

# Global Value Chains and Inequality with Endogenous Labor Supply\*

Eunhee Lee<sup>†</sup>

Kei-Mu Yi<sup>‡</sup>

November 20, 2017

## Abstract

We assess the role of global value chains transmitting global integration shocks to aggregate trade as well as distributional outcomes. We develop a multi-country general equilibrium trade model that features multi-stage production, with different stages having different productivities and using factors (occupations) with different intensities. The model also features a Roy mechanism, in which heterogeneous workers endogenously choose their sector and occupation. Country- and worker-level comparative advantages interact. A reduction in trade costs leads to countries specializing in their comparative advantage sectors and production stages. This specialization changes labor demand and also leads to more workers shifting to their comparative advantage sectors and occupations. With a special case of our model, we show that the intensity of the global value chain (GVC) magnifies the aggregate effects of trade liberalization, but it has a non-monotonic effect on the skill premia. We calibrate our model to the U.S., China, and the rest of the world in 2000 and we simulate a decline in China's costs of trade, designed to mimic China's entry into the WTO. Our simulation results imply an increase in the skill premium in both the U.S. and China, and the GVC, i.e., stage-level specialization, is critical to this outcome.

---

\*The views expressed here are those of the authors and are not necessarily reflective of views of the Federal Reserve Banks of Dallas, Minneapolis or the Federal Reserve System. We thank Pol Antras, Gordon Hanson, Elhanan Helpman, Chinhui Juhn, Steve Redding and especially Alonso de Gortari for very helpful discussions. We also thank participants at the Asian Meetings of the Econometric Society, at the University of Virginia, and at the NBER Trade and Labor Markets Conference for their comments. Heesuk Jung provided excellent research assistance. All errors are our own.

<sup>†</sup>University of Maryland

<sup>‡</sup>University of Houston, NBER, Federal Reserve Bank of Dallas, and Federal Reserve Bank of Minneapolis

# 1 Introduction

One of the most significant economic developments over the past half-century is the increased fragmentation of production across borders. Goods are produced in sequential stages that traverse multiple countries – a global value chain. Countries specialize in particular stages of a good’s production process. This increase in vertical specialization has occurred under a backdrop of a broad increase in international trade, one of the defining features of globalization across the world during this period.

Partly because of this backdrop, most of the research examining the effects of global integration on wages, employment, and other variables has focused on total trade. [Autor et al. \(2013\)](#) is a recent example. This has also been exemplified in the factor content studies that trade and labor economists have conducted since the 1990s. The purpose of our paper is to assess the role of global value chains as a propagation mechanism transmitting global integration shocks, such as China joining the WTO, to aggregate trade outcomes, as well as distributional outcomes, such as the skill premia.

Our approach is to build a model of global value chains and international trade and then to calibrate it and use it to study global integration shocks. We introduce global value chains following the work of [Antràs and de Gortari \(2017\)](#) and [de Gortari \(2017\)](#). They develop a tractable framework for incorporating multi-stage production in an international trade model that generalizes and extends previous research on this subject. In addition, a key feature of our model is to include for multiple sectors, multiple factors, and a labor supply channel. In particular, following [Lee \(2017\)](#), we include Roy selection effects, in which heterogeneous workers choose occupations and sectors based on their individual productivities in these occupations and sectors, as well as on prevailing prices. [Lee \(2017\)](#) and others have shown that these channels enhance our understanding of how trade affects inequality and are quantitatively important in explaining the increase in inequality.

The core elements of our model revolve around the production of a final good and the worker’s choice of sector and occupation. A final good is made in a sequence of stages. Each stage involves labor, a composite intermediate, and output from the previous stage. There are several labor inputs, which we call “occupations”. Different stages use these occupations with different intensities. The presence of the composite intermediate and the previous stage’s output helps generate both “roundabout” and “snake” features in production. The final goods have two uses, consumption and input into the composite intermediate. On the worker’s side, each worker is of an exogenous type. Within each type, a worker draws occupation and sector specific productivities. Based on these productivities, as well as on prevailing prices, workers choose their optimal sector and occupation. Our individual goods and workers are embedded

in a multi-country general equilibrium framework. This framework features both country- and worker-level comparative advantages.

For our analysis, we first introduce a general version of the model and then study a simplified version of the model in order to develop intuition. We study a “2<sup>5</sup>” version of the model in terms of countries, worker types, sectors, stages, and occupations. We examine the response of GVCs, skill premia, and other variables to lower trade costs. The lower trade costs are mediated through several demand and supply forces before ultimately affecting GVCs and skill premia. The lower trade costs facilitate specialization at the sector-level and at the production stage-level. In addition, this changing specialization pattern shifts the relative demand for occupations based on stage-specific occupation intensities. This affects the equilibrium wage, which then affects workers’ choices of occupations and sectors. Ultimately, the skill premia are affected.

The 2-stage version of our model illustrates the role of GVC intensity on the skill premium. A higher GVC intensity implies a greater reliance on the stage-one output used in stage-two production. Numerical exercises show that, in response to a decline in trade costs, aggregate outcomes are magnified if the GVC intensity is higher, but the skill premium responds non-monotonically to higher GVC intensity. The largest effect occurs with intermediate GVC intensities. Extreme GVC intensities shut down stage-level specialization, which is an important margin through which trade shocks change the skill premium. In addition, conditional on the stage-level comparative advantage channel, differences in the GVC intensity across sectors put different weights on the shift of labor demand across sectors and occupations.

We then calibrate the general version of our model for three countries, China, U.S.A, and constructed rest of the world; five worker types; four sectors; two stages; and five occupations. Some of our parameters draw directly from the data, others are assigned, and the others – including the worker productivity parameters, and the production function parameters (productivities of sector and stage, occupational intensity coefficients, value-added share, and GVC intensity parameters) – are calibrated to match moments in the data. Our calibrated parameters reveal several patterns. First, based on relative endowments and productivities, China has a comparative advantage in the manufacturing sector and the downstream production stage, and the U.S. has a comparative advantage in services and the upstream production stage. Second, production stages have different occupation intensities across countries. For example, the downstream production stage is relatively high-skilled-occupation-intensive in China, but low-skilled-occupation-intensive in the U.S.. Third, sectors significantly differ in GVC intensity. Upstream production stages have relatively larger value-added in the agriculture and manufacturing sectors than in the service sector. Lastly, workers with different

levels of skill have a clear comparative advantage both across sectors and occupations.

We use our calibrated model to perform counterfactual exercises quantifying aggregate and distributional impacts of the China shock. We study a 50 percent decline in China's trade costs with its trading partners. When trade costs with China go down, all countries specialize further in their comparative advantage stages and sectors. The degree of stage-level specialization is larger in sectors with a higher GVC intensity, e.g., manufacturing. The greater the GVC intensity, the larger the magnification of aggregate effects such as trade. This is consistent with previous research.

In addition, we find that the skill premium rises in all three countries. In the U.S. and China, the lower trade costs induce specialization to shift towards sectors and stages that use high-skilled-occupations more intensively. As indicated above, for China that involves manufacturing and the downstream stage, and for the U.S., that involves the service sector and the upstream stage. In addition, the worker-level productivity estimates imply that better educated workers are better off in the high-skilled occupations. Hence, our rich framework is able to reproduce the stylized fact that trade liberalizations are often associated with skill premia increases in both skill-abundant and non-skill-abundant countries. We show that in the absence of GVCs, this result would not occur.

On the other hand, our counterfactual shows that the increase in skill premia is limited in magnitude, around 1% or less. This is because, according to our calibrated parameters, each country specializes in sectors and stages that do not have a large share of value-added in the entire production chain. Hence, while there are large changes in specialization owing to the lower trade costs, these large changes do not translate into large skill premia effects.

## 1.1 Related Literature

Our research is connected to several strands of research. One strand is the trade and wages research that sought to examine the effects of increased U.S. imports from developing countries on the skill premia. This research was especially active in the mid-1990s, and includes [Katz and Murphy \(1992\)](#), [Lawrence and Slaughter \(1993\)](#), [Krugman \(1995\)](#), and [Feenstra and Hanson \(1999\)](#) among others. All of these papers essentially employed a Heckscher-Ohlin type (HO) framework with its Stolper-Samuelson and factor content of trade implications. The main findings tended to be that the effect of trade was not large. However, the survey article by [Goldberg and Pavcnik \(2007\)](#) showed that the predictions of a simple Heckscher-Ohlin (HO) framework do not hold up in the data. In particular, skill premia tended to rise in both developed and developing countries following trade liberalizations. [Krugman \(2008\)](#) revisits the trade and wage issues from the mid-1990s with the benefit of 15 years

of additional data. In addition, Krugman argues that increased vertical specialization can generate inequality via Stolper-Samuelson effects. To our knowledge, Krugman’s paper is the only paper that makes a case for examining the consequences of vertical specialization for inequality.

In recent years, there has been a new wave of interest on the employment and wage effects of increased trade. This is not surprising, because the emergence of China as a significant global economic force has only come about in the past 10-15 years. [Autor et al. \(2013\)](#), [Pierce and Schott \(2016\)](#), and many other papers in the literature document significant effects of China on labor markets of major partner countries such as the U.S. With the new interest has come an expanded set of methodologies. One new approach involves applying models with numbers, i.e., quantitative theory. [Burststein and Vogel \(2016\)](#) combine an HO framework in a model that features heterogeneous firms and skill-biased productivity. Our framework is in this vein.

Our paper is also related to a literature about offshoring and skill upgrading. [Feenstra and Hanson \(1995\)](#), [Costinot and Vogel \(2010\)](#), and [Zhu and Trefler \(2005\)](#) discuss how offshoring may increase the skill premium in both North and South by making both countries specialize in high-skill-intensive sectors. These papers do not explicitly model a vertical production structure. Our model looks at this argument through the lens of GVCs, because offshoring involves vertical specialization across production stages by nature.

A second strand of research is on documenting the extent of global value chains, vertical specialization, value-added exports, and related concepts, as well as on building models of these concepts. Contributions on the documentation side include [Hummels et al. \(2001\)](#), [Johnson and Noguera \(2012\)](#); [Antràs and Chor \(2013\)](#), and [Koopman et al. \(2014\)](#). Contributions on the modeling side include [Yi \(2003, 2010\)](#), [Johnson and Moxnes \(2016\)](#), and most recently, [Antràs and de Gortari \(2017\)](#) and [de Gortari \(2017\)](#). The latter two papers develop a general framework for GVCs and show how to map special cases of this framework into the [Eaton and Kortum \(2002\)](#) framework. Our modeling of GVCs draws from [Antràs and de Gortari \(2017\)](#); it combines that paper with [Lee \(2017\)](#).

To investigate the link between trade and labor market outcomes, such as wage inequality and labor reallocation, increasingly, papers focus on heterogeneous workers. While traditional trade models such as the HO model and the specific factors model assume that workers are all homogeneous in their productivities conditional on observable characteristics, this assumption misses the fact that workers differ in their productivities in reality. This worker-level heterogeneity is important especially when we study the effect of trade on labor market outcomes, because workers with same observable characteristics may respond to trade shocks differently depending on their idiosyncratic productivities. In recent years,

trade models bring the idea of the Roy (1951) model to introduce worker heterogeneity under the setting of assignment models: e.g., Teulings (2005), Ohnsorge and Trefler (2007), and Costinot and Vogel (2010, 2015). Worker heterogeneity is introduced to trade models also based on a search and matching framework: e.g., Grossman et al. (2015), Helpman and Itskhoki (2010), and Helpman et al. (2016).

Our paper is also closely related to a recent strand of literature on quantitative models with the Roy-based assignment structure. One of the key assumptions in this literature is that workers' idiosyncratic productivity is randomly drawn from a type-II extreme value distribution, a Fréchet distribution. Hsieh et al. (2013), Burstein et al. (2015), Lagakos and Waugh (2013), Galle et al. (2017), and Lee (2017) use this assumption to investigate the role of worker heterogeneity in disentangling labor market outcomes in one country from labor demand shocks such as technological change or trade liberalization. Our paper also relies on this distributional assumption when we characterize workers' heterogeneous productivities. We introduce this Roy-based assignment framework into a multi-stage GVC model, where each stage of production is formulated based on the EK model. We can thus investigate the general equilibrium relation between workers' endogenous labor supply and trade through GVC in our model. To numerically solve our multi-country GVC model for a general equilibrium, we base our work on the iterative algorithm provided by Alvarez and Lucas (2007).

