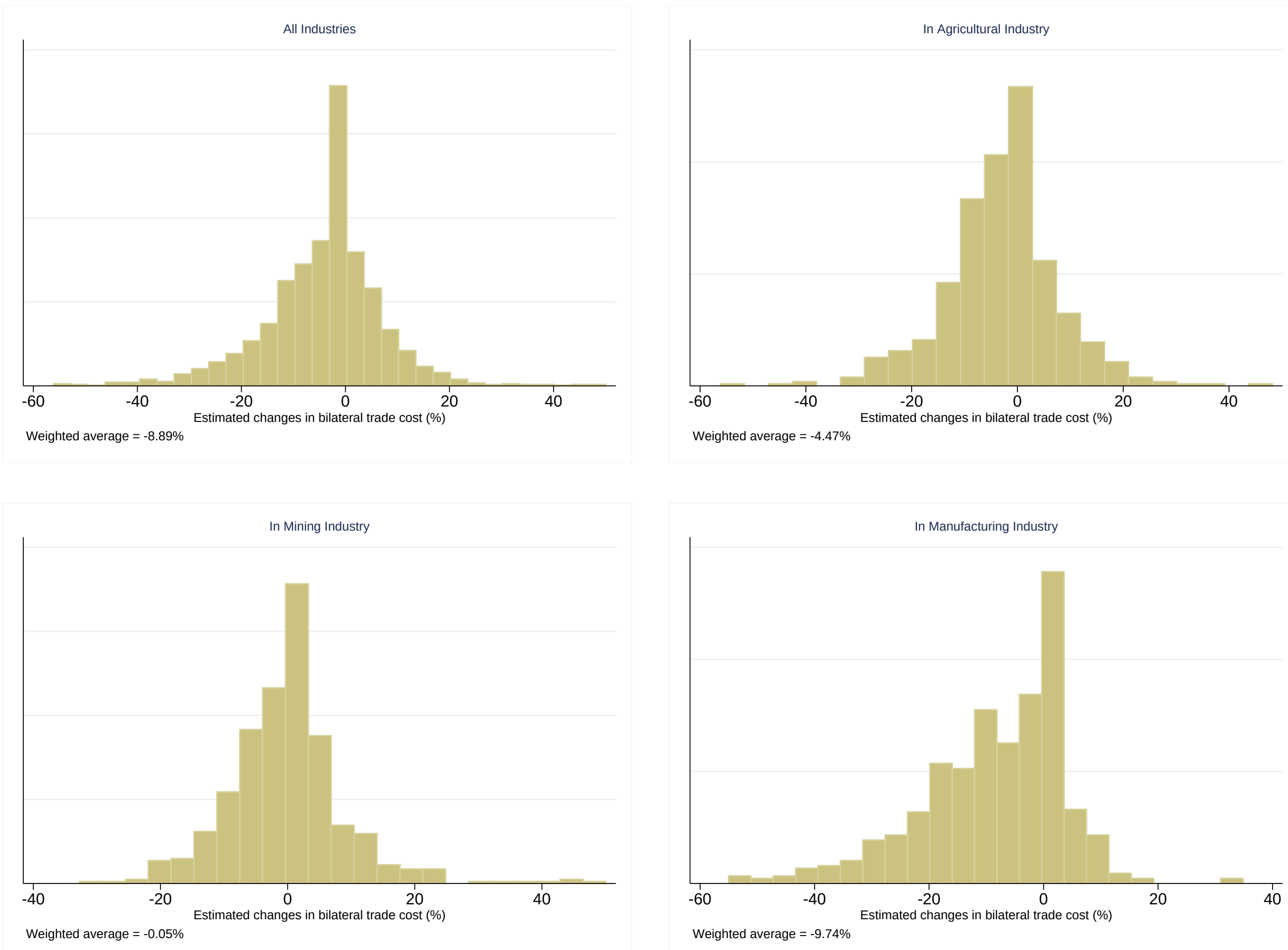


Figure A4: Counterfactual Changes in Welfare and Calibrated Changes in Bilateral Trade Costs

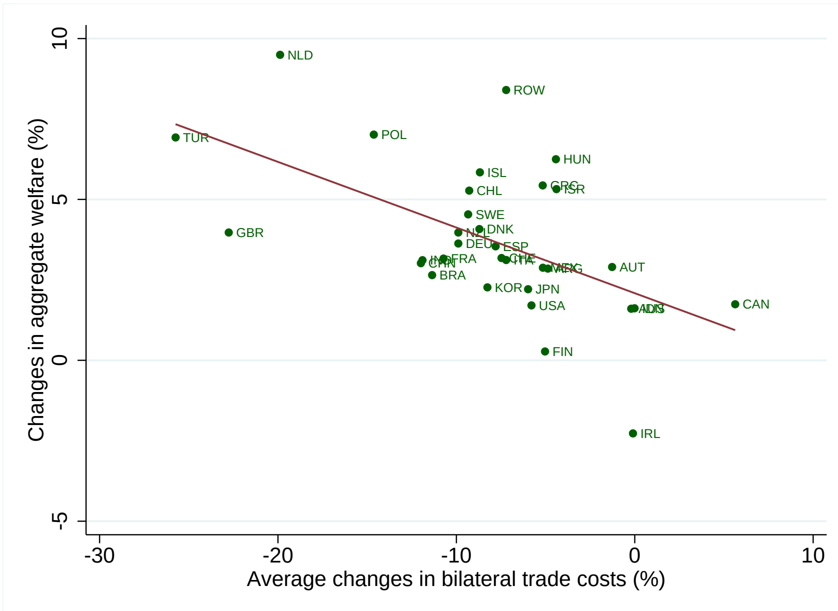


Figure A5: Counterfactual Changes in the Skill Premium and Calibrated Changes in Bilateral Trade Costs

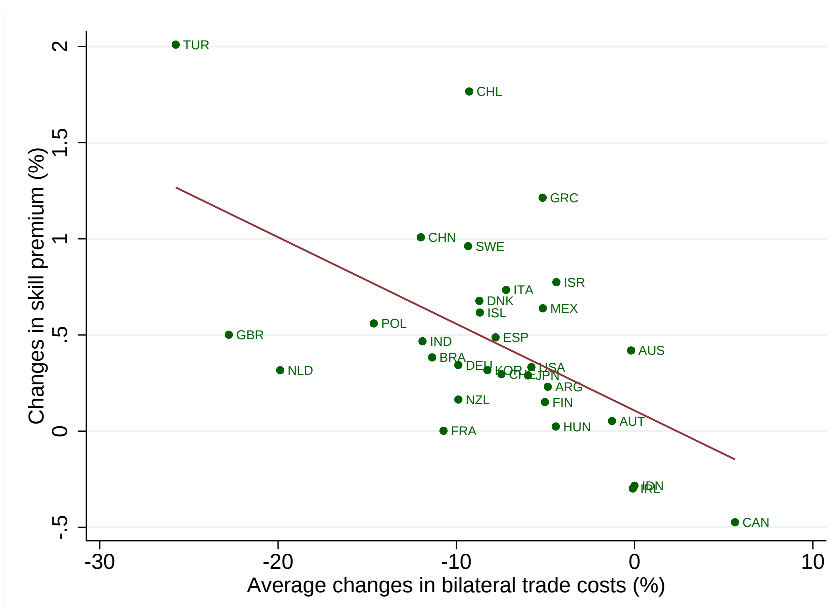
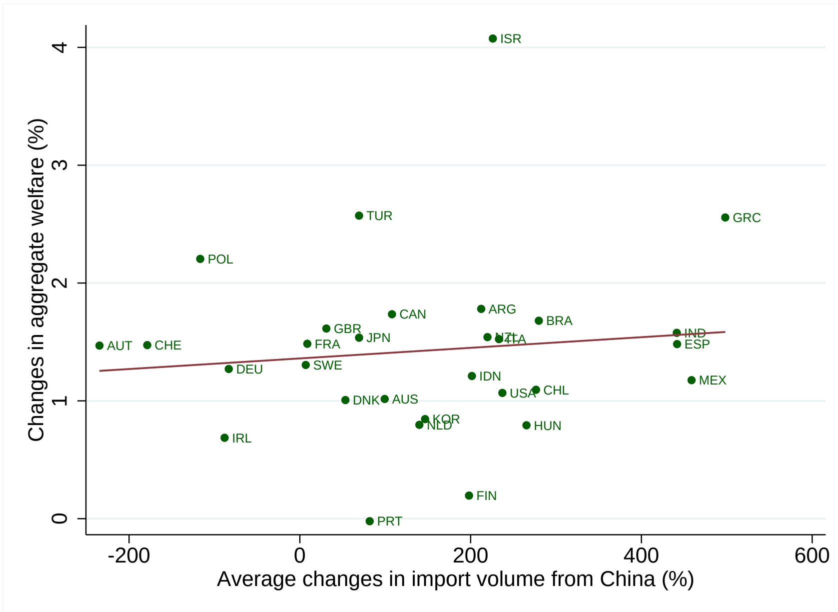
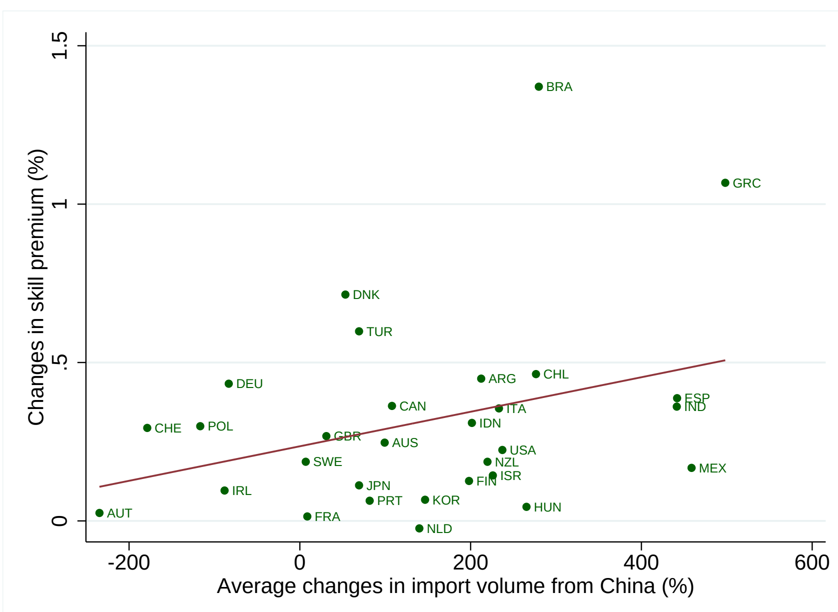


Figure A6: Counterfactual Changes in Welfare and Changes in Imports from China



Note: For expositional purposes, this figure excludes China and ROW.

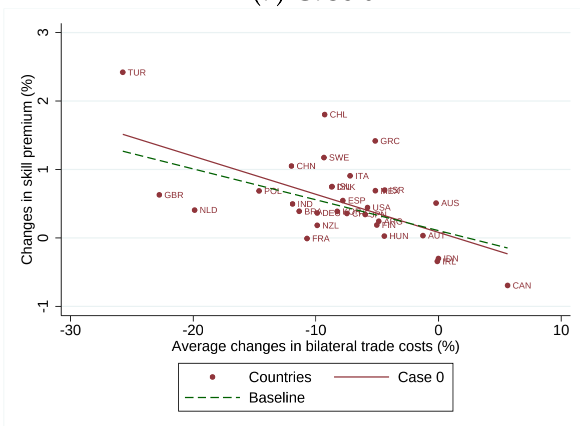
Figure A7: Counterfactual Changes in the Skill Premium and Changes in Imports from China



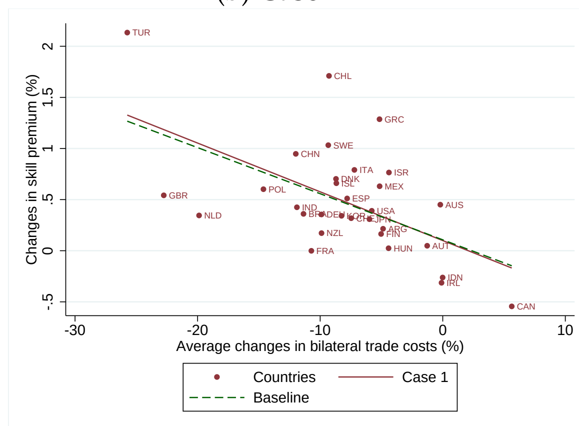
Note: For expositional purposes, this figure excludes China and ROW.

Figure A8: Counterfactual Changes in the Skill Premium and Calibrated Changes in Bilateral Trade Costs for Different $\theta_{i,\tau}$

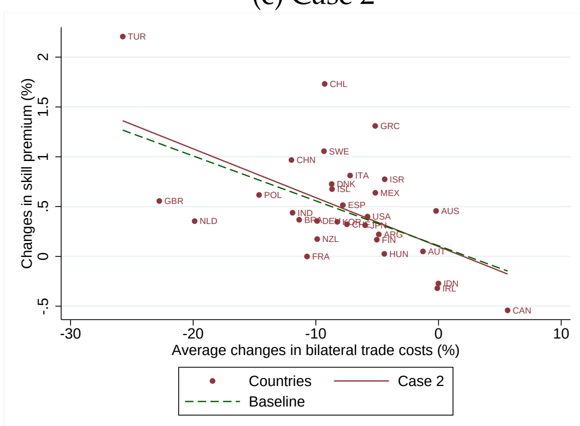
(a) Case 0



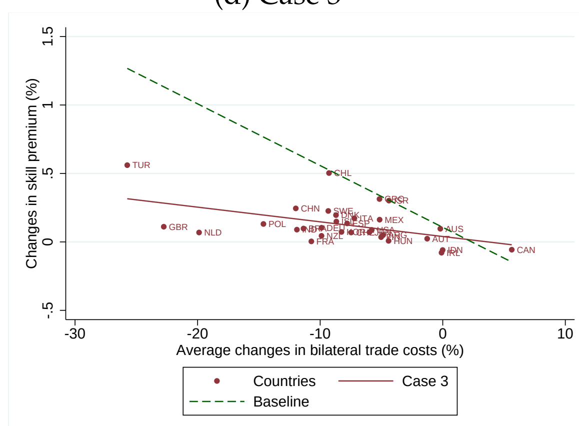
(b) Case 1



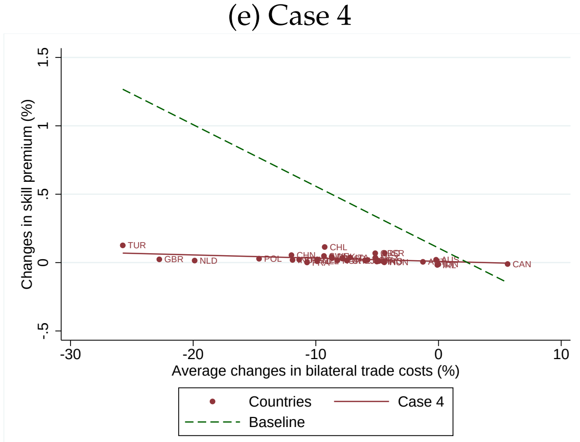
(c) Case 2



(d) Case 3



(e) Case 4



(f) Limit Case

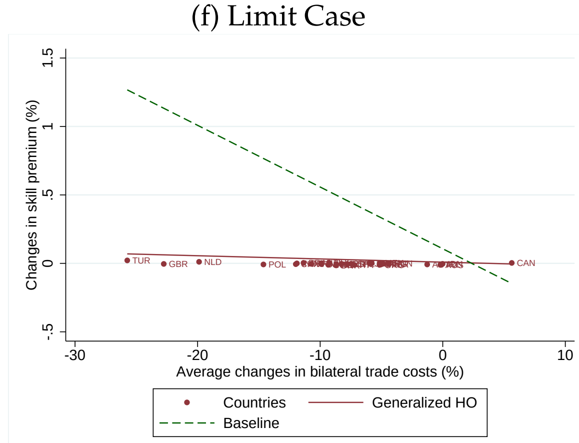
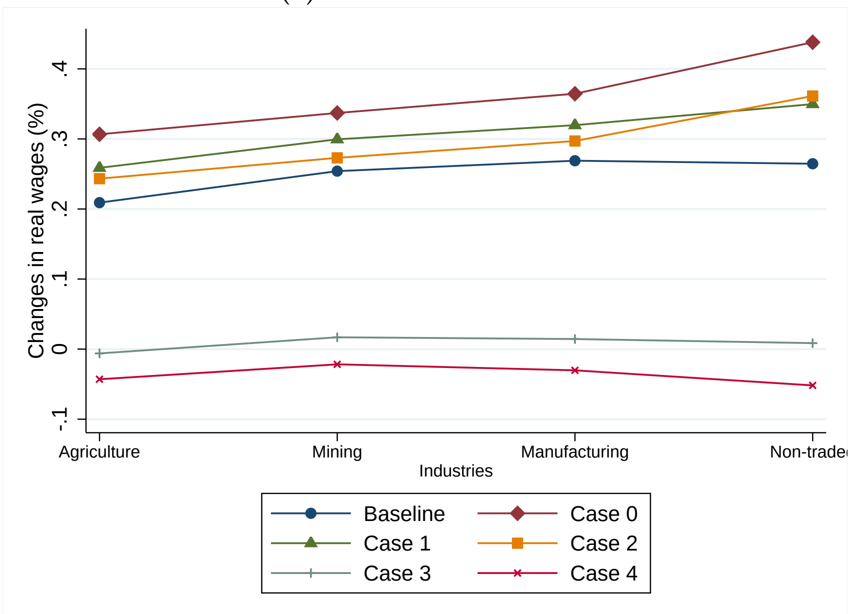


Figure A9: Changes in Real Wages Resulting from Changes in Trade Costs in the U.S. for Different $\theta_{i,\tau}$