More papers in the literature recently focus on the occupational dimension as an important channel through which trade shocks are disseminated across workers--e.g., Autor et al. (2015), Ebenstein et al. (2014), Traiberman (2016), Harrigan et al. (2016). Our framework also allows workers to endogenously choose occupations in response to trade shocks under the GVC setting. We show that worker heterogeneity plays also a significant role for occupation-level labor reallocation. The occupational dimension is important in the GVC context, because different production stages have different occupation intensities.

The core mechanism of our model can be further connected to the literature on trade, inequality, and a declining labor share around the world. A recent paper by Dao et al. (2017) provides suggestive evidence about the effect of increased participation in GVCs on declining labor shares in both developed and developing countries. Countries specialize in their capital-intensive and high-skilled-task-intensive stages as they participate in GVCs more. Although we do not explicitly consider capital in our model, the stage-wise specialization pattern and stage-specific occupation intensities that we quantify in this paper can be linked to explain declining labor shares with capital-skill complementarity as in Grossman et al. (2017).

The next section lays out our baseline model. This is followed by a description of a simpler version of our model with just two stages of production, two countries, two occupations, and

two labor types. We solve the simpler version of the model and conduct several numerical exercises to illustrate how the model works. Section 4 describes our calibration, and section 5 discusses our counterfactual exercises with the model.

## 2 Model

In this section, we describe our model. Because the model has many features, we provide an overview first. Our model draws from the general global value chain (GVC, hereafter) model developed by [Antràs and de Gortari \(2017\)](#). We extend their framework by adding three features: multiple factors of production, multiple sectors, and heterogeneous workers. All three features are essential to investigate the role of GVCs in the effect of increased trade on inequality.

In our model, each sector is comprised of a continuum of final goods. Each final good is produced through a specific global value chain encompassing multiple stages of production that can potentially cross multiple countries. Each stage of production is produced with value-added and with intermediate inputs. Value-added consists of multiple factors of production, called occupations. There are two categories of intermediate inputs. One category is a composite aggregate good. The second category of intermediates is good and stage-specific: the previous stage's output. The inclusion of the previous stage's output is the key GVC component.

Countries have comparative advantages both across sectors and stages. To distinguish these two types of comparative advantages, we assume that the primary source of each comparative advantage is different. Sector-wise comparative advantage is primarily from the *Ricardian channel* based on difference in Ricardian productivities as in [Eaton and Kortum \(2002\)](#). On the other hand, stage-wise comparative advantage arises mainly from the standard *Heckscher-Ohlin (HO) channel*, as we assume that different stages of production have different factor intensities and that countries have different factor endowments.

In addition, workers are heterogeneous in their sector and occupation-specific productivities. Workers endogenously choose their occupation and sector based on their productivities: the *Roy channel*. Introducing the Roy framework into a general equilibrium trade model is based on [Lee \(2017\)](#). Our model will deliver interaction between the Ricardian and HO channels, the Roy channel, and GVCs.

## 2.1 Preferences, Technologies, and Workers

Our model features  $N$  countries,  $S$  sectors, value chains of fixed length  $J$ ,  $O$  occupations, and  $T$  worker types. Each country is distinguished by its production technologies and endowment of worker types. Within each sector  $s$ ,  $s = 1, \dots, S$ , there is a continuum of final goods over a set  $\Omega^s$  of mass 1. Each final good  $\omega \in [0, 1]$  is produced following a specific value chain of length  $J$ . The optimal value chain for a final good  $\omega$  consumed in country  $n$  is a  $J$ -dimensional vector of countries where each stage  $j$  of production takes place. In other words, intermediate stages of a product can cross multiple borders along the value chain. For each stage, the production factors are occupations (managers, clerical staff, etc.)  $o$ ,  $o = 1, \dots, O$ . Occupation intensities vary across stages of production and countries. As mentioned above, the production technology also consists of two categories of intermediates, an aggregate composite intermediate, and a good and stage-specific intermediate.

Each country  $i$ ,  $i = 1, \dots, N$ , is exogenously endowed with  $\bar{L}_{i,t}$  workers of type  $t$ ,  $t = 1, \dots, T$ . In our quantitative analysis, these types will be associated with observable worker characteristics, such as education. Each worker of each type "draws" a sector and occupation specific productivity, and on the basis of that productivity and prevailing occupation-sector-specific wages, chooses to work in the occupation and sector that delivers the highest return.

**Preferences** Consumers have common nested CES preference over final goods

$$U_i = \prod_{s=1}^S (C_i^s)^{b^s},$$

$$\text{where } C_i^s \equiv \left( \int_{\Omega^s} (C_i^{s,F}(\omega))^{(\sigma-1)/\sigma} d\omega \right)^{\sigma/(\sigma-1)}.$$

$C_i^{s,F}(\omega)$  is consumption of a final good  $\omega$  of sector  $s$  in country  $i$ . The expenditure share of each sector is given by  $b^s$  with  $\sum_s b^s = 1$ .  $\sigma > 0$  is the elasticity of substitution between goods within the sector.

**Production Technology** As outlined above, each final good  $\omega$  is produced from a specific value chain of length  $J$  during production, and this value chain is potentially spread over multiple countries. We denote the sequence of producing countries for a product  $\omega$  by  $l(\omega) = (l^1(\omega), \dots, l^J(\omega))$ . At each stage  $j$  of the value chain for a product  $\omega$ , firms use domestic labor, the stage  $j - 1$  good for  $\omega$ , and a composite intermediate. The use of the immediately preceding stage captures the "snake" structure of production (as in Yi (2003)) and is the key feature of the value chain.

Countries possess technologies for any intermediate stage of production from  $j = 1$  to

$j = J - 1$ , and also for final assembly of stage  $J$ , for all goods in all sectors. The production function in country  $i$  for stage  $j$  of good  $\omega$  in sector  $s$  is Cobb-Douglas:

$$\begin{aligned} f_i^{s,j}(x_i^{s,j}, L_i^{s,j,1}(\omega), \dots, L_i^{s,j,O}(\omega), m_i^{s,j-1}(\omega)) \\ = z_i^{s,j}(\omega) ((x_i^{s,j})^{1-\alpha_i^s} \prod_o (L_i^{s,j,o}(\omega))^{\beta_i^{j,o} \alpha_i^s} \gamma^{s,j} (m_i^{s,j-1}(\omega))^{1-\gamma^{s,j}}). \end{aligned}$$

Focusing first on the intermediate inputs into production,  $x_i^{s,j}$  is the composite intermediate good used by stage  $j$  producers of sector  $s$  in country  $i$ . It is a nested CES aggregate of the final goods, and has the same structure as the utility function. This captures the “roundabout” structure of production, as in [Caliendo and Parro \(2015\)](#) and [Eaton and Kortum \(2002\)](#). Our roundabout structure is simpler than that of [Caliendo and Parro \(2015\)](#) and also [de Gortari \(2017\)](#) in that the input-output share between sectors is completely determined by the expenditure share and the sector-specific value-added share. The other papers consider a more general input-output structure between sectors focusing on aggregate outcomes of the model.

Value-added inputs into production are occupational tasks  $L_i^{s,j,o}(\omega)$  from each of  $O$  occupations. Finally, the snake structure of our model is described by  $m_i^{s,j-1}(\omega)$ , the stage  $j - 1$  good for  $\omega$  of sector  $s$ . We assume a constant elasticity of substitution for all inputs to focus on the role of GVCs in generating differential gains from trade between worker types. An alternative approach would be to model the complementarity between intermediate inputs and different skill levels of occupations. [Krusell et al. \(2000\)](#) and [Parro \(2013\)](#) have shown that this capital-skill complementarity is important in explaining macroeconomic and international trade behavior.

The three key parameters governing the importance of each of these inputs are  $\beta_i^{j,o}$ ,  $\gamma^{s,j}$ , and  $\alpha_i^s$ . All three parameters range from 0 to 1.  $\beta_i^{j,o}$  captures the importance of each occupational input  $o$ . This parameter varies across occupations, stages, and countries. For each stage  $j$  and country  $i$ ,  $\sum_o \beta_i^{j,o} = 1$ .  $1 - \gamma^{s,j}$  captures the importance of the  $j - 1$  stage input in stage  $j$ . This parameter varies across stages and sectors. A lower value of  $\gamma^{s,j}$  corresponds to a greater importance of the snake structure, and a lower importance of the composite intermediate and value-added taken together.<sup>1</sup> More formally, as  $\gamma^j \rightarrow 0$ , the snake or value chain term dominates the roundabout and value-added terms, and vice versa for  $\gamma^j \rightarrow 1$ .  $\alpha_i^s$  captures the relative importance of value-added and the composite intermediate with higher values of  $\alpha_i^s$  corresponding to greater importance of value-added. This parameter varies across sectors and countries. We will call this parameter as value-

---

<sup>1</sup>Note that these two terms constitute the “typical” Eaton and Kortum (EK) structure of production; hence,  $\gamma^{s,j}$  can also be thought of as capturing the importance of the EK structure.

added share. Finally, we assume that the initial stage 1 is produced using only occupations and composite intermediates; in other words, we assume  $\gamma^{s,1} \equiv 1$  for every  $s = 1, \dots, S$ .

To summarize, for each stage of production, the importance of the previous stage, i.e., of the value chain, is captured by  $1 - \gamma^{s,j}$ , the importance of the composite intermediate, i.e., the roundabout term, is captured by  $(1 - \alpha_i^s)\gamma^{s,j}$ , and the importance of the occupations, taken together, i.e., value-added, is captured by  $\alpha_i^s\gamma^{s,j}$ .

Factor-neutral productivity for stage  $j$  of sector- $s$  product  $\omega$  in country  $i$  is denoted by  $z_i^{s,j}(\omega)$ . We assume the productivity follows a Fréchet distribution from Eaton and Kortum (hereafter, EK, 2002). Productivity  $z_i^{s,j}(\omega)$  is randomly drawn from

$$F_i^{s,j}(z) = \exp(-A_i^s z^{-\nu\tilde{\gamma}^{s,j}}),$$

where  $\tilde{\gamma}^{s,j} \equiv \prod_{j'=j+1}^N (1 - \gamma^{s,j'}) \in [0, 1]$ . We further assume that productivity draws are independent across sectors and stages.  $A_i^s$  governs the scale of productivity for sector  $s$  in country  $i$ . We assume that this scale parameter does not vary by stage.  $\nu\tilde{\gamma}^{s,j}$  captures the dispersion of stage  $j$  productivities.  $\nu$  is the standard Fréchet shape parameter, and governs the common variance of stage  $j$  productivity. The effective variance of stage  $j$  is stage-specific and is based on  $\tilde{\gamma}^{s,j}$ .

The stage-specific shape parameter  $\nu\tilde{\gamma}^{s,j}$  has two advantages. First, as argued in Antràs and de Gortari (2017), this probability distribution makes a sequential sourcing decision equivalent to the case where a lead firm chooses the entire sourcing path from the beginning. This feature provides great analytic tractability, which we will discuss in more detail in the next subsection. Second, we can conveniently characterize the magnification effect of GVC as discussed in Yi (2003). At the equilibrium, the effective trade elasticity  $\nu\tilde{\gamma}^{s,j}$  is larger in downstream production stages, as  $\tilde{\gamma}^{s,j}$  is monotonically increasing in  $j$  for every  $s$ . The magnification effect of GVC is thus active through  $\tilde{\gamma}^{s,j}$  and potentially different across sectors. (In addition,  $\sum_j \gamma^{s,j}\tilde{\gamma}^{s,j} = 1$  for every  $s$  by the definition of  $\tilde{\gamma}^{s,j}$ , and we assume  $\tilde{\gamma}^{s,J} \equiv 1$  for every  $s$ .)