(a) Across Industries



(b) Across Occupations

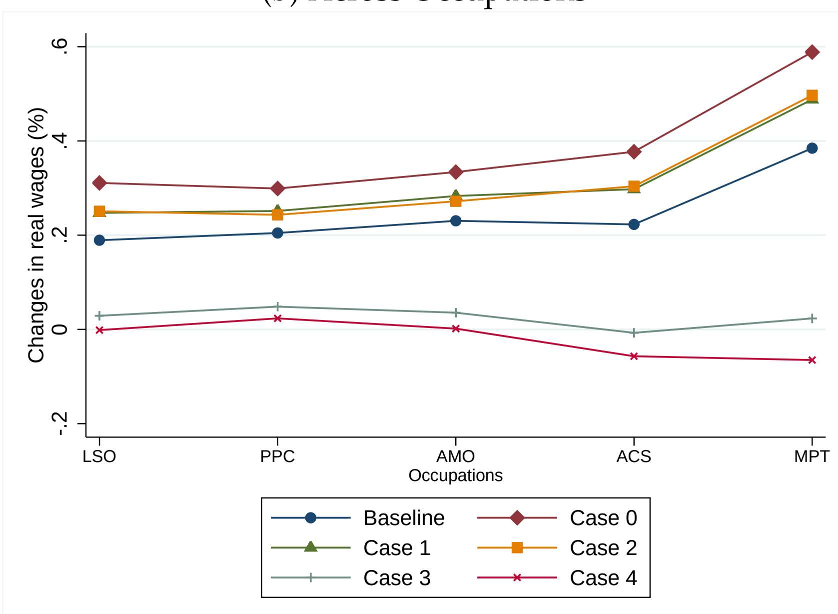


Figure A10: Changes in the Type-level Welfare for Different γ

(a) U.S. (b) China

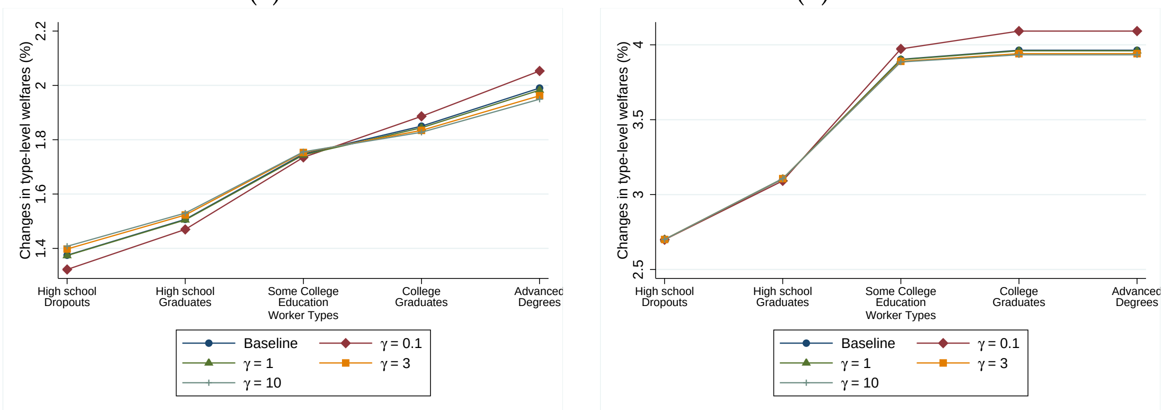


Figure A11: Changes in the Industry-level Real Wages for Different γ

(a) U.S. (b) China

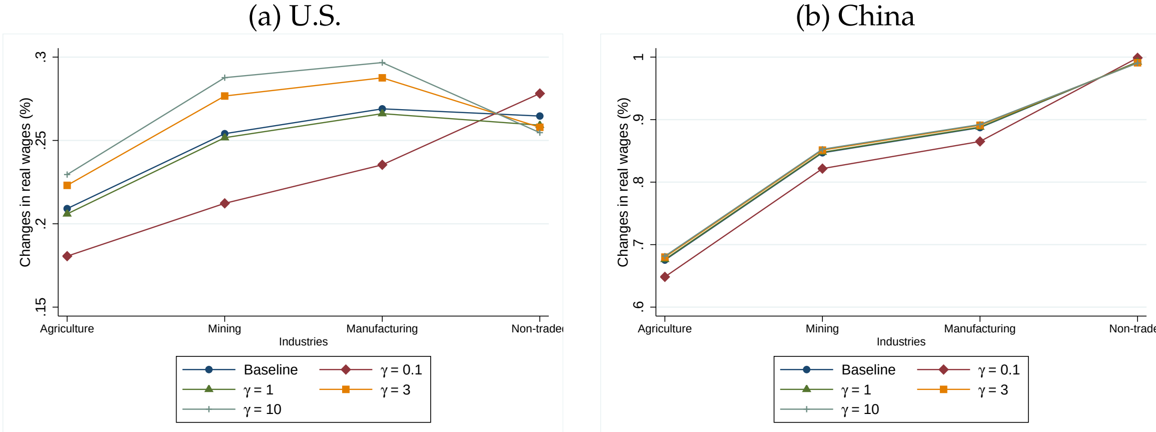


Figure A12: Changes in Occupation-level Real Wages for Different γ

(a) U.S. (b) China

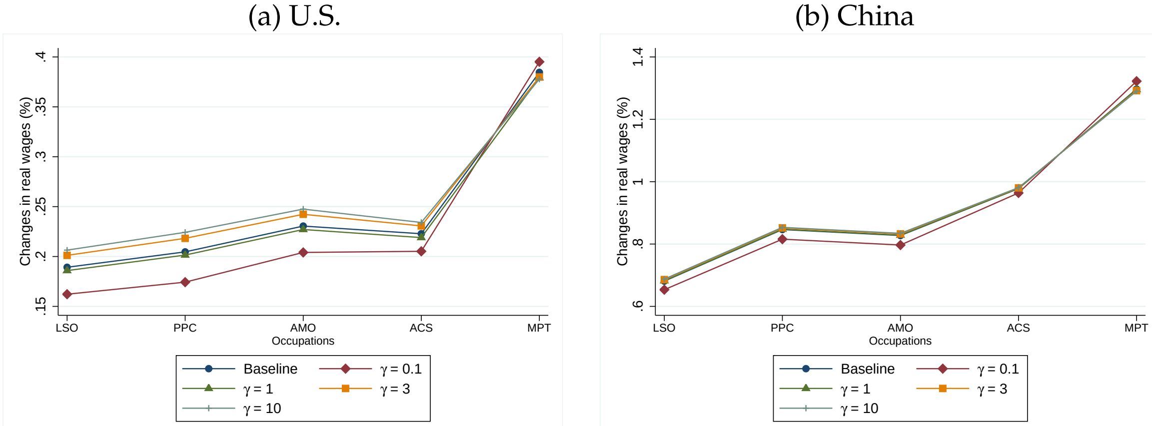
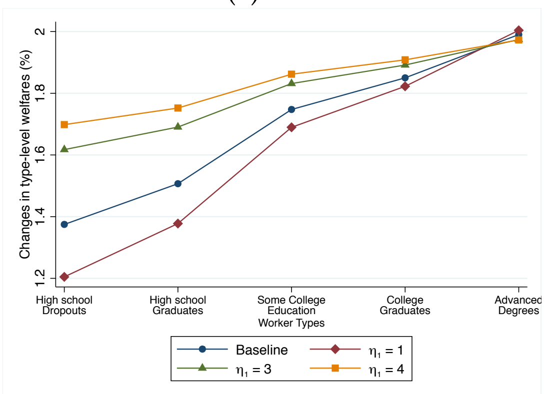


Figure A13: Changes in Type-level Welfare for Different η_1

(a) U.S.



(b) China

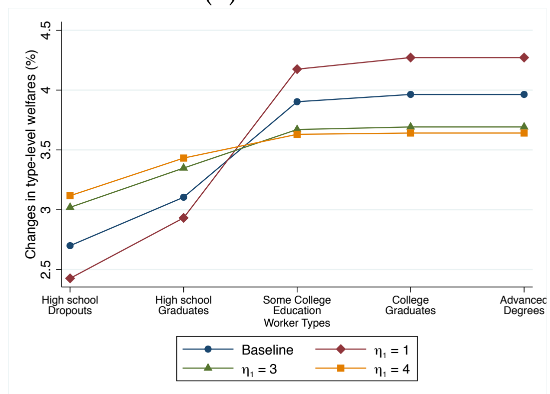
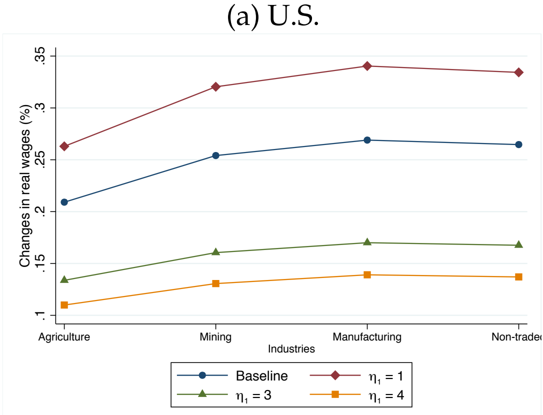


Figure A14: Changes in Industry-level Real Wages for Different η_1

(a) U.S.



(b) China

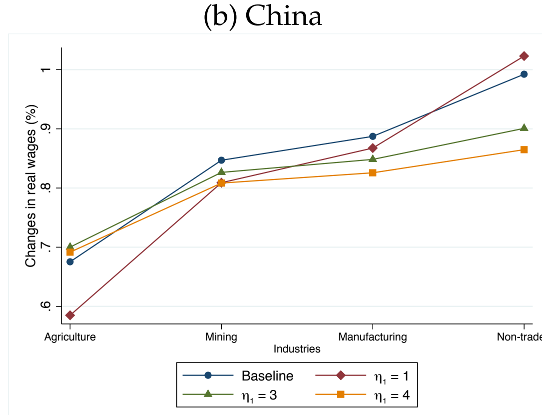
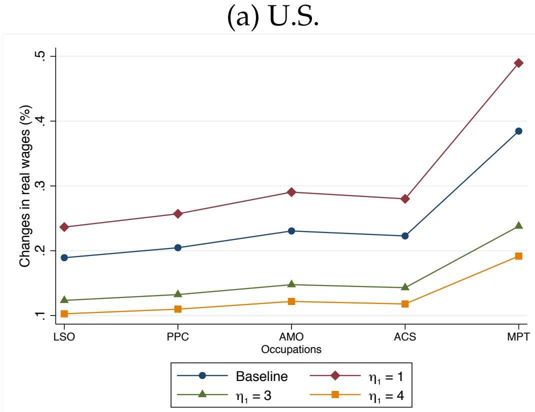


Figure A15: Changes in Occupation-level Real Wages for Different η_1

(a) U.S.