Our rich structure provides Ricardian and HO motives for trade. The Ricardian channel is captured by  $z_i^{s,j}(\omega)$ , and is present across stages and sectors. The HO channel operates through  $\beta_i^{j,o}$ . Different stages use occupations with different intensities. For example, a design stage would use more designers or engineers, while an assembly stage would employ relatively more production workers. Note that the value-added by a particular occupation depends on the stage, not on the sector. However, the effective occupation intensity  $\beta_i^{j,o}\alpha_i^s\gamma^{s,j}$  depends also on sectors.

**Workers** Workers are heterogeneous in their productivities for each sector and occupation

pair  $(s, o)$ . A characterization of worker heterogeneity is based on Lee (2017). Each worker supplies one unit of time. Workers vary in their efficiency units of that time. The number of efficiency units  $\epsilon^{s,o}$  that each individual worker of type  $t$  can supply for a specific  $(s, o)$  is randomly drawn from the following Fréchet distribution:

$$G_t^{s,o}(\epsilon) = \exp(-T_t^{s,o} \epsilon^{-\theta_t}).$$

We assume that these distributions do not vary by country. Worker heterogeneity characterized by  $G_t^{s,o}(\epsilon)$  in this model is related to fundamental complementarity between workers' skills and sector- and occupation-specific tasks, which is not necessarily different across countries.

Two types of stochastic comparative advantage arise from this probabilistic assumption. First, between-worker-type comparative advantage is governed by the relative magnitude of parameters  $T_t^{s,o}$ . For example, if  $\frac{T_t^{s,o}}{T_t^{s',o'}} > \frac{T_{t'}^{s,o}}{T_{t'}^{s',o'}}$  holds, then it is more likely that a type  $t$  worker has comparative advantage for sector  $s$  and occupation  $o$  compared to another worker of type  $t'$  and for another pair  $(s', o')$ . Second, within-worker-type comparative advantage depends on the shape parameter  $\theta_t$ . If workers' productivities are more dispersed within a type—i.e., lower  $\theta_t$ —, then effects from the within-worker-type comparative advantage will be stronger than in the case of a larger  $\theta_t$ . We further assume that draws of idiosyncratic productivity for each  $(s, o)$  are independent, which gives us the following joint distribution for a vector of worker productivity  $\epsilon = (\epsilon^{1,1}, \dots, \epsilon^{s,o}, \dots, \epsilon^{S,O})$ :

$$G_t(\epsilon) = \exp\left(-\sum_{s',o'} T_t^{s',o'} \epsilon^{-\theta_t}\right).$$

This framework for the labor supply side is an important channel which has not been widely studied in the literature. While changes in trade costs operate as one of the labor demand shocks along the GVC, workers potentially respond to these shocks differently based on their own comparative advantage. This Roy channel allows for a more general sorting pattern of workers. Instead of assuming an exact one-to-one relationship between workers skills and occupations, we allow for endogenous matching between skills, sectors, and occupations.<sup>2</sup>

---

<sup>2</sup>The standard trade model with fixed, homogeneous, factors can be recovered via the following assumptions, which eliminate the Roy channel:

1.  $\theta_t \rightarrow \infty$  for all worker types. In this case, workers have the same productivity conditional on their type and their choice of sector and occupation.
2. Each occupation has a corresponding worker type.
3.  $T_t^{s,o} \rightarrow 0$  for every  $o \neq t$  and  $T_t^{s,t} = 1$  for all  $s$  and  $t$ .

## 2.2 Equilibrium Sourcing Decision

In the above model, a final producer for  $\omega$  chooses the entire path of  $l(\omega) = (l^1(\omega), \dots, l^J(\omega))$  by minimizing the total cost of production across all  $J$  stages. However, this approach makes solving the model challenging, because we can no longer take advantage of the convenient characteristics of the Fréchet distribution. To deal with this issue, [Antràs and de Gortari](#) (hereafter, [AG, 2017](#)) introduce two alternative approaches. The first is a “sequential” approach in which each stage  $j$  producer chooses an optimal source for the  $j - 1$  stage by minimizing only its stage-specific production cost. The key assumption that they introduce is that stage  $j$  producers know the **exact productivity draw of the stage  $j - 1$  producers**, but do not know that of stage  $1, \dots, j - 2$  producers. Instead, stage  $j$  producers know **only the productivity distribution of upstream producers up to stage  $j - 2$** ; thus, they take the expectation of productivity up to stage  $j - 2$  as given when they minimize the production cost for stage  $j$ . Thus, this is a limited information approach. The second approach is a “lead-firm” approach in which the assumption of a country-stage-specific Fréchet productivity parameter is replaced by a single Fréchet productivity parameter for an entire GVC. So, in a world with  $N$  countries and  $J$  stages, there are  $N^J$  possible GVCs, each with its own Fréchet productivity parameter. [AG](#) show that these two approaches are equivalent at the equilibrium under the probabilistic assumption of  $z_i^{s,j}(\omega)$  as previously described. Our model draws from their result and, hereafter, we apply the sequential approach.

Another key assumption for the sourcing problem of this model is that each stage’s sourcing decision is independent. Combining this assumption and the assumption of limited information on upstream productivities, we can derive an analytical solution for the equilibrium GVC probability. We assume perfect competition for final goods and intermediate inputs, so each country sources from the lowest-cost supplier around the world. Given per-unit wages  $w_i^{s,o}$  for each country, sector, and occupation, and a CES price index for final goods  $P_i$ , the unit cost for the input bundle excluding materials from the previous stage is given by  $c_i^{s,j} \equiv \varphi_i^{s,j} (P_i)^{1-\alpha_i^s} \prod_o (w_i^{s,o})^{\alpha_i^s \beta_i^{j,o}}$ , where  $\varphi_i^{s,j} \equiv (1 - \alpha_i^s)^{-(1-\alpha_i^s)} \prod_o (\alpha_i^s \beta_i^{j,o})^{-\alpha_i^s \beta_i^{j,o}}$  is a Cobb-Douglas constant.

Whenever stage  $j$  materials in country  $i$  are shipped to another country  $n$  to be used in stage  $j + 1$  production, there is an iceberg trade cost  $\tau_{in}^s \geq 1$ . Trade costs vary by sector. We adopt standard assumptions for iceberg trade costs:  $\tau_{ii}^s = 1$  and  $\tau_{in}^s \geq \tau_{ik}^s \tau_{kn}^s$  for every  $s, i, n$ , and  $k$ . Given these assumptions, stage 2 producers of sector  $s$  in country  $i$  choose the optimal source  $l_i^{s,1}(\omega)$  for stage 1 materials of product  $\omega$  by solving the following problem:

$$l_i^{s,1}(\omega) = \arg \min_l [(p_l^{s,1}(\omega) \tau_{li}^s)^{1-\gamma^{s,2}}] = \arg \min_l \left[ \left( \frac{c_l^{s,1}}{z_l^{s,1}(\omega)} \tau_{li}^s \right)^{1-\gamma^{s,2}} \right],$$

where  $c_i^{s,1} = \varphi_i^{s,1} (P_i)^{1-\alpha_i^s} \prod_o (w_i^{s,o})^{\alpha_i^s \beta_i^{1,o}}$ .

Before we derive the sourcing decision for stage  $j + 1$  producers, we define the following expectation variable as introduced by AG using the law of iterated expectations:

$$\begin{aligned} \Theta_i^{s,j}(x) &\equiv E_j[(P_{l_i^{s,j}(\omega)}^{s,j}(\omega) \tau_{l_i^{s,j}(\omega)i}^s)^x] \\ &= E_j\left[\left(\frac{(c_{l_i^{s,j}(\omega)}^{s,j})^{\gamma^{s,j}}}{z_{l_i^{s,j}(\omega)}^{s,j}(\omega)}\right)^x \times \Theta_{l_i^{s,j}(\omega)}^{s,j-1}(x(1 - \gamma^{s,j})) \times (\tau_{l_i^{s,j}(\omega)i}^s)^x\right]. \end{aligned}$$

We denote the optimal source for stage  $j$  materials of sector- $s$  product  $\omega$  for stage  $j + 1$  producers of sector  $s$  in country  $i$  by  $l_i^{s,j}(\omega)$ . Then, this expectation variable  $\Theta_i^{s,j}(x)$  describes the expected price of stage  $j$  materials of sector- $s$  product  $\omega$  to the power of some constant  $x$ , if they are shipped from the optimal source country  $l_i^{s,j}(\omega)$  to country  $i$ . The sourcing decision for stage  $j + 1$  producers in country  $i$  can be written using this expectation variable.

$$l_i^{s,j}(\omega) = \arg \min_l \left\{ \left( \frac{(c_l^{s,j})^{\gamma^{s,j}}}{z_l^{s,j}(\omega)} \right)^{1-\gamma^{s,j+1}} \times \Theta_l^{s,j-1}((1 - \gamma^{s,j+1})(1 - \gamma^{s,j})) \times (\tau_{li}^s)^{1-\gamma^{s,j+1}} \right\}$$

Similarly, final good consumers in country  $i$  buy  $\omega$  from  $l_i^{s,J}(\omega)$  which solves

$$l_i^{s,J}(\omega) = \arg \min_l \left\{ \frac{(c_l^{s,J})^{\gamma^{s,J}}}{z_l^{s,J}(\omega)} \times \Theta_l^{s,J-1}(1 - \gamma^{s,J}) \times \tau_{li}^s \right\}$$

**Probability of GVC** The probability that stage  $j + 1$  producers of sector  $s$  in country  $i$  source stage  $j$  materials from another country  $n$  is

$$\begin{aligned} \Pr(l_i^{s,j}(\omega) = n) &= \Pr\left[\left(\frac{(c_n^{s,j})^{\gamma^{s,j}}}{z_n^{s,j}(\omega)}\right)^{1-\gamma^{s,j+1}} \times \Theta_n^{s,j-1}((1 - \gamma^{s,j+1})(1 - \gamma^{s,j})) \times (\tau_{ni}^s)^{1-\gamma^{s,j+1}}\right. \\ &\quad \left. \leq \min_{n'} \left( \frac{(c_{n'}^{s,j})^{\gamma^{s,j}}}{z_{n'}^{s,j}(\omega)} \right)^{1-\gamma^{s,j+1}} \times \Theta_{n'}^{s,j-1}((1 - \gamma^{s,j+1})(1 - \gamma^{s,j})) \times (\tau_{n'i}^s)^{1-\gamma^{s,j+1}} \right]. \end{aligned}$$

For notational simplicity, we define  $B_{ni}^{s,j} \equiv (c_n^{s,j})^{\gamma^{s,j}(1-\gamma^{s,j+1})} \times \Theta_n^{s,j-1}((1 - \gamma^{s,j+1})(1 - \gamma^{s,j})) \times (\tau_{ni}^s)^{1-\gamma^{s,j+1}}$  for each  $s$  and  $j = 1, \dots, J-1$ , and  $B_{ni}^{s,J} \equiv (c_n^{s,J})^{\gamma^{s,J}} \times \Theta_n^{s,J-1}(1 - \gamma^{s,J}) \times \tau_{ni}^s$ . Using the Fréchet distribution of product-specific productivity for each stage and each country, the equilibrium probability of the sourcing decision by stage  $j + 1$  producers of sector  $s$  in country

$i$  can be written as

$$\Pr(l_i^{s,j}(\omega) = n) = \frac{A_n^s (B_{ni}^{s,j})^{-\nu \tilde{\gamma}^{s,j} / (1 - \gamma^{s,j+1})}}{\sum_{n'} A_{n'}^s (B_{n'i}^{s,j})^{-\nu \tilde{\gamma}^{s,j} / (1 - \gamma^{s,j+1})}}$$

for  $j = 1, \dots, J - 1$ . Similar to the EK model, this probability is equal to the share of stage  $j$  goods of sector  $s$  that are produced in country  $n$  and used for stage  $j + 1$  production in country  $i$ .

This GVC probability clearly shows the magnification effect of hierarchical production as we go downstream. Because  $\tilde{\gamma}^{s,j}$  is increasing in  $j$  for a given sector  $s$ , the effective elasticity of bilateral trade flows  $\nu \tilde{\gamma}^{s,j}$  is increasing in  $j$ . Therefore, the effect of changes in trade costs between two countries is magnified in downstream production compared to upstream production. As different production stages use occupations with different intensities, the demand for occupations will depend on this magnification effect. To the extent  $\gamma^{s,j}$  varies across sectors, the size of the magnification effect will also vary by sector.

Using the GVC probability result and the independence assumption for sourcing decisions, we derive the equilibrium probability of an entire GVC path. The probability that a final good  $\omega$  of sector  $s$  consumed in country  $i$  has followed a specific GVC path  $l = (l^1, \dots, l^J)$  is

$$\begin{aligned} \lambda_{l,i}^s &= \Pr(l_i^{s,J}(\omega) = l^J | l_{l^J}^{s,J-1}(\omega) = l^{J-1}) \times \Pr(l_{l^J}^{s,J-1}(\omega) = l^{J-1} | l_{l^{J-1}}^{s,J-2}(\omega) = l^{J-2}) \times \dots \\ &\quad \dots \times \Pr(l_{l^2}^{s,1}(\omega) = l^1) \\ &= \frac{\prod_{j=1}^J A_{l^j}^s [(c_{l^j}^{s,j})^{\gamma^{s,j}} (\tau_{l^j l^{j+1}}^s)]^{-\nu \tilde{\gamma}^{s,j}}}{\sum_{l' \in \mathbf{N}^J} \prod_{j=1}^J A_{l'^j}^s [(c_{l'^j}^{s,j})^{\gamma^{s,j}} (\tau_{l'^j l'^{j+1}}^s)]^{-\nu \tilde{\gamma}^{s,j}}}, \end{aligned}$$

where  $\mathbf{N}^J$  is the set of all possible sequences of  $N$  countries along  $J$  stages, and  $l^{J+1} = i$  and  $l'^{J+1} = i$  for all  $l' \neq l \in \mathbf{N}^J$ . The derivation of this probability again uses the law of iterated expectation and characteristics of the Fréchet distribution.

The expression for bilateral trade flows of final goods of sector  $s$  from the location of final assembly  $n$  to country  $i$  is derived similarly:

$$\Pr(l_i^{s,J}(\omega) = n) = \frac{A_n^s (B_{ni}^{s,J})^{-\nu}}{\sum_{n'} A_{n'}^s (B_{n'i}^{s,J})^{-\nu}}.$$

The exact price index of final goods is also derived in a similar way to EK:

$$P_i = \prod_{s=1}^S \left( \frac{P_i^s}{b^s} \right)^{b^s},$$

$$\text{where } P_i^s = \left[ \Gamma\left(\frac{\nu+1-\sigma}{\nu}\right) \right]^{1/(1-\sigma)} \left( \sum_{l' \in \mathbf{N}^J} \prod_{j=1}^J A_{l'j}^s [(c_{l'j}^{s,j})^{\gamma^{s,j}} (\tau_{l'j}^s)^{-\nu\tilde{\gamma}^{s,j}}]^{-1/\nu} \right). \quad (1)$$

Again, in this price index,  $l^{J+1} = i$  and also  $l'^{J+1} = i$  for all  $l' \neq l \in \mathbf{N}^J$ . We assume  $\sigma < \nu + 1$  so that the gamma function in the price index is well-defined.

### 2.3 Equilibrium Labor Supply

Workers' labor supply response à la Roy model is based on Lee (2017). We assume that every worker inelastically supplies all of their time for working. Hence, the worker's labor supply decision is only about allocating that time to a sector, occupation pair. Each worker chooses a pair of sector  $s$  and occupation  $o$  to maximize her potential labor income conditional on her  $(S \times O)$ -dimensional productivity matrix  $\epsilon$ . In other words, worker's problem can be written as

$$\max_{s,o} w_i^{s,o} \epsilon^{s,o},$$

where  $w_i^{s,o}$  is per-unit wage for workers in sector  $s$  of country  $i$  with occupation  $o$ . Workers take the per-unit wages as given. Since  $\epsilon$  is randomly drawn from a joint Fréchet distribution  $G_t(\epsilon)$ , the equilibrium labor supply decision for workers of type  $t$  for sector  $s$  and occupation  $o$  is

$$\pi_{i,t}^{s,o} = \frac{T_t^{s,o} (w_i^{s,o})^{\theta_t}}{\sum_{s',o'} T_t^{s',o'} (w_i^{s',o'})^{\theta_t}}.$$

The shape parameter  $\theta_t$  for type  $t$  workers' productivity distribution is thus the labor supply elasticity of type  $t$  workers at the sector and occupation level. Different worker types are allowed to potentially have different labor supply elasticity in this model. Conditional on the optimal labor supply decision, the equilibrium average wage of type  $t$  workers can be derived as

$$\bar{w}_{i,t} = \left[ \sum_{s',o'} T_t^{s',o'} (w_i^{s',o'})^{\theta_t} \right]^{1/\theta_t} \Gamma\left(1 - \frac{1}{\theta_t}\right).$$

If we define worker types based on educational attainment, the relative  $\bar{w}_{i,t}$  of high-skilled workers over low-skilled workers will be a model counterpart of the skill premium, which is one of our core objects of interest in the quantitative exercises.

### 2.4 General Equilibrium

The equilibrium per-unit wages  $w_i^{s,o}$  and the prices  $P_i^s$  are solved in general equilibrium from market clearing conditions for each occupation. We have occupation market clearing

conditions for each country, sector, and occupation:

$$\sum_t \bar{w}_{i,t} \pi_{i,t}^{s,o} \bar{L}_{i,t} = \alpha_i^s \sum_j \gamma^{s,j} \tilde{\gamma}^{s,j} \beta_i^{j,o} b^s \sum_{n=1}^N \sum_{l \in A_i^j} \lambda_{l,n}^s \left( \sum_t \bar{w}_{n,t} \bar{L}_{n,t} + \sum_{s'} \frac{(1 - \alpha_n^{s'})}{\alpha_n^{s'}} \sum_o \sum_t \bar{w}_{n,t} \pi_{n,t}^{s',o} \bar{L}_{n,t} \right), \quad (2)$$

where we define

$$A_i^j \equiv \{l = (l^1, \dots, l^J) \in \mathbf{N}^J | l^j = i\}$$

as the set of GVCs that produce the  $j$ -th stage in country  $i$ . The left-hand side of the above occupation market clearing condition is the total labor income earned by workers in sector  $s$  of country  $i$  with occupation  $o$ . This term should be equal to the right-hand side, which is the total payment for those specific workers. The goods market clearing condition is embedded in the share of sector  $s$  in total income on the right-hand side.

Let us now discuss the components of the right-hand side in more detail. A key part of the right-hand side is total spending from the countries "purchasing" the goods and services produced by the particular country-sector-occupation. The spending has two sub-parts, spending for final use (consumption), and spending for intermediate use. This spending is then multiplied by a factor related to the roundabout nature of production, which is in turn multiplied by the probability  $\lambda_{l,n}^s$  that country  $i$  is producing stage  $j$  of a GVC that winds up in the purchasing country. This term is then multiplied by the sectoral consumption share, so we now have total spending on the particular stage and sector, controlling for roundabout effects. This is then multiplied by the value-added component of this spending, which is the product of the relevant  $\alpha$ ,  $\gamma$ , and  $\beta$  terms. Finally, the right-hand side is summed over all stages of production.

To solve the model, we first normalize the wages to satisfy  $\sum_{i,s,o} w_i^{s,o} = 1$ . With this normalization, and with the occupation market clearing conditions and the exact price index as derived above, we can solve the model for the equilibrium  $w_i^{s,o}$  and  $P_i^s$  using the [Alvarez and Lucas \(2007\)](#) algorithm. We first guess initial  $w_i^{s,o}$  and solve for  $P_i^s$  following equation (1). With the initial guess of  $w_i^{s,o}$  and the solved  $P_i^s$ , we calculate all equilibrium variables of the model to construct the occupation market clearing conditions (2). We then update  $w_i^{s,o}$  according to the excess demand or supply of labor calculated from (2). Iterations continue until the excess occupational demand or supply is sufficiently close to zero.

## 2.5 Discussion

The core mechanism of our model is the interaction between country-level comparative advantage (*the Ricardian and HO channels*) and worker-level comparative advantage (*the Roy*

*channel*) along the GVC. If trade costs change in this economy, the relative demands for country  $i$ 's intermediate materials and final goods change in all sectors, which, in turn will affect each country's specialization pattern across sectors and stages. These changes in specialization patterns, in conjunction with the relative occupation intensity of each production stage and the sector-specific GVC intensities, induce changes in the relative labor demand for sectors and occupations. This labor demand change, in turn, affects sector- and occupation-specific per-unit wages. Workers then re-optimize their choice of sector and occupation. Even though workers observe the same change in wages for each sector and each occupation, the individual worker's response will differ depending on his/her idiosyncratic productivity.

We now discuss how particular parameters of the model map into comparative advantage. For countries, there is comparative advantage at the sector-level and at the stage-level. Sector-level comparative advantage of countries is based primarily on the relative magnitude of  $A_i^s$ . Relative factor endowments also shape sector-level comparative advantage of countries through  $\bar{L}_{i,t}$  and  $T_{i,t}^{s,o}$ , because sectors also use different occupations with different intensities based on  $\beta^{j,o}\alpha_i^s\gamma^{s,j}$ . Note that if both  $\alpha_i^s$  and  $\gamma^{s,j}$  are the same across sectors, then sector-level comparative advantage of countries is determined only by the Ricardian channel.

A country's stage-level comparative advantage is driven primarily from the HO channel through the relative endowment governed by  $\bar{L}_{i,t}$  and  $T_{i,t}^{s,o}$ , and the occupation intensities  $\beta^{j,o}$ . The Ricardian channel also shapes the stage-level comparative advantage through the interaction between  $A_i^s$  and  $\gamma^{s,j}$ . If  $\gamma^{s,j}$  does not vary by sector, then the stage-level comparative advantage is determined entirely by the HO force. Therefore, in the most general case without any restriction on the model parameters, we can have both sector-level and stage-level comparative advantages, each of which is affected by both the Ricardian and the HO forces as explained above.

Workers have heterogeneous productivities,  $T_t^{s,o}$ , at the sector and occupation level; thus, they have comparative advantage along these two dimensions, as well as between types  $t$ . The combination of  $\bar{L}_{i,t}$  and  $T_t^{s,o}$  determine the effective labor endowment, which links to country-level comparative advantage and specialization across sectors and stages. Note that there is overlap between the Roy and Ricardian channels (primarily at the sector level), and between the Roy and HO channels (primarily at the stage level). When trade costs decline, the effective labor endowment affects specialization patterns, which in turn affects the fundamental wages  $w_i^{s,o}$ .

Sector-level specialization has first-order effects on relative wages across sectors, while stage-level specialization has first-order effects on relative wages across occupations. These changes in sector- and occupation-level wages, in combination with workers' comparative advantage, represented by the relative magnitudes of  $T_t^{s,o}$ , lead to changes in the skill premium.

We note that stage-level specialization, which occurs only because of the GVC structure of our model, provides a potentially important margin of changes in the skill premium through labor demand shifts at the occupation level owing to the stage-specific occupation intensities. Also, Lee (2017) shows that workers’ comparative advantage is much more clearly pronounced across occupations than across sectors. Therefore, the GVC channel of our model captures an important facet of the Roy mechanism by accounting for countries’ specialization across production stages.

In order to further study the effect of GVCs, we need to focus on the role of  $\gamma^{s,j}$ .  $\gamma^{s,j}$  captures the relative importance of the “roundabout” structure over the “snake” structure. Because  $(1 - \gamma^{s,j})$  denotes the share of stage  $j - 1$  used for production of stage  $j$  in sector  $s$ , the sequential structure of production through GVC becomes less important as  $\gamma^{s,j} \rightarrow 1$ . In the extreme case where  $\gamma^{s,j} = 1$  for all  $j = 1, \dots, J$ , only stage  $J$  production remains active using only domestic labor inputs and composite intermediates of finished goods through the roundabout structure. Our baseline model would then be equivalent to the multi-sector EK model with intermediate inputs (but with just one production stage).