(b) China

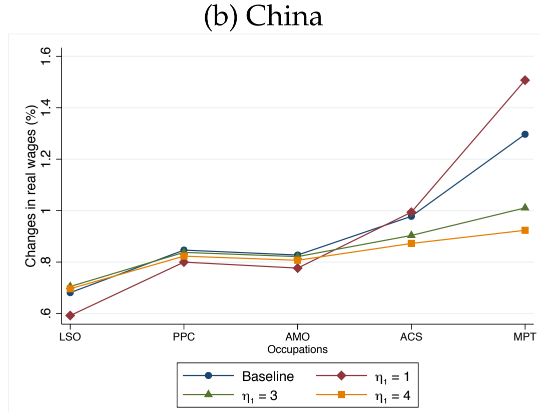
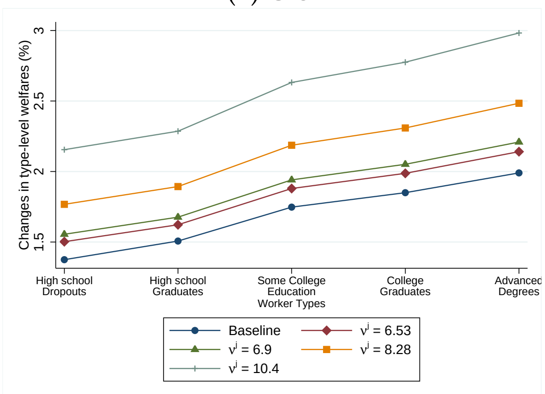


Figure A16: Changes in Type-level Welfare for Different ν^j

(a) U.S.



(b) China

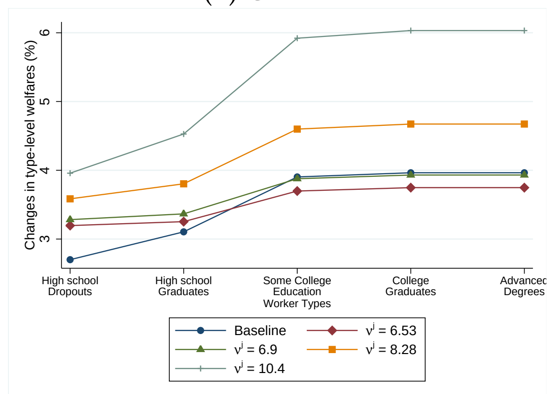
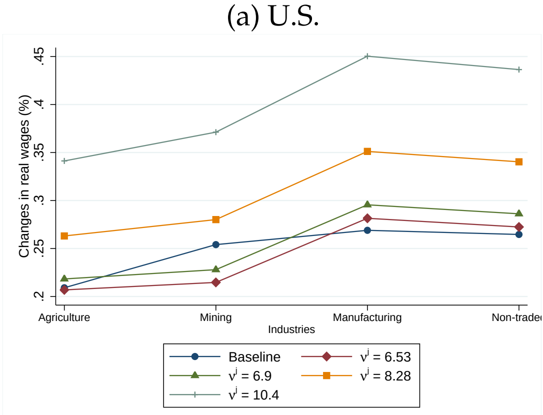


Figure A17: Changes in Industry-level Real Wages for Different ν^j

(a) U.S.



(b) China

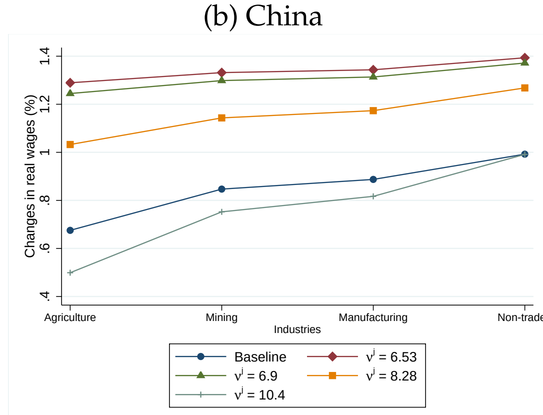
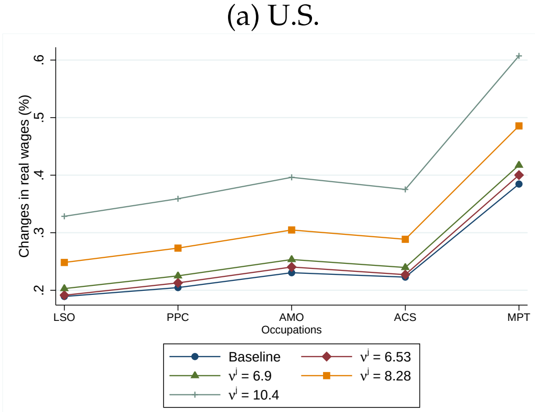
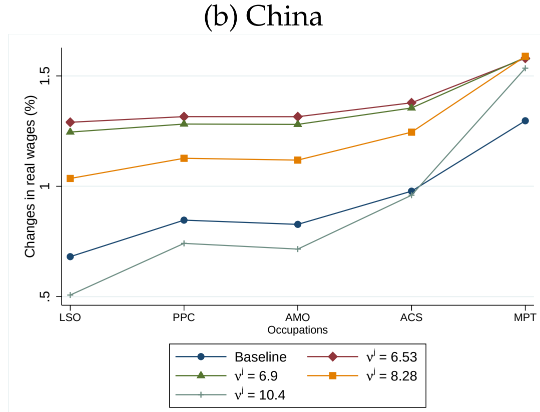


Figure A18: Changes in Occupation-level Real Wages for Different ν^j

(a) U.S.



(b) China



B Derivations of Equations in the Model

B.1 Occupational Choice Problem

Derivations of labor allocation, distribution of type-level wage and corresponding average wage for each worker type are all from a Fréchet property. First, each worker ω in country i solves the following occupational choice problem

$$\max_{j,o} w_{i,\omega}^{j,o} = p_i^{j,o}\epsilon_\omega^{j,o},$$

where $p_i^{j,o}$ is an endogenous per-unit price for labor input and $\epsilon_\omega^{j,o}$ is an idiosyncratic productivity of worker ω for (j,o). In the partial equilibrium analysis, $p_i^{j,o}$ is given.

Within-type labor allocation $\pi_{i,\tau}^{j,o}$ The labor allocation in equation (3) can be derived by using a Fréchet property. The equilibrium probability that a worker ω of type τ works in occupation o^* and industry j^* of country i is given as below.

$$\begin{aligned}
\pi_{i,\tau}^{j,o} &= \Pr[w_{i,\omega}^{j,o} > w_{i,\omega}^{j',o'}\ \forall j' \neq j \text{ and } \forall o' \neq o] \\
&= \Pr[p_i^{j,o}\epsilon_\omega^{j,o} > p_i^{j',o'}\epsilon_\omega^{j',o'}\ \forall j' \neq j \text{ and } \forall o' \neq o] \\
&= \Pr[\epsilon_\omega^{j',o'} < (\frac{p_i^{j,o}}{p_i^{j',o'}})\epsilon_\omega^{j,o}\ \forall j' \neq j \text{ and } \forall o' \neq o] \\
&= \prod_{\substack{j'\neq j\\ o'\neq o}} \Pr[\epsilon_\omega^{j',o'} < (\frac{p_i^{j,o}}{p_i^{j',o'}})\epsilon_\omega^{j,o}] \quad \text{, from independence assumption} \\
&= \int F_{i,\tau}^{j,o}((\frac{p_i^{j,o}}{p_i^{j_1,o_1}})\epsilon, \ldots, (\frac{p_i^{j,o}}{p_i^{j_J,o_O}})\epsilon)d\epsilon \\
&\qquad \text{where } F_{i,\tau}^{j,o}(\epsilon) \text{ is a marginal distribution of } F_{i,\tau}(\epsilon) \text{ with respect to } (j,o)\text{-th} \\
&\qquad \text{dimension of } (J \times O)\text{-dimensional vector } \epsilon \\
&= \int \theta_{i,\tau} T_{i,\tau}^{j,o}\epsilon^{-\theta_{i,\tau}-1}\exp(-\sum_{j',o'} T_{i,\tau}^{j,o}(\frac{p_i^{j,o}}{p_i^{j',o'}})^{-\theta_{i,\tau}}\epsilon^{-\theta_{i,\tau}})d\epsilon \\
&= \frac{\bar{T}_{i,\tau}^{j,o}}{\sum_{j',o'}\bar{T}_{i,\tau}^{j',o'}} \int \theta_{i,\tau}(p_i^{j,o})^{-\theta_{i,\tau}} \sum_{j',o'} \bar{T}_{i,\tau}^{j',o'} \epsilon^{-\theta_{i,\tau}-1} \exp(-(p_i^{j,o})^{-\theta_{i,\tau}} \sum_{j',o'} \bar{T}_{i,\tau}^{j',o'}\epsilon^{-\theta_{i,\tau}})d\epsilon \\
&\qquad \text{where } \bar{T}_{i,\tau}^{j,o} \equiv T_{i,\tau}^{j,o}(p_i^{j,o})^{\theta_{i,\tau}} \text{ is an effective productivity.} \\
&= \frac{\bar{T}_{i,\tau}^{j,o}}{\sum_{j',o'}\bar{T}_{i,\tau}^{j',o'}} \int d\tilde{F}_{i,\tau}(\epsilon) \\
&\qquad \text{where } \tilde{F}_{i,\tau}(\epsilon) = \exp(-(p_i^{j,o})^{-\theta_{i,\tau}} \sum_{j',o'} \bar{T}_{i,\tau}^{j',o'}\epsilon^{-\theta_{i,\tau}}) \text{ is another Fréchet distribution.} \\
&= \frac{\bar{T}_{i,\tau}^{j,o}}{\sum_{j',o'}\bar{T}_{i,\tau}^{j',o'}}
\end{aligned}$$