As discussed in many papers in the literature including Yi (2003, 2010) and Johnson and Noguera (2012), introducing GVCs into standard trade models can yield magnified effects of changes in trade costs on aggregate outcomes such as bilateral and aggregate trade flows and prices. Our result is in line with the implication for the magnification effect from the literature. As  $\gamma^{s,j} \rightarrow 0$ , production stages become more inter-dependent, and the effective trade elasticity  $\nu \tilde{\gamma}^{s,j}$  becomes larger. Thus, aggregate effects from trade liberalization are increasingly magnified with GVC intensity.

By contrast, the distributional effect of a reduction in trade costs is not necessarily monotonic in GVC intensity. As  $\gamma^{s,j} \rightarrow 0$  in all sectors and stages, the full snake structure occurs. But, note that the model effectively reduces to just one value-added stage. By definition, occupational intensity variation across stages disappears. Hence, stage-level comparative advantage also disappears. As  $\gamma^{s,j} \rightarrow 1$  in all sectors and stages, the difference in occupation intensity across production stages also becomes irrelevant, because previous-stage materials have essentially zero demand and thus are essentially unused in downstream stages. Because the stage-level comparative advantage plays an important role in endogenous changes in the skill premium in conjunction with the Roy channel, as discussed above, a reduction in trade costs can have small effects on between-worker-type inequality—e.g., the skill premium—, if a trade model features either the full roundabout structure ( $\gamma^{s,j} \rightarrow 1$ ) or the full snake structure ( $\gamma^{s,j} \rightarrow 0$ ) in all sectors.

Furthermore, variation in GVC intensity  $\gamma^{s,j}$  across sectors puts different weights on labor demand shifts across sectors and stages. How much of specialization effect across sectors and

stages translates into wage responses is governed by the contribution of each stage in each sector.  $\gamma^{s,j}$  accounts for the size of the contribution. We will further discuss interaction of distributional effects of trade with the GVC intensity using a simple 2-stage version of our model in the next section.

### 3 A Simple “Two” Model

In this section, we simplify our baseline model to two countries, sectors, production stages, occupations, and worker types. We first describe the set up of the simplified model and derive the labor market equilibrium conditions. We then conduct numerical exercises with this simplified model to convey intuition on the role of GVCs in aggregate and distributional outcomes.

#### 3.1 Model Setup and Equilibrium

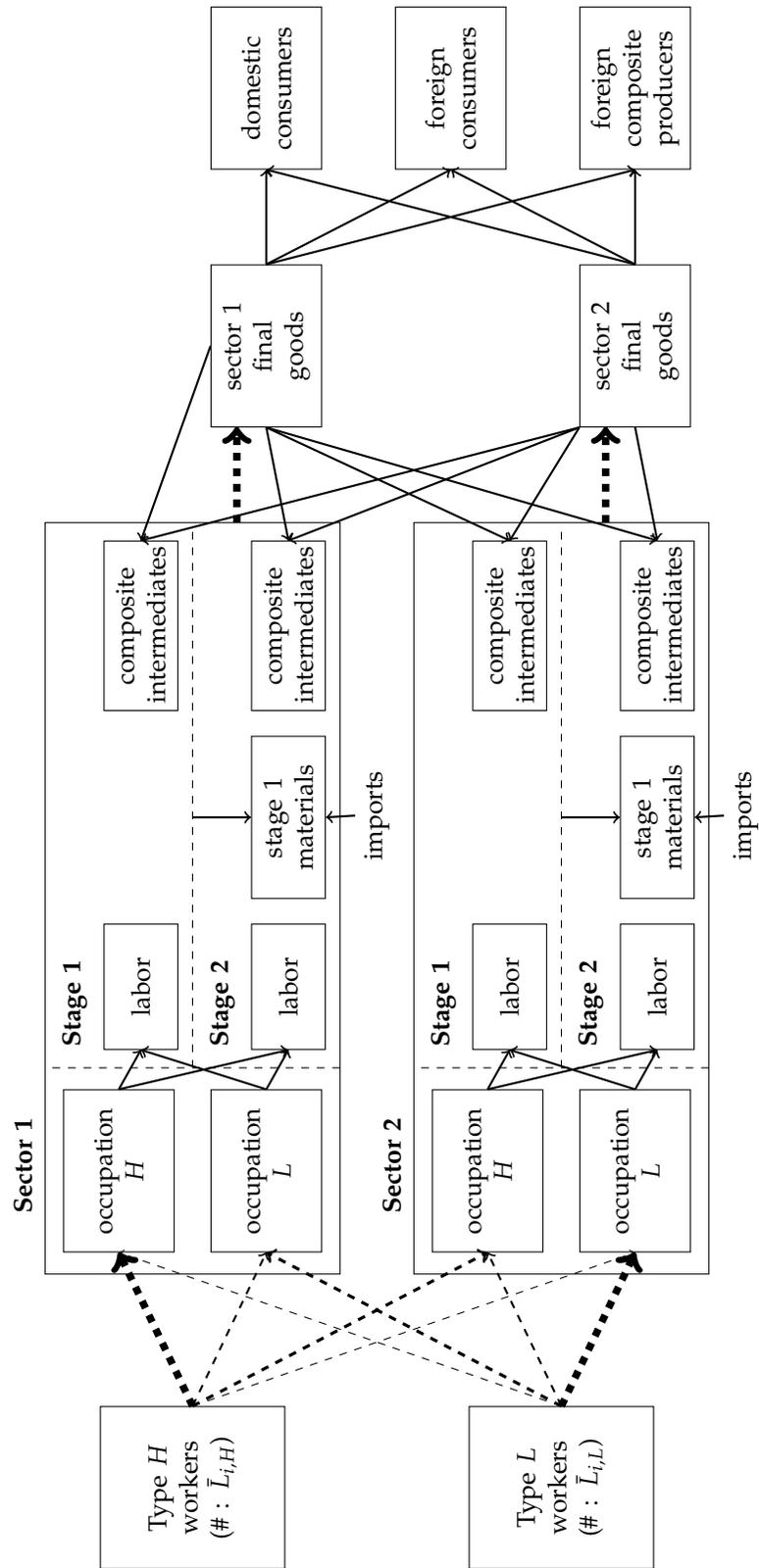
We begin by briefly reviewing the big picture of worker choice, production, and aggregation, and then we set up the simplified model. Each country has an exogenous supply of two types of workers. Each worker draws a productivity for each sector-occupation pair. Based on the productivity draw, and the market wages for the sector-occupation pairs, the worker chooses the sector-occupation that maximizes his/her income. This corresponds to the left part of Figure 1 below.

Individual goods (in a given sector and country) are produced in two stages. First, a composite intermediate and the occupational factor inputs are combined to make the stage 1 good. Then, the stage 1 good is combined with a composite intermediate and occupational factors to make the stage 2 good. The use of the stage 1 good in stage 2 production captures the GVC part of our model. The production process is illustrated in the boxes in the middle of Figure 1 below.

Finally, the individual goods are aggregated (across sectors) into a composite good, which is used for final consumption at home and abroad, and also as a composite intermediate in stage 1 and stage 2 production. The flows of the composite intermediate capture the roundabout production part of the model. This is illustrated in the right part of Figure 1 below.

We now describe the worker choice and production of an individual good more formally. We denote countries by  $i = 1, 2$ , sectors by  $s = 1, 2$ , production stages by  $j = 1, 2$ , worker types by  $t = H, L$ , and occupations by  $o = 1, 2$ .

Figure 1: A 2-stage GVC Model with Endogenous Labor Supply



The production function varies by country, sector, and stage:  $f_i^{s,j}(\cdot)$ . Hence, we denote the Fréchet productivity of goods as  $z_i^{s,j}$ , the composite intermediate as  $x_i^{s,j}$ , the stage 1 good used in stage 2 production as  $m_i^{s,1}$ , and the use of occupational factors 1 and 2 as  $L_i^{s,j,1}$  and  $L_i^{s,j,2}$ , respectively.

The first and second stage production functions in country  $i$ , sector  $s$  for a good  $\omega$  are given by:

$$\begin{aligned} f_i^{s,1}(x_i^{s,1}, L_i^{s,1,1}(\omega), L_i^{s,1,2}(\omega)) &= z_i^{s,1}(\omega)(x_i^{s,1})^{1-\alpha_i^s}((L_i^{s,1,1}(\omega))^{\beta^{1,1}}(L_i^{s,1,2}(\omega))^{\beta^{1,2}})^{\alpha_i^s} \\ f_i^{s,2}(x_i^{s,2}, L_i^{s,2,1}(\omega), L_i^{s,2,2}(\omega), m_i^{s,1}(\omega)) &= z_i^{s,2}(\omega)[(x_i^{s,2})^{1-\alpha_i^s}((L_i^{s,2,1}(\omega))^{\beta^{2,H}}(L_i^{s,2,2}(\omega))^{\beta^{2,2}})^{\alpha_i^s}]^{\gamma^s} \\ &\quad \times (m_i^{s,1}(\omega))^{1-\gamma^s}. \end{aligned}$$

The relative importance of the composite intermediate, value-added, and the stage 1 good in production depends on two parameters,  $\alpha_i^s$ , and  $\gamma^s$ .  $1 - \alpha_i^s$  governs the importance of the composite intermediate, i.e., the roundabout structure.  $1 - \gamma^s$  governs the importance of the stage 1 good in stage 2 production. We associate greater GVC intensity with a larger  $1 - \gamma^s$ . Note that, as with any production function with a roundabout structure, the composite good  $x_i^{s,j}$  can be netted out, and the “effective” value-added of stage 2 is  $\gamma^s$ . Note that the coefficient on the occupational factor only varies by stage and occupation:  $\beta^{j,o}$ .

The Fréchet productivity distribution for each country  $i$  and sector  $s$  is given by:

$$\begin{aligned} z_i^{s,1}(\omega) &\sim F_i^{s,1}(z) = \exp(-A_i^s z^{-\nu(1-\gamma^s)}) \\ z_i^{s,2}(\omega) &\sim F_i^{s,2}(z) = \exp(-A_i^s z^{-\nu}). \end{aligned}$$

We continue to maintain the sequential independence and the limited information assumptions of [Antràs and de Gortari \(2017\)](#) that final good consumers in this two-stage setup do not know the exact productivity draw of stage 1 producers.

For each good  $\omega$ , stage 2 producers source the lowest cost supplier of stage 1 goods, and, similarly, final good consumers source the lowest cost suppliers of the stage 2 goods. Owing to our assumption that productivities are drawn from country- and sector- and stage-specific Fréchet distributions, these sourcing problems imply the following bilateral GVC probabilities:

$$\begin{aligned} \Pr(l_i^{s,1}(\omega) = n) &= \frac{A_n^s (c_n^{s,1} \tau_{ni}^s)^{-\nu(1-\gamma^s)}}{\sum_{n'} A_{n'}^s (c_{n'}^{s,1} \tau_{n'i}^s)^{-\nu(1-\gamma^s)}} \\ \Pr(l_i^{s,2}(\omega) = n) &= \frac{A_n^s ((c_n^{s,2})^{\gamma^s} \Theta_n^s \tau_{ni}^s)^{-\nu}}{\sum_{n'} A_{n'}^s ((c_{n'}^{s,2})^{\gamma^s} \Theta_{n'}^s \tau_{n'i}^s)^{-\nu}}. \end{aligned}$$

Using the above sourcing probabilities, and the [Antràs and de Gortari \(2017\)](#) assumptions

of independence for the stage-specific productivity draws, and of limited information across stages, the equilibrium probability that a sector- $s$  product consumed by country  $i$  consumers follows a specific GVC  $l = (l^1, l^2)$  is given by:

$$\lambda_{l,i}^s = \frac{A_{l^1}^s (c_{l^1}^{s,1} \tau_{l^1 l^2}^s)^{-\nu(1-\gamma^s)} \times A_{l^2}^s [(c_{l^2}^{s,2})^{\gamma^s} \tau_{l^2 i}^s]^{-\nu}}{\sum_{l' \in \mathbf{N}^2} A_{l'^1}^s (c_{l'^1}^{s,1} \tau_{l'^1 l'^2}^s)^{-\nu(1-\gamma^s)} \times A_{l'^2}^s [(c_{l'^2}^{s,2})^{\gamma^s} \tau_{l'^2 i}^s]^{-\nu}},$$

where  $\mathbf{N}^2 = \{(l_1, l_2) : (1, 1), (1, 2), (2, 1), (2, 2)\}$ . The above equation shows that, as in the baseline model, the effective trade elasticity varies by production stage with (weakly) larger effective trade elasticities for stage 2 goods than for stage 1 goods.