Average wage for each type $w_{i,\tau}$ The average wage for each type τ in each country i is an expectation of distribution of equilibrium wage of each type τ conditional on worker's equilibrium choice of industry and occupation. The unconditional distribution of type τ worker's potential wage for a certain pair (j, o) is

$$\begin{aligned} G^{j,o}_{i,\tau}(w) &= \Pr[w^{j,o}_{i,\omega} \leq w] \\ &= \Pr[\epsilon^{j,o}_{\omega} \leq \frac{w}{p^{j,o}_i}] \\ &= \exp[-\bar{T}^{j,o}_{i,\tau} w^{-\theta_{i,\tau}}] \end{aligned}$$

from the distributional assumption for the idiosyncratic productivity $\epsilon^{j,o}_{\omega}$. This distribution is again a Fréchet distribution with a location parameter $\bar{T}^{j,o}_{i,\tau}$ and a shape parameter $\theta_{i,\tau}$. I derive the equilibrium distribution of wage of type τ workers conditional on the choice of industry and occupation in worker's occupational choice problem by simply deriving the distribution of the maximum of potential wages. From the property of the extremum distribution, the distribution $G^{*}_{i,\tau}(w)$ is again a Fréchet distribution.

$$G^{*}_{i,\tau}(w) = \exp[-\sum_{j',o'} \bar{T}^{j',o'}_{i,\tau} w^{-\theta_{i,\tau}}]$$

Since the distribution of equilibrium wage only depends on the type, within-type heterogeneity is summed out once the equilibrium occupational choice is given. The average wage for each type is straight-forward by taking an expectation of the distribution function $G^{*}_{i,\tau}(w)$, which gives

$$w_{i,\tau} = (\sum_{j',o'} \bar{T}^{j',o'}_{i,\tau})^{\frac{1}{\theta_{i,\tau}}} \Gamma(1 - \frac{1}{\theta_{i,\tau}}),$$

where $\Gamma(\cdot)$ is a Gamma function.

B.2 Production

Assume that there is an intermediate labor-input-producing unit in each industry which produces the labor input using workers' labor supply and sells it to final goods producers with zero profit. In a perfectly competitive market, a unit in each industry j employs the total labor of $\pi^{j,o}_{i,\tau}$ of type τ workers for occupation o by paying a per-unit occupational price $p^{j,o}_i$ for each efficiency unit of labor. It then produces an occupational labor input of

$$y^{j,o}_i = \sum_{\tau} L_{i,\tau} \pi^{j,o}_{i,\tau} E_{i,\tau}(\epsilon^{*}_{\omega})$$

using the total employment for occupation o, and sells this amount of labor input to final goods producers at the unit price $p^{j,o}_i$. The equilibrium labor allocation $\pi^{j,o}_{i,\tau}$ is as derived above, and the average productivity of workers who are optimally choosing (j, o) is given by

$$E_{i,\tau}(\epsilon^{*}_{\omega}) = (\sum_{j',o'} T^{j',o'}_{i,\tau})^{1/\theta_{i,\tau}} \Gamma(1 - \frac{1}{\theta_{i,\tau}}).$$

Final goods producers choose the equilibrium demand for occupational input $y_i^{j,o}$ to minimize their costs. The cost minimization problem of a final good producer for product e^j of industry j in country i is given by

$$\min_{y_i^{j,o}} \sum_o p_i^{j,o} y_i^{j,o} \quad \text{s.t.} \quad Y_i(e^j) = z_i(e^j)(\sum_o \mu_i^{j,o} (y_i^{j,o})^{\frac{\gamma-1}{\gamma}})^{\frac{\gamma}{\gamma-1}},$$

with the CES production technology and a factor-neutral productivity $z_i(e^j)$. The first-order conditions of this problem are

$$\begin{aligned} p_i^{j,o} &= \lambda z_i(e^j)^{\frac{\gamma-1}{\gamma}} \mu_i^{j,o} \frac{\gamma-1}{\gamma} (y_i^{j,o})^{-\frac{1}{\gamma}} \quad \text{for} \quad o = 1, \ldots, O & (24) \\ Y_i(e^j)^{\frac{\gamma-1}{\gamma}} &= z_i(e^j)^{\frac{\gamma-1}{\gamma}} (\sum_o \mu_i^{j,o} (y_i^{j,o})^{\frac{\gamma-1}{\gamma}}), & (25) \end{aligned}$$

where λ is a Lagrange multiplier. Rearranging (24) and (25) gives a conditional demand function for occupational labor input $y_i^{j,o}$.

$$y_i^{j,o} = z_i(e^j)^{-1} (\mu_i^{j,o})^{\gamma} (p_i^{j,o})^{-\gamma} (\sum_o (\mu_i^{j,o})^{\gamma} (p_i^{j,o})^{1-\gamma})^{\frac{\gamma}{1-\gamma}} Y_i(e^j)$$

The total cost function is thus given by

$$TC_i(e^j) = z_i(e^j)^{-1} (\sum_o (\mu_i^{j,o})^{\gamma} (p_i^{j,o})^{1-\gamma})^{\frac{1}{1-\gamma}} Y_i(e^j),$$

which gives an effective unit cost of $z_i(e^j)^{-1}(\sum_o (\mu_i^{j,o})^{\gamma} (p_i^{j,o})^{1-\gamma})^{\frac{1}{1-\gamma}}$. An industry-level unit cost function for occupational input bundle is

$$c_i^j = (\sum_o (\mu_i^{j,o})^{\gamma} (p_i^{j,o})^{1-\gamma})^{\frac{1}{1-\gamma}}.$$

B.3 International Trade

Equilibrium results for the international trade part of the model are generalizations of Eaton and Kortum (2002) to the multi-industry and multi-factor setting. The distribution of final good price can be derived from a Fréchet property, as the productivity parameter $z_i(e^j)$ follows a Fréchet distribution which is country- and industry-specific as in equation (2). The equilibrium bilateral trade flows are thus multi-industry generalization of the EK results.

Distribution of final good price The distribution of final good price can be derived from a distributional assumption for factor-neutral productivity $z_i(e^j)$ for each within-industry product variety e^j produced in country i. Given each country's equilibrium per-unit price of occupational task $p_i^{j,o}$ and iceberg trade cost, a price of product in industry j produced in country i purchased by country

j follows the following distribution.:

$$\begin{aligned} H^j_{in}(p) &= \Pr[\frac{c^j_i d^j_{in}}{z_i(e^j)} \le p] \\ &= 1 - \Pr[z_i(e^j) < \frac{c^j_i d^j_{in}}{p}] \\ & \quad 1 - \exp(-(A_i(\frac{c^j_i d^j_{in}}{p})^{-\nu^j})) \end{aligned}$$

A country buys e^j from the lowest-cost supplier in a perfectly competitive market, thus the distribution of price of a good e^j in industry j that a country n actually buys is

$$\begin{aligned} H^{*j}_n(p) &= 1 - \prod_{i=1}^{N} \Pr[P_{in}(e^j) > p] \\ &= 1 - \exp[-\Phi^j_n p^{\nu^j}] \end{aligned}$$

where $\Phi^j_n \equiv \sum_{i=1}^N A_i(c^j_i d^j_{in})^{-\nu^j}$ is an effective price parameter for industry j in country n. Since this model follows a multi-industry EK framework, the effective price parameter depends on the state of technology around the world, input costs around the world, and the geographic barriers which are industry-specific in this case.

Exact price index First, a corresponding probability density function of the distribution function $H^{*j}_n(p)$ is

$$h^{*j}_n(p) = \Phi^j_n \nu^j p^{\nu^j - 1} \exp(-\Phi^j_n p^{\nu^j}).$$

From the nested CES preference of consumers, the exact price index for industry j in country j is derived as follows.

$$\begin{aligned} (P^j_n)^{1-\eta_2} &= \int p^{1-\eta_2} dH^{*j}_n(p) \\ &= \int \Phi^j_n \nu^j p^{\nu^j - \eta_2} \exp(-\Phi^j_n p^{\nu^j}) dp \\ & \qquad \text{Define } x \equiv \Phi^j_n p^{\nu^j} \text{ to have} \\ &= (\Phi^j_n)^{\frac{\eta_2 - 1}{\nu^j}} \int x^{\frac{1-\eta_2}{\nu^j}} \exp(-x) dx \\ &= (\Phi^j_n)^{\frac{\eta_2 - 1}{\nu^j}} \Gamma(\frac{1 - \eta_2 + \nu^j}{\nu^j}), \end{aligned}$$

where $\Gamma(\cdot)$ is a gamma function, and $\nu^j + 1 > \eta_2$.

Bilateral trade flows Given the previous results, the gravity equation for each industry j is derived as follows. A probability that a country n buys good in industry j from a country i is

$$\begin{aligned}
\lambda_{in}^{j} &= \Pr[P_{in}(e^j) \leq \min_{i' \neq i}\{P_{i'n}(e^j)\}] \\
&= \int \prod_{i' \neq i}[1 - H_{i'n}^{j}(p)]dH_{in}^{j}(p) \\
&= \int A_i(c_i^j d_{in}^j)^{-\nu^j} \nu^j p^{\nu^j - 1} \exp(-\Phi_n^j p^{\nu^j})dp \\
&= \frac{A_i(c_i^j d_{in}^j)^{-\nu^j}}{\Phi_n^j} \int dH_n^{*j}(p) \\
&= \frac{A_i(c_i^j d_{in}^j)^{-\nu^j}}{\Phi_n^j}.
\end{aligned}$$

This is equal to the expenditure share $\lambda_{in}^{j} = \frac{X_{in}^j}{X_n^j}$, where X_n^j is a total expenditure for industry j in country n, and X_{in}^j is an expenditure made by country n for all industry-j products made in country i. This equality holds because $X_{in}^j = \Pr[P_{in}(e^j) \leq \min_{i' \neq i}\{P_{i'n}(e^j)\}]X_n^j$ in a perfectly competitive market.

B.4 General Equilibrium in Proportional Changes

The counterfactual equilibrium is defined by $\hat{p}_i^{j,o}$ for each $i = 1, \ldots, N$, $j = 1, \ldots, J$, and $o = 1, \ldots, O$ that satisfies the following equilibrium conditions which rewrite (3), (5)-(13) in terms of proportional changes. I use the 'hat' algebra technique developed in Dekle et al. (2008). The labor supply function for each industry and occupation in (3) becomes

$$\hat{\pi}_{i,\tau}^{j,o} = \frac{(\hat{p}_i^{j,o})^{\theta_{i,\tau}} \hat{T}_i^j}{\sum_{j',o'} (\hat{p}_i^{j',o'})^{\theta_{i,\tau}} \hat{T}_i^{j'} \pi_{i,\tau}^{j',o'}}, \tag{26}$$

and changes in the equilibrium type-level average wage is

$$\hat{w}_{i,\tau} = [\sum_{j,o} (\hat{p}_i^{j,o})^{\theta_{i,\tau}} \hat{T}_i^j \pi_{i,\tau}^{j,o}]^{\frac{1}{\theta_{i,\tau}}}. \tag{27}$$

Assuming that the occupation intensity in production $\mu_i^{j,o}$ does not vary over time i.e., $\hat{\mu}_i^{j,o} = 1$ for every i,j,o, firms' equilibrium unit cost function (6) becomes

$$\hat{c}_i^j = [\sum_o \xi_i^{j,o} (\hat{p}_i^{j,o})^{1-\gamma}]^{1/(1-\gamma)}, \tag{28}$$

where $\xi_i^{j,o} \equiv \frac{(\mu_i^{j,o})^{\gamma} (p_i^{j,o})^{1-\gamma}}{\sum_{o'} (\mu_i^{j,o'})^{\gamma} (p_i^{j',o'})^{1-\gamma}}$ is a cost share of occupation o in the unit cost of production in industry j. Change in industry-level price index is derived as

$$\hat{P}_n^j = [\sum_{i=1}^{N} \lambda_{in}^j (\hat{c}_i^j \hat{d}_{in}^j)^{-\nu^j}]^{-1/\nu^j}. \tag{29}$$

The gravity relation is reformulated in terms of changes as

$$\frac{\hat{X}^j_{in}}{\hat{X}^j_n} = (\frac{\hat{c}^j_i \hat{d}^j_{in}}{\hat{P}^j_n})^{-\nu^j} = \hat{\lambda}^j_{in}, \tag{30}$$

using changes in the unit cost and the price index that are derived as functions of $\hat{p}^{j,o}_i$ in (28) and (29). Changes in the industry-level expenditure share are

$$\hat{\lambda}^j_i = \frac{(\hat{P}^j_i)^{1-\eta_1}}{\sum_{j'} \lambda^{j'}_i (\hat{P}^{j'}_i)^{1-\eta_1}}. \tag{31}$$

Assuming $\hat{L}_{i,\tau} = 1$, the occupation market clearing condition in the counterfactual equilibrium is

$$(\frac{\hat{p}^{j,o}_i}{\hat{c}^j_i})^{1-\gamma} \hat{E}^j_i \quad = \quad \sum_\tau (\frac{w_{i,\tau} L_{i,\tau} \pi^{j,o}_{i,\tau}}{\sum_{\tau'} w_{i,\tau'} L_{i,\tau'} \pi^{j,o}_{i,\tau'}}) \hat{w}_{i,\tau} \hat{\pi}^{j,o}_{i,\tau}. \tag{32}$$

Rewriting the final goods market clearing condition derives changes in the total industry-level output $\hat{E}^j_i$,

$$\hat{E}^j_i \quad = \quad \sum_{n=1}^{N} \frac{\lambda^j_{in} X^j_n}{\sum_{n'=1}^{N} \lambda^j_{in'} X^j_{n'}} \hat{\lambda}^j_{in} \hat{X}^j_n, \tag{33}$$

where the change in the industry-level total expenditure is $\hat{X}^j_i = \hat{\lambda}^j_i \hat{I}_i$. The world total output is kept constant before and after shocks as a normalization: $\sum_{i,j} E^j_i = \sum_{i,j} E'^j_i = E$. Change in the total spending in country i is $\hat{I}_i = \frac{\sum_{j,o} \psi'^{j,o}_i + D'_i}{\sum_{j,o} \psi^{j,o}_i + D_i}$, where $\psi'^{j,o}_i = \sum_\tau w_{i,\tau} L_{i,\tau} \pi^{j,o}_{i,\tau} \hat{w}_{i,\tau} \hat{\pi}^{j,o}_{i,\tau}$ is the total labor income of workers with occupation o in industry j of country i at the counterfactual equilibrium.

C Data Description

C.1 Size of the Model

As explained in Section 3.1, there are $N = 33$ countries, $T = 5$ worker types, $J = 4$ industries, and $O = 5$ occupations. Detailed list and classification are as follows.

List of Countries The sample consists of the following 32 countries: Argentina, Australia, Austria, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Poland, Portugal, Spain, Sweden, Switzerland, Turkey, UK, and US. The last country is the rest of the world (ROW) who takes up all the remaining outputs, expenditures, and trade flows. Among the total 33 countries, Argentina, Brazil, Chile, China, India, Indonesia, Israel, and ROW are classified as non-OECD members during the sample period from 2000 to 2010. Chile and Israel joined the OECD in 2010, thus they are considered as non-OECD member countries during the sample period between 2000 and 2010.

Worker Types Any observable worker characteristics such as educational attainment, age, gender, or race technically can be used to define worker types. In this paper, worker types are defined solely by educational attainment to restrict the total dimension of the model as well as to relate the trade effect and productivity effect to the skill premium. Workers are categorized into five types defined by the educational attainment level: high school dropouts (HD), high school graduates (HG), workers with some college education (SC), college graduates (CG), and workers with advanced degrees (AD). The definition of educational attainment is specific to each country and each household-level survey. Details are discussed in the next subsection with the explanation on the dataset used for each country.

Industries I consider an aggregate sector-level definition of industries based on the major divisions (1-digit level) of the International Standard Industrial Classification (ISIC) Revision 3 classification: three tradable industries (Agriculture, Mining, and Manufacturing) and a non-traded industry which aggregates the major divisions from D to U. Household-level survey, industry-level macro data, and trade data are all aggregated up to these four industry classifications based on corresponding crosswalks.

Occupations Dorn (2009) provides a new occupation classification based on the skill levels that are required for each occupation's task and the routineness of required tasks. At the most disaggregate level, this system consists of 330 occupations which are consistent over time for the U.S. Census data. I aggregate these occupation categories into 5 upper-level groups and reorder them based on the required skill levels similar to Autor and Dorn (2013).

1. "Low-skill Occupations (LSO)" include two broad occupation groups that engage mostly in manual tasks in their classification; low-skill service occupations and transportation/construction/mechanic/mining/agriculture occupations. To expand the analysis to many other countries as well, I combine these two occupation groups into one category, since these two groups are not distinguished in the International Standard Classification of Occupations (ISCO) which most household-level survey in the other countries are based on. ISCO 06 and 09 occupations belong to this category. Thus, this occupation category describes occupations that do low-skill and manual tasks, which are distinguished from routine tasks.