With two countries, two sectors, and two occupations, there are eight labor market clearing conditions. For each country  $i$ , sector  $s$ , and occupation  $o$ , the labor market clearing condition sets the value of wage income earned by the occupational factor – the left-hand side – equal to the implicit demand for these occupational services across the two stages, and across both final goods and intermediate goods – the right-hand side:

$$\begin{aligned} \sum_t \bar{w}_{i,t} \pi_{i,t}^{s,o} \bar{L}_{i,t} &= (1 - \gamma^s) \beta^{1,o} \alpha_i^s b^s \sum_{n=1}^N \sum_{l \in \Lambda_i^1} \lambda_{l,n}^s \left( \sum_t \bar{w}_{n,t} \bar{L}_{n,t} + \sum_{s'} \frac{(1 - \alpha_n^{s'})}{\alpha_n^{s'}} \sum_o \sum_t \bar{w}_{n,t} \pi_{n,t}^{s',o} \bar{L}_{n,t} \right) \\ &+ \gamma^s \beta^{2,o} \alpha_i^s b^s \sum_{n=1}^N \sum_{l \in \Lambda_i^2} \lambda_{l,n}^s \left( \sum_t \bar{w}_{n,t} \bar{L}_{n,t} + \sum_{s'} \frac{(1 - \alpha_n^{s'})}{\alpha_n^{s'}} \sum_o \sum_t \bar{w}_{n,t} \pi_{n,t}^{s',o} \bar{L}_{n,t} \right), \end{aligned}$$

where  $\Lambda_i^1, \Lambda_i^2 \in \mathbf{N}^2$  are defined as in the baseline model. The key term on the left-hand side of the above equation is  $\pi_{i,t}^{s,o}$ , which, as a reminder, is the share of type  $t$  workers who choose sector  $s$  and occupation  $o$ . On the right-hand side, the two terms are the implicit demand for occupational service  $o$  to make stage 1 goods and stage 2 goods, respectively. For each stage, there is the implied occupational demand from final use (the term that includes  $\sum_t \bar{w}_{n,t} \bar{L}_{n,t}$ ), as well as the implied occupational demand for intermediate use (the term that includes  $\sum_{s'} \frac{(1 - \alpha_n^{s'})}{\alpha_n^{s'}} \sum_o \sum_t \bar{w}_{n,t} \pi_{n,t}^{s',o} \bar{L}_{n,t}$ ). As in [Caliendo and Parro \(2015\)](#) and [de Gortari \(2017\)](#), this term depends on the exact expenditure from each sector  $s'$  on intermediates, which requires identification of the exact input-output coefficients between sectors. However, the Roy feature of our model makes that calculation straightforward. All downstream demand can be characterized as proportional to the payments to the workers in a given sector, which equals total expenditure in that sector in general equilibrium.

We now discuss the implications of this model for the skill premium and for the role of the GVC intensity  $1 - \gamma^s$  in propagating declines in trade costs to the skill premium. The decline in trade costs leads, of course, countries to specialize further in their comparative

advantage sector and stage. There are at least three sources of comparative advantage: Heckscher-Ohlin, Ricardian, and Roy.

Owing to our assumption that the occupation intensity coefficients  $\beta^{j,o}$  do not vary by sector, the textbook Heckscher-Ohlin (HO) channel is not present. However, there are two other sources of HO forces. The first is that the occupation intensity coefficients vary by stage, so this variation across stages, in conjunction with differences in supplies of the two types of labor,  $\bar{L}_{it}$ , will generate the HO channel. Clearly, without GVCs, in the form of multi-stage production, this channel would not exist. The second is that to the extent the roundabout parameter  $1-\alpha^s$ , and/or GVC intensity  $1-\gamma^s$  vary across sectors, it will generate differences in the “effective” factor intensity of the occupations across sectors. This, in turn, generates the classic HO sector-level specialization. Hence, Stolper-Samuelson effects occur, and the question becomes one of magnitude.<sup>3</sup>

Ricardian comparative advantage also occurs according to relative differences in  $z_i^{s,j}$  across countries. Under typical circumstances, this type of comparative advantage would have no effect on the skill premium. However, in conjunction with the Roy feature – type  $H$  workers draw from a different distribution of sector-by-occupation productivities than do type  $L$  workers – Ricardian comparative advantage can impact the skill premium. The sector that a country will have a Ricardian comparative advantage in will draw relatively more workers from the type that has relatively higher productivity in that sector. Moreover, these workers will choose the occupation for which they have the relatively higher productivity. Hence, this Ricardian-Roy channel can generate changes in skill premium independent of the Stolper-Samuelson effect from the HO channel. Finally, the GVC intensity  $1-\gamma^s$  plays a role, because it determines how much the sector-level specialization feeds into the demand for occupations.

The discussion above highlights several channels through which the GVC intensity can affect the nature of specialization across sectors and stages, and, in turn, affect the skill premium. Even in this simple model, it should be clear that it is not obvious that there is a monotonic relationship between higher GVC intensity, i.e., higher  $1-\gamma^s$ , and a higher change in the skill premium in one or both countries induced by lower trade barriers. We provide two examples to illustrate this before we turn to our numerical exercises.

In the first example, the GVC intensity  $1-\gamma^s$  is the same across both sectors. This rules out the HO channel at the sector level, but it still exists at the stage level. In addition, there is still the Ricardo-Roy mechanism at the sector level. Now, let us consider an extreme

---

<sup>3</sup>In our calibrated model, we allow for occupational intensities to vary by country, i.e.,  $\beta_i^{j,o}$ ; this variation by country, in conjunction with variation across sectors in the GVC intensity,  $1-\gamma^s$  can also generate changes in skill premia that go in the same direction in both countries.

case in which  $\gamma = 0$  or  $\gamma = 1$ , i.e., in which the GVC intensity is maximized or minimized, respectively. In each case, there is no HO channel at the stage level, because there is effectively only one stage of production. There is only the Ricardo-Roy channel to affect the skill premium. This suggests the possibility that the effects of declining trade costs on the skill premium may not be monotonic in the GVC intensity, because the less extreme values of  $\gamma^s$  are associated with two channels for affecting the skill premium, while the extreme values are associated with just one channel. We explore this case further in the numerical exercises in the next sub-section, as well as in one of the alternative counterfactuals in the main results section.

In the second example, suppose that a country has a comparative advantage in sector 1 and stage 1. In other words, the distribution of goods productivities and worker productivities favor sector 1, and the production function coefficient  $\beta^{j,o}$ , in conjunction with the distribution of worker productivities, also favors stage 1. Then, if  $1 - \gamma^1$  is as high as possible, it will maximize the impact on the skill premium, because it ensures that more of the specialization effect translates into wage responses. We also explore this case further in the numerical exercises in the next subsection.

The effects of lower trade costs on the skill premia are in sharp contrast with the effects on aggregate trade, which are increasingly magnified as  $1 - \gamma^s$  increases. When  $\gamma^s \rightarrow 0$  for all  $s = 1, 2$ , our model has only the pure snake channel of trade in intermediates. Thus, the effect of a reduction in trade costs on aggregate trade flows has the maximum magnification.

In summary, a simple 2-stage case of our model reiterates the importance of having an accurate measure of sector-level GVC intensity when we investigate the effect of GVC on inequality. Even though aggregate effects are monotonically magnified with a larger GVC intensity, distributional effects of GVC will not necessarily be monotonic in GVC intensity. In addition, sector-level variation in the GVC intensity is important for the magnitude of the Ricardian, HO and Roy effects.

## 3.2 Numerical Exercises

In this section, we solve the “Two” model to provide further intuition. We focus on the HO comparative advantage channels. In other words, we eliminate the Ricardian comparative advantage motive by setting the productivity distribution for goods production equal across sectors and countries.

The parameters and exogenous variables of our simple model are set so that country 1 is relatively abundant in type  $L$  workers, who have a comparative advantage in sector 1 and occupation 1. Moreover, stage 1 production uses occupation 1 more intensively; hence,

country 1 has a comparative advantage in stage 1 production, as well. It should be clear that the HO comparative advantage depends on the interaction of the endogenous labor supply and worker heterogeneity in productivity (Roy channel) with occupational intensity variation across stages.<sup>4</sup>

The particular parameters and exogenous variables are given by: 1) Ricardian comparative advantage parameter  $A_i^s = 1$  for all  $i$  and  $s$ ; 2) type-level labor supply  $(\bar{L}_{1,H}, \bar{L}_{1,L}, \bar{L}_{2,H}, \bar{L}_{2,L}) = (0.3, 0.7, 0.7, 0.3)$ ; 3) occupation intensity for each production stage  $(\beta^{1,1}, \beta^{1,2}, \beta^{2,1}, \beta^{2,2}) = (\frac{2}{3}, \frac{1}{3}, \frac{1}{3}, \frac{2}{3})$ ; 4) the scale parameter of workers' productivity distribution  $(T_H^{1,1}, T_H^{1,2}, T_H^{2,1}, T_H^{2,2}) = (1, 3, 2, 4)$  and  $(T_L^{1,1}, T_L^{1,2}, T_L^{2,1}, T_L^{2,2}) = (4, 2, 3, 1)$ ; and 5)  $\gamma^1 = 0.3$  and  $\gamma^2 = 0.7$ . We set the trade elasticity (i.e., the part common across the two stages),  $\nu = 4$ ; the elasticity of substitution across products in preferences,  $\sigma = 2$ ; and the labor supply elasticity,  $\theta_t = 2$  for all  $t$ . Consumers are assumed to have the same expenditure share across sectors—i.e.,  $b^1 = b^2 = 0.5$ , and the roundabout parameter is the same across all sectors and countries—i.e.,  $\alpha_i^s = 0.3$  for all  $i$  and  $s$ .

In the exercises below, we compare a high trade cost case to a free trade cost case. Specifically, we compare the case with  $\tau_{in}^s = 2$  for  $i \neq n$  and  $\tau_{ii}^s = 1$  (“high trade cost case”) to a “free trade case” with  $\tau_{in}^s = 1$  for all  $i, n, s$ . Given trade costs and parameter values, we solve the occupation market clearing conditions and the exact price indices for the equilibrium  $w_i^{s,o}$  and  $P_i^s$  following the [Alvarez and Lucas \(2007\)](#) algorithm. In so doing, we normalize wages to satisfy  $\sum_{i,s,o} w_i^{s,o} = 1$ . From the solutions for the wages and prices, we can solve for all the other variables.

We will define the skill premium as the ratio of the average wage of the type  $H$  worker to the average wage of the type  $L$  worker:  $SP_i = \bar{w}_{i,H}/\bar{w}_{i,L}$ . Owing to the importance of the GVC intensity parameter  $\gamma^s$  for both aggregate and distributional effects of reduction in trade costs, we will experiment with different values of  $\gamma^s$  and with a sector-level variation in  $\gamma^s$  later in this section.

**Results** We first discuss the effects of lower trade costs on aggregate prices and the pattern of GVCs  $\lambda_{i,i}^s$ . We then turn to the worker allocation pattern  $\pi_{i,t}^{s,o}$  and the skill premium.

A reduction in trade costs enables producers to source intermediates from the lowest cost supplier and also enables consumers to purchase final goods from the lowest cost producer. Consequently, not surprisingly, as trade costs fall to zero, the aggregate price index decreases in each country – by 91% in country 1 and by 89% in country 2.

---

<sup>4</sup>Both sector- and stage-level comparative advantages come from the HO force in this numerical exercise. Because the model assumes that the occupation intensity does not vary by sector, sector-level HO comparative advantage is of second-order.

The first two columns of numbers in Table 1 give the prevalence of particular GVCs when trade costs  $\tau_{in}^s = 2$  for  $i \neq n$ . For example, 83.7 percent of the sector 1 GVCs whose final destination is country 1 involve both stage 1 and stage 2 made in country 1. Because trade costs are high, both countries source stage 1 materials and final goods primarily domestically. The next two columns show the prevalence of particular GVCs when trade costs are uniformly reduced to zero, i.e.,  $\tau_{in} = 1$  for all  $i$  and  $n$ . Now, there is more specialization according to comparative advantage. For example, the particular GVC mentioned above represents only 26.4 percent of all the sector 1 GVCs whose final destination is country 1. By contrast, a “vertical specialization” GVC, such as one in which stage 1 is made in country 1 and stage 2 is made in country 2, rises in prevalence from 0.08 percent under high trade costs to 26.5 under free trade (for final consumers of sector 1 goods in country 1).

Table 1: Changes in  $\lambda_{l,i}^s$  from the Benchmark Simulation

|                   |           | (1) $\tau_{in}^s = 2$ |           | (2) $\tau_{in}^s = 1$ |           | (3) change (pp) |           |
|-------------------|-----------|-----------------------|-----------|-----------------------|-----------|-----------------|-----------|
|                   |           | $l_2 = 1$             | $l_2 = 2$ | $l_2 = 1$             | $l_2 = 2$ | $l_2 = 1$       | $l_2 = 2$ |
| $\lambda_{l,1}^1$ | $l_1 = 1$ | 0.837                 | 0.008     | 0.264                 | 0.265     | -57             | 26        |
|                   | $l_1 = 2$ | 0.108                 | 0.048     | 0.235                 | 0.236     | 13              | 19        |
| $\lambda_{l,1}^2$ | $l_1 = 1$ | 0.644                 | 0.021     | 0.236                 | 0.265     | -41             | 24        |
|                   | $l_1 = 2$ | 0.286                 | 0.049     | 0.235                 | 0.264     | -5              | 22        |
| $\lambda_{l,2}^1$ | $l_1 = 1$ | 0.056                 | 0.129     | 0.264                 | 0.265     | 21              | 14        |
|                   | $l_1 = 2$ | 0.007                 | 0.808     | 0.235                 | 0.236     | 23              | -57       |
| $\lambda_{l,2}^2$ | $l_1 = 1$ | 0.034                 | 0.284     | 0.236                 | 0.265     | 20              | -2        |
|                   | $l_1 = 2$ | 0.015                 | 0.666     | 0.235                 | 0.264     | 22              | -40       |

These results mirror those in Yi (2003, 2010). One additional point to highlight is that when trade costs fall, domestic sourcing ( $(l_1, l_2) = (1, 1)$ ) falls by more in sector 1 than in sector 2. This is because  $\gamma^1 = 0.3 < \gamma^2 = 0.7$ ; in other words, stage 1 goods are more important in stage 2 production in sector 1, which implies the effective trade elasticity is higher in sector 1.

Table 2 shows the within-type labor allocation pattern predicted by our simple model. The table shows that regardless of trade costs, workers are more likely to work in their comparative advantage sector and occupation. Also, even though each worker type has a comparative advantage in a particular sector and occupation, owing to heterogeneity in

productivity within each type, the within-type labor allocation does not involve complete specialization. For example, about 8.1% of type  $H$  workers in country 1 work in sector 1 in occupation 1, even though type  $H$  workers have on average a comparative advantage in sector 2 and occupation 2.

Table 2: Changes in  $\pi_{i,t}^{s,o}$  from the Benchmark Simulation

|                     | $\pi_{i,t}^{s,o}$ | (1) $\tau_{in}^s = 2$ |         | (2) $\tau_{in}^s = 1$ |         | (3) change (pp) |         |
|---------------------|-------------------|-----------------------|---------|-----------------------|---------|-----------------|---------|
|                     |                   | $o = 1$               | $o = 2$ | $o = 1$               | $o = 2$ | $o = 1$         | $o = 2$ |
| Country 1, Type $H$ | $s = 1$           | 0.081                 | 0.255   | 0.084                 | 0.261   | 0.3             | 0.6     |
|                     | $s = 2$           | 0.138                 | 0.526   | 0.138                 | 0.516   | 0.02            | -0.9    |
| Country 1, Type $L$ | $s = 1$           | 0.391                 | 0.204   | 0.398                 | 0.205   | 0.8             | 0.1     |
|                     | $s = 2$           | 0.248                 | 0.157   | 0.244                 | 0.152   | -0.4            | -0.5    |
| Country 2, Type $H$ | $s = 1$           | 0.157                 | 0.249   | 0.152                 | 0.244   | -0.5            | -0.4    |
|                     | $s = 2$           | 0.204                 | 0.390   | 0.205                 | 0.398   | 0.08            | 0.8     |
| Country 2, Type $L$ | $s = 1$           | 0.524                 | 0.138   | 0.516                 | 0.138   | -0.8            | -0.02   |
|                     | $s = 2$           | 0.256                 | 0.081   | 0.261                 | 0.084   | 0.5             | 0.3     |

When trade costs fall, and specialization according to comparative advantage increases, workers of both types move between sectors accordingly. For example, because country 1 has a comparative advantage in sector 1, both type  $H$  and  $L$  workers in country 1 shift to sector 1, and similarly in country 2. In addition, workers choose different occupations when they move between sectors. This pattern depends on worker-level comparative advantage for occupations. For example, while some of both type  $H$  and  $L$  workers in country 1 move from sector 2 to sector 1, type  $H$  workers in occupation 2 increase by 0.6 percentage points, and type  $H$  workers in occupation 1 increase by 0.3 percentage points within sector 1. By contrast, type  $L$  workers of country 1 in occupation 1 increase by 0.8 percentage points, and those type workers in occupation 2 increase by 0.1 percentage points, in sector 1.

To summarize, in response to the reduction in trade costs, the Roy channel of our model reallocates workers across sectors and occupations within their type. Workers may stay in the same sector, but move to a different occupation, an outcome not present in standard trade models with homogeneous workers. This endogenous labor supply reallocation mirrors what is in Lee (2017). However, what is different here is the importance of stage-level specialization. Owing to our choice of parameters – identical factor intensities and distribution

of productivities across sectors – in the absence of two stages of production, and the different GVC intensity  $(1 - \gamma^s)$  across sectors, there would be no Roy channel impacting the HO mechanism. The GVCs provide additional propagation mechanisms for Roy and HO.

The reduction in trade costs changes the skill premium in the direction predicted by the Stolper-Samuelson theorem. As a reminder, country 1 is abundant in type  $L$  workers, who have a comparative advantage in occupation 1, which is used more intensively by stage 1 and sector 1. Therefore, as trade costs go down, the relative demand for type  $L$  workers increases in country 1 and decreases in country 2. The opposite is true for type  $H$  workers. Hence, our model implies that as trade costs decline, the skill premium increases by 1.1% in country 2, and decreases by 1.1% in country 1. This numerical exercise is set up to highlight the Stolper-Samuelson effect through the GVC. As we have mentioned above, our general model allows for non-Stolper-Samuelson effects.

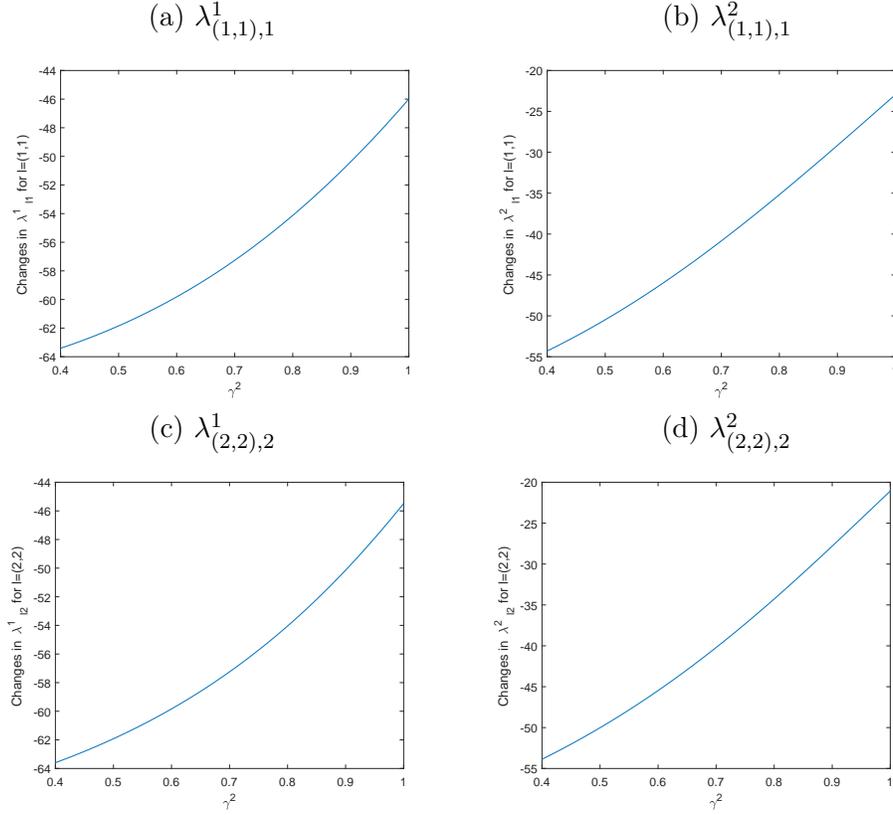
**Two Exercises to Highlight The Role of GVC Intensity** The key parameter of our two-stage model that governs the relative importance of the GVC is  $1 - \gamma^s$  for each sector  $s = 1, 2$ . The effective GVC intensity, as well as the effective trade elasticity, decreases in  $\gamma^s$ . In the extreme case of  $\gamma^s = 1$ , the effective trade elasticity for stage 1 is zero. This might suggest that the  $\gamma^s = 0$  generates the strongest GVC effect. It does for aggregate trade, but not for the skill premium, as we will see below.

To illustrate the role of the  $1 - \gamma^s$ , we repeat the exercise of a reduction in trade costs with different values of  $\gamma^s$ . We continue to assume that  $\gamma^1 < \gamma^2$ , which means that in sector 1, stage 1 plays a more important role in stage 2 production. We conduct two exercises. In the first exercise, we assume  $\gamma^2 \equiv \gamma$  and  $\gamma^1 = \gamma - 0.4$  to have the same difference between  $\gamma^1$  and  $\gamma^2$  as in the baseline simulation. Then, we vary  $\gamma$  from 0.4 to one to assess how the distributional effects of a decline in trade costs are affected by the GVC intensity. In the second exercise, we set  $\gamma^2 = 0.5$ , i.e., the average of the two  $\gamma$ 's in the baseline simulation, and vary  $\gamma^1$  within  $[\frac{\gamma^2}{2}, \gamma^2]$  to investigate the effect of sectoral variation in  $\gamma^s$ .

Figure 2 shows for each sector, the changes in the two GVCs involving domestic sourcing for both stages of production. Notice first that the y-axis on all four graphs contains negative numbers signifying that when trade costs decline, the prevalence of domestic sourcing declines. The key point of the figure is that as we move from right to left in each panel, the extent of the decline in domestic sourcing increases. In other words, as the GVC intensity, and the effective trade elasticity, increase, the substitution of GVCs involving trade and vertical specialization for the domestic sourcing GVCs increases. The multi-stage production and intermediate trade through GVCs magnify the effect of the reduction in trade costs, and the magnification effect is monotonically increasing in the GVC intensity. Changes of all other aggregate variables from the model, such as the price index and other elements of

$\lambda_{l,i}^s$  matrices are also monotonic in  $1 - \gamma$ .