2. "Assemblers and Machine Operators (AMO)" include relatively middle-skilled and routine occupations. Operators of any kind of equipments or machines such as textile cutting or sewing machines and drilling machines belong to this occupation group. Assemblers of equipment are also included in this category. (ISCO 08)

3. "Precision Production and Crafts Occupations (PPC)" also include relatively middle-skilled and routine occupations. General production workers as well as workers engaging in the production that requires precision all belong to this category: e.g., precision grinders and fitters, furniture/wood finishers, shoemakers, and bookbinders. (ISCO 07)

4. "Administrative, Clerical, and Sales Occupations (ACS)" are also classified as middle-skilled and routine occupations, but they require relatively more high-skilled tasks than the last two routine occupations do. This category includes sales and administrative support occupations such as salespersons, cashiers, secretaries, and bank tellers. (ISCO 04 and 05)

5. "Managers, Professionals, and Technicians (MPT)" include the most high-skilled occupations that engage in abstract tasks. For example, this occupation category includes CEOs, engineers, doctors, and professors. (ISCO 01, 02, and 03)

C.2 Labor Market Information from the IPUMS - International

The Integrated Public Use Microdata Series (IPUMS)-International database provides the detailed labor allocation information for around 2000 for the following countries in the sample: Argentina (2001), Austria (2001), Brazil (2000), Canada (2001), Chile (2002), France (1999), Greece (2001), Hungary (2001), India (1999), Indonesia (2000), Ireland (2002), Italy (2001), Mexico (2000), Netherlands (2001), Portugal (2001), Spain (2001), Switzerland (2000), Turkey (2000), UK (2001), USA (2000). For China, Germany, and Israel where only the data for earlier periods are available, I use the household survey for the years of 1990, 1987, and 1995, respectively, and then adjust them to 2000 with the variable 'Employment by economic activity and occupation' in the ILOSTAT database. For the other countries where the household-level survey data are not available, the OECD and non-OECD averages are applied depending on a country's membership to the OECD and also adjusted with the ILOSTAT data. I supplement type-level labor supply $L_{i,\tau}$ with the variable 'Working-age population by sex, age, geographical coverage, school attendance status and education' in the ILOSTAT database and Barro and Lee (2013).

Since the information on worker's educational attainment in household-level surveys is collected based on different definitions of the education level in different countries, it is important to have a consistent definition of educational attainment across countries. The baseline definition follows years of schooling in the U.S. Census data. People with strictly less than 12 years of schooling are considered high school dropouts, exactly 12 years as high school graduates, 13 to 15 years as workers with some college education, exactly 16 years as college graduates, and strictly more than 16 years as workers with advanced degrees.

Countries where the years of schooling variable is available in their household-level survey, worker types are defined by this rule. For the other countries where the years of schooling variable is not available but the more detailed categorical variable for the educational attainment is available, the educational attainment information – especially, distinction between college graduates and workers with advanced degrees – is defined by this detailed categorical variable. For the remaining countries where only a coarse level of categorical variable for educational attainment is available – Austria, Switzerland, and Turkey –, I assume that the ratio of workers with advanced degrees within the total workers with bachelor's degrees is the same as that of the U.S. The other three less-educated workers types are all well-defined with the available variable for the educational attainment for all countries in the sample. Based on this information on the educational attainment, I define 5 worker types.

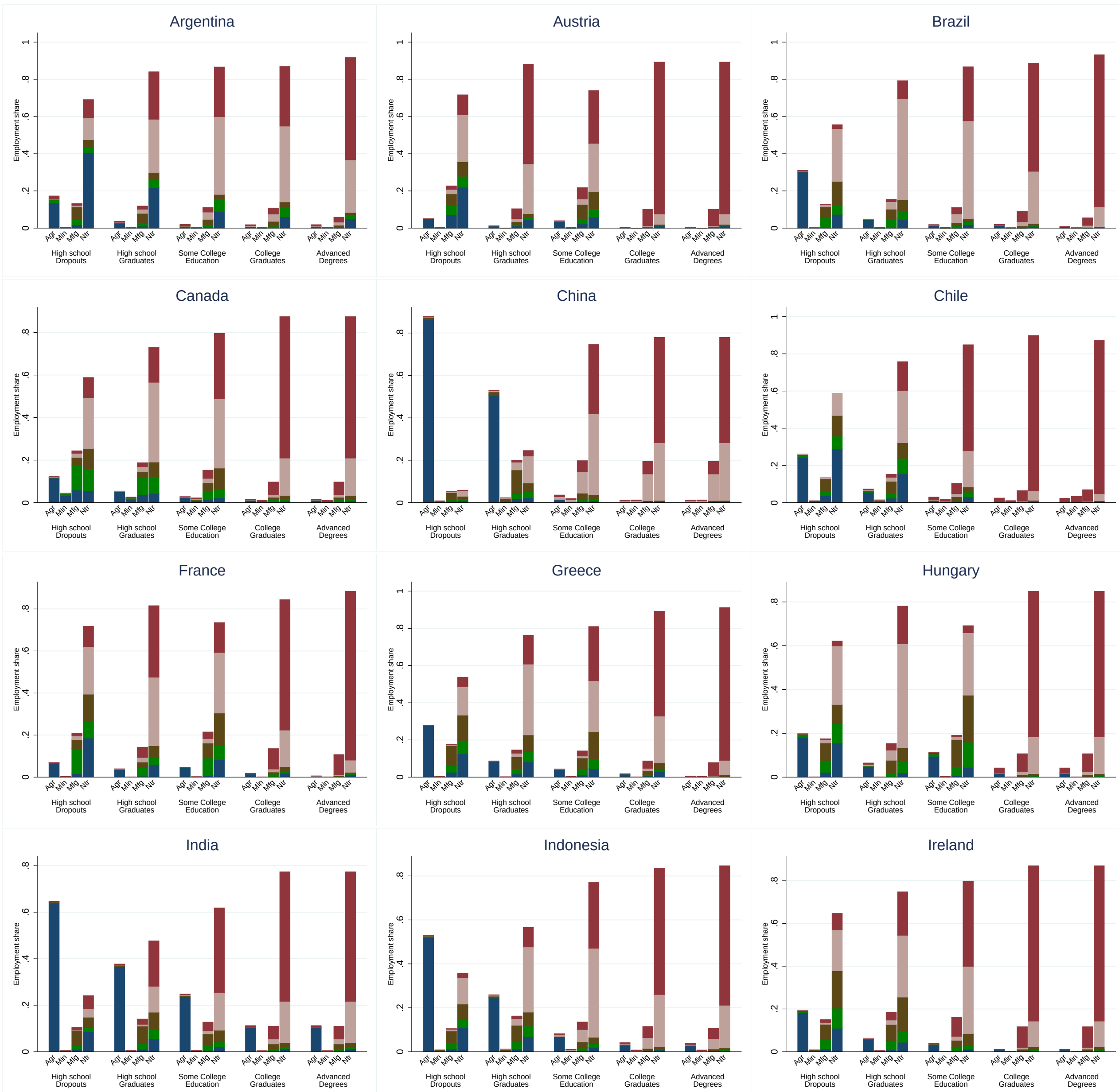
Individual worker's industry affiliation is recoded in all household-level surveys I use in this paper. The information roughly conforms the ISIC classification at 2-digit level, thus it can be exactly aggregated to four industry classification in the quantitative analysis of this paper without any additional adjustment needed. Worker's occupation affiliation information is gathered as described in the previous subsection using the ISCO information available in the survey data for each country except for Argentina and the U.S. For Argentina, the occupation information is not recoded to match the ISCO classification, so I classify the four-digit level occupation information of the survey into five occupation categories. I use Dorn (2009)'s crosswalk to categorize the U.S. census occupation codes into five categories. Collecting all this information, I measure $\pi_{i,\tau}^{j,o}$ as described in Figure A19.[59]

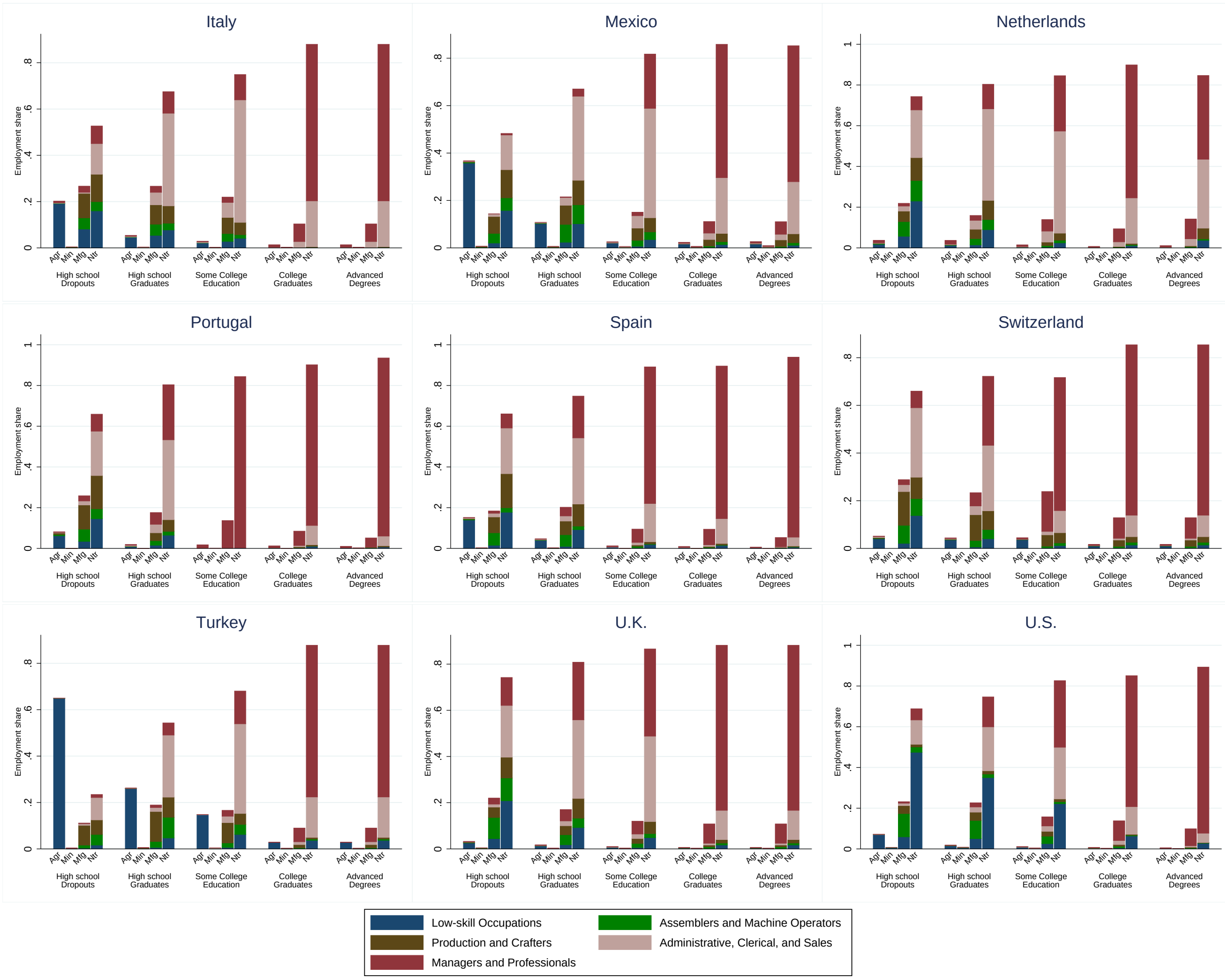
Individual wage or earned income profiles for around the base year of 2000 are available in Brazil, India, Mexico and the U.S. For all four countries, I consider only workers older than the age of 15 and also only workers whose employment status, educational attainment, industry af-

[59]These figures are a country-specific version of Figure A1.

filiation, and occupation affiliation are available. Hourly wage data are available for the U.S. I multiply 1.5 for top-coded observations. For Brazil and Mexico, I use monthly earned income profiles and divide them by the usual working hours. Once the hourly wages are derived, top-coded observations in Mexico are multiplied by 1.5. Weekly wage and salary income is available for India in 1999, so I again use the usual working hours to derive hourly wages.

Figure A19: Within-type Labor Allocation across Industries and Occupations around the Base Year





C.3 Macro Variables

Industry-level gross output of each country is obtained mostly from the UN National Accounts by Industry database and the OECD STructural ANalysis (STAN) database for the base year 2000. For countries where the industry-level gross output data are not available in either source, I use the WIOD table (Australia, Brazil, China, Indonesia, and Mexico) or the data from national statistics bureau (Iceland and Turkey.) For ROW, I calculate the industry-level gross output by re-defining it as the rest of the world in the WIOD and the other countries not included in my sample.

To measure the occupation share in the CES production function for each industry $\mu_i^{j,o}$, I use the variable 'Employment by economic activity and occupation' from the ILOSTAT database.[60] For countries where the data are not available for the base year, I again use the OECD or non-OECD average depending on a country's OECD membership. The cost share $\xi_i^{j,o}$ of occupation o in the unit cost of production in industry j is calculated with the industry- and occupation-specific average hourly wage available in the Occupational Wages around the World (OWW) database. For countries where the data are not available for 2000, I proxy the measure with the data for 1999 (Argentina, Brazil, Chile, Denmark, and Poland.) For countries where the data are not available for

[60] All results are very robust to the alternative measure of $\mu_i^{j,o}$ with the total payment, instead of the employment count.

around 2000, I use the OECD or non-OECD average. Changes in industry-level labor productivity is first calibrated to match patterns of labor reallocation from the IPUMS database, and this is used as an instrument to eliminate the proxy measure, changes in industry-level capital, for the changes in labor productivity. Changes in industry-level capital is obtained by the KLEMS database and the OECD STAN database.

C.4 Bilateral Trade Data

I obtain bilateral trade flows from the UN Commodity Trade (COMTRADE) database for 2000 and 2010. Trade flows are in HS 6-digit level, which I aggregate up to three tradable industries. Bilateral trade flows between ROW and each partner country is calculated by subtracting the total trade flow between corresponding partner country and the other countries in the sample from the total trade flow of that partner country.

D Technical Details of the Algorithm to Solve for the Equilibrium

The system of equations is solved for the unknowns $\hat{p}_i^{j,o}$ at the equilibrium.[61] I denote the vector of unknowns by $\hat{\mathbf{p}} = (\hat{p}_1^{1,1}, \ldots, \hat{p}_1^{1,O}, \ldots, \hat{p}_1^{J,1}, \ldots, \hat{p}_1^{J,O}, \ldots, \hat{p}_N^{1,1}, \ldots, \hat{p}_N^{1,O}, \ldots, \hat{p}_N^{J,1}, \ldots, \hat{p}_N^{J,O})'$, which is a $(N \times J \times O)$-dimensional vector. First, guess the initial $\hat{\mathbf{p}}$; e.g., $\hat{\mathbf{p}} = (1, \ldots, 1)'$. Given $\xi_i^{j,o}$ and λ_{in}^j from the data in the base year 2000, parameter values for γ and ν^j, and counterfactual changes in bilateral trade costs $\hat{d}_{in}^j$ which are calibrated to the data, solve for changes in the unit cost $\hat{c}_i^j$ and changes in the industry-level price index $\hat{P}_i^j$ using the equations (28) and (29). Next, solve for changes in the outcomes of the occupational choice problem using the equations (26) and (27), given $\pi_{i,\tau}^{j,o}$ from the data in 2000, the estimated parameter $\theta_{i,\tau}$, and the counterfactual changes in the industry-level labor productivity $\hat{T}_i^j$ calibrated to the data. Therefore, $\hat{c}_i^j(\hat{\mathbf{p}})$, $\hat{P}_i^j(\hat{\mathbf{p}})$, $\hat{\pi}_{i,\tau}^{j,o}(\hat{\mathbf{p}})$, and $\hat{w}_{i,\tau}(\hat{\mathbf{p}})$ are all derived as functions of $\hat{\mathbf{p}}$ given the initial guess.

Counterfactual changes in the total expenditure are solved as functions of $\hat{\mathbf{p}}$ as well. First, counterfactual changes in the industry-level expenditure share $\hat{\lambda}_i^j(\hat{\mathbf{p}})$ are derived given λ_i^j from the data in 2001 and $\hat{P}_i^j(\hat{\mathbf{p}})$ using the equation (31). Second, changes in the total income in country i, $\hat{I}_i$, are solved as functions of $\hat{\mathbf{p}}$ as well from $\hat{I}_i = \frac{\sum_{j,o} \psi_i'^{j,o} + D_i'}{\sum_{j,o} \psi_i^{j,o} + D_i}$, where $\psi_i'^{j,o} = \sum_\tau w_{i,\tau} L_{i,\tau} \pi_{i,\tau}^{j,o} \hat{w}_{i,\tau}(\hat{\mathbf{p}}) \hat{\pi}_{i,\tau}^{j,o}(\hat{\mathbf{p}})$. Therefore, changes in the industry-level expenditure is solved from $\hat{X}_i^j(\hat{\mathbf{p}}) = \hat{\lambda}_i^j(\hat{\mathbf{p}}) \hat{I}_i(\hat{\mathbf{p}})$. With counterfactual changes in bilateral trade costs $\hat{d}_{in}^j$ and the trade elasticity parameter ν^j, counterfactual changes in the total industry-level output is derived also as functions of $\hat{\mathbf{p}}$ using the equation (33) which is the final goods market clearing condition in proportional changes. Therefore, the final goods market clearing conditions and the occupation market clearing conditions are reduced to the following system of independent equations plus $\sum_{i,j} E_i^j = \sum_{i,j} E_i'^j = E$ as a normalization,

[61] The algorithm to numerically solve for the equilibrium is based on Alvarez and Lucas (2007) and Caliendo and Parro (2015). This paper is without intermediate inputs in the model but has multiple industries and multiple factors. Alvarez and Lucas (2007) consider a single industry, and both papers consider only a single type of labor as a production factor.

given that $\mu_i^{j,o}$ and $L_{i,\tau}$ do not change over time.

$$(\frac{\hat{p}_i^{j,o}}{\hat{c}_i^j(\hat{\mathbf{p}})})^{1-\gamma}\hat{E}_i^j(\hat{\mathbf{p}}) \quad = \quad \sum_\tau(\frac{w_{i,\tau}L_{i,\tau}\pi_{i,\tau}^{j,o}}{\sum_{\tau'} w_{i,\tau'}L_{i,\tau'}\pi_{i,\tau'}^{j,o}})\hat{w}_{i,\tau}(\hat{\mathbf{p}})\hat{\pi}_{i,\tau}^{j,o}(\hat{\mathbf{p}}) \tag{34}$$

These equations directly imply the trade balance condition for each country. Therefore, I have $(N \times J \times O)$ independent equations and the same number of unknowns in $\hat{\mathbf{p}}$. I check if the initial guess of $\hat{\mathbf{p}}$ satisfies (34). If not, update the initial guess and repeat until (34) is satisfied.