Figure 2: Changes in  $\lambda_{(1,1),1}^s$  and  $\lambda_{(2,2),2}^s$  with Different Values of  $\gamma$  (%)



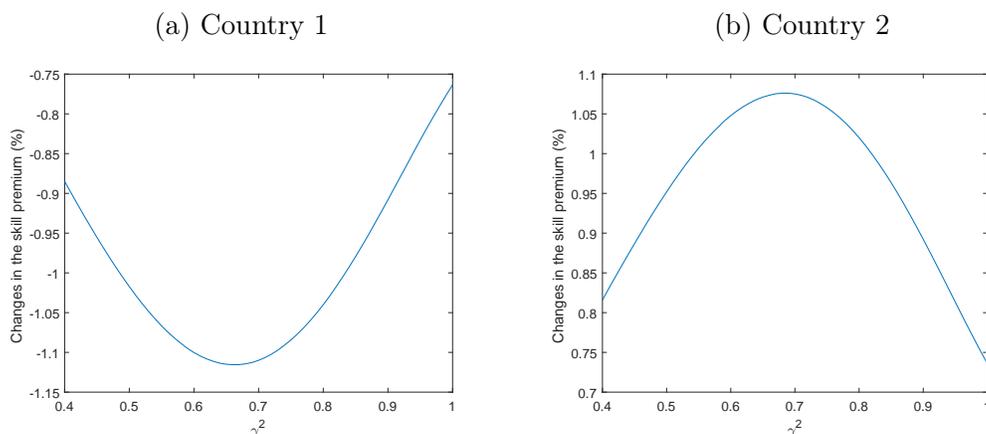
The distributional effect of a reduction in trade costs, on the other hand, is not monotonic in the GVC intensity. Figure 3 shows the change in the skill premium in each country when trade costs are reduced under different values of  $\gamma$  with  $\gamma^2 \equiv \gamma$  and  $\gamma^1 = \gamma - 0.4$ . While the skill premium decreases in country 1 and increases in country 2 for all values of  $\gamma$ , the figure clearly shows the magnitude of the change in the skill premium (resulting from the reduction in trade costs) is not monotonic in the GVC intensity – rather, it is largest at intermediate values of average  $\gamma^s$ .

This result illustrates the importance of comparative advantage across stages in generating large skill premia effects from reductions in trade costs. When the GVC intensity takes extreme values, i.e., at least one of the sectoral  $\gamma^s$  approaches 0 or 1, then, at least one of the sectors effectively has only one stage of production. By reducing the effective number of stages, we will get smaller effects on the skill premium. Put differently, workers have fewer opportunities to sort into the sectors and stages that provide the best fit, which reduces the

variation in wages across worker types.

We offer an additional interpretation. It is not the GVC intensity,  $1 - \gamma^s$ , per se, that is crucial, but rather, the presence of multi-stage production, with its additional opportunities for specialization, that can lead to larger skill premia effects from reduced trade costs. When the GVC intensity is maximized, it ironically eliminates multi-stage production, which then reduces skill premia.

Figure 3: Changes in the Skill Premium with Different Values of  $\gamma$  (%)

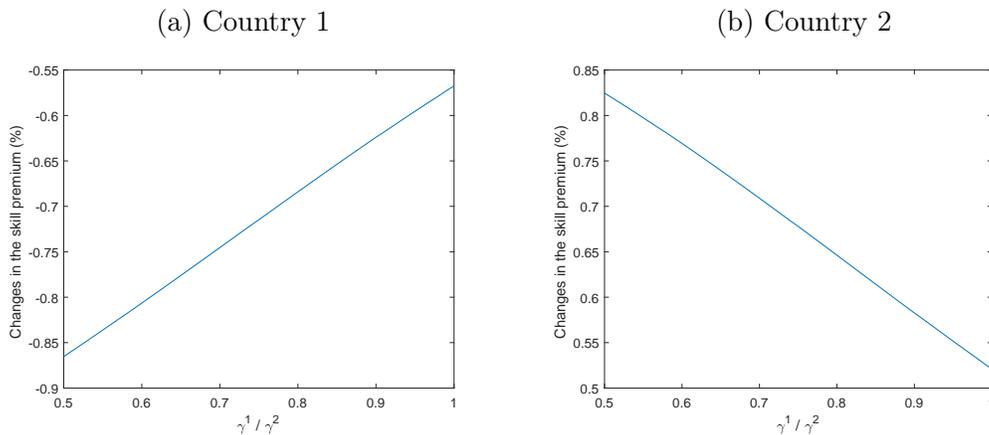


Our results also suggest that GVCs transfer country-level comparative advantages to worker-level comparative advantages by putting different value-added weights on different production stages in different sectors. This mechanism makes the distributional impact of trade shocks non-monotonic in GVC intensities. Therefore, we should expect sectoral variation in the GVC intensity to play an important role. In our first exercise, the difference in  $\gamma^s$  between sector 1 and sector 2 was fixed.

To further explore the importance of sectoral variation in  $\gamma^s$ , in our second exercise, we set  $\gamma^2 = 0.5$  and explore different ratios  $\gamma^1/\gamma^2 \in [0.5, 1]$ . Sector 1 depends relatively more on stage 1 (for stage 2 production) as in the baseline simulation. As  $\gamma^1$  gets smaller, we put larger relative weights on each country's comparative advantage sector and stage combination, because our baseline parameter values assume that country 1 (country 2) has a comparative advantage in sector 1 and stage 1 (sector 2 and stage 2.) Figure 4 shows that the size of increase (decrease) of the skill premium in country 2 (country 1) is larger when  $\gamma^1$  and  $\gamma^2$  are further apart (geometrically.) In our model, sectoral variation in the GVC intensity governs how much country-level comparative advantage is transmitted into worker-level comparative advantage by putting different weights on each sector and each

stage. Equivalently, it affects how much trade shocks affect relative gains among different types of workers. As long as the relative magnitude of the GVC intensity does not reverse the HO comparative advantage, i.e.,  $\gamma^1 < \gamma^2$ , the effect of a decline in trade costs on skill premia is larger the larger the weights on their comparative advantage stages.

Figure 4: Changes in the Skill Premium with Different Values of  $\gamma$  (%)



In summary, the results from our numerical exercises show how the GVC mechanism and the Roy mechanism interact with standard HO comparative advantage. As trade costs decline, countries specialize in their comparative advantage production stage, which shifts relative labor demand for occupations in our model. Second, depending on different GVC intensities across sectors, sector-level labor demand is also affected. Third, the Roy mechanism makes workers respond to trade shocks differently across sectors and occupations, even though workers are exposed to the same trade shock. Fourth, as predicted in existing papers in the literature, aggregate effects of reduction in trade costs on trade flows and prices are monotonically increasing in the GVC intensity. Lastly, the distributional effects of the reduction in trade costs are not monotonic in the GVC intensity. The effects on the skill premium are larger, when both sector- and stage-level comparative advantages operate with intermediate GVC intensity values. In addition, the skill premium changes more when GVCs put larger weights on each country's comparative advantage sector and stage combination.

## 4 Calibration

Our numerical exercise above shows the basic mechanism of our model in a simple two-stage case with only two countries, two worker types, two occupations, and two sectors. We now

calibrate the general version of our model to data. Our goal is to assess the role of GVCs as a propagation mechanism transmitting global integration shocks, such as China joining the WTO, for aggregate trade outcomes, as well as distributional outcomes, such as the skill premia. In particular, our focus is on the role of sectoral variation in the GVC intensity.

## 4.1 Countries, Worker Types, Occupations, and Production Stages

We calibrate the model to three countries—China, U.S.A, and a constructed rest of the world (ROW) for the year 2000, the year before China joined the WTO. Workers are classified by  $T = 5$  types, defined by educational attainment: 1) high school dropouts; 2) high school graduates; 3) workers with some college education; 4) college graduates; and 5) workers with advanced degrees. When we calculate the skill premium, we define skilled workers as those who have at least some college education. We define five occupation categories ( $O = 5$ ) following [Dorn \(2009\)](#): 1) low-skilled service occupations and agricultural workers; 2) assemblers and machine operators; 3) precision production and crafts occupations; 4) administrative, clerical, and sales occupations; and 5) managers, professionals, and technicians. This categorization is based on both skill levels required by occupation and the routineness of occupation.

In addition, we use the World Input-Output Database (WIOD) for 2000. We reduce the WIOD tables for that year into one with China, U.S.A, and the rest-of-the-world, and with four sectors ( $S = 4$ ): agriculture, mining, manufacturing, and services. [AG](#) and [de Gortari \(2017\)](#) show how to map the GVC concepts into input-output flows. We will do this from our framework with two stages of production. In AG, the number of stages that fit their data the best is  $J = 2$ . Accordingly, we calibrate our model with two production stages,  $J = 2$ .<sup>5</sup>

## 4.2 Assigned Parameters or Exogenous Variables

We assign  $\nu = 4$  from [Simonovska and Waugh \(2014\)](#) for the common stage-invariant part of trade elasticity. Conditional on the assigned value of  $\nu$ , we calibrate bilateral trade costs for each country pair and each sector using bilateral trade flows of final goods in the WIOD 2000. Type-level labor supply ( $\bar{L}_{i,t}$ ) is obtained from [Barro and Lee \(2013\)](#), and the sector expenditure share  $b^s$  is calibrated to exactly match the sector expenditure share in the WIOD. We set  $\sigma = 2$  for the elasticity of substitution between within-sector product varieties. Finally, we jointly calibrate the sector-specific GVC intensity  $\gamma^s$ , the value-added

---

<sup>5</sup>In a more general version of calibration,  $J$  can be also jointly calibrated with other parameters of the model.

share  $\alpha_i^s$ , Ricardian productivities  $A_i^s$ , and country- and stage-specific occupation intensity  $\beta_i^{j,o}$ . We now turn to the details of calibrating the bilateral trade costs, the parameters related to worker productivity (i.e., the Roy parameters), and the production function parameters.

### 4.3 Calibration of Bilateral Trade Costs

Our model delivers a mapping from the GVC probability  $\lambda_{l,n}^s$  to bilateral trade flows of goods. Similarly to AG, trade flows of final goods from country  $i$  to country  $n$  are defined by  $\tilde{\lambda}_{in}^{F,s} = \sum_{l \in \Lambda_i^J} \lambda_{l,n}^s$ , where  $\Lambda_i^J$  is a set of all GVC paths which perform the final production stage in country  $i$ . We obtain the data counterparts to these bilateral trade flows from the WIOD. In order to use  $\tilde{\lambda}_{in}^{F,s}$  from the WIOD to calibrate bilateral trade costs, we impose two identifying assumptions. First, there is no trade cost for domestic transactions—i.e.,  $\tau_{ii}^s = 1$  for every  $i$  and  $s$ . Second, bilateral trade costs are symmetric—i.e.,  $\tau_{in}^s = \tau_{ni}^s$  for every  $(i, n)$  and  $s$ .

Using the expression of  $\lambda_{l,n}^s$  from the model, the common trade elasticity  $\nu$ , and these two identifying assumptions, we can back out bilateral trade costs  $\tau_{in}^s$  by following the [Head and Ries \(2001\)](#) method:

$$\tau_{in}^s = \left[ \frac{\tilde{\lambda}_{in}^{F,s} \tilde{\lambda}_{ni}^{F,s}}{\tilde{\lambda}_{ii}^{F,s} \tilde{\lambda}_{nn}^{F,s}} \right]^{-\frac{1}{2\nu}}$$

Table 3 summarizes calibrated trade costs for each country-pair and sector. Not surprisingly, bilateral trade costs are lowest in the manufacturing sector and highest in the service sector on average. We will use these trade costs to calibrate other parameters of the model from the 2000 WIOD.

Table 3: Calibrated  $\tau_{in}^s$

| Country pair | Agriculture | Mining | Manufacturing | Service |
|--------------|-------------|--------|---------------|---------|
| China - U.S. | 5.9         | 5.3    | 2.6           | 7.8     |
| China - ROW  | 2.7         | 1.9    | 2.1           | 1.8     |
| U.S.- ROW    | 3.0         | 3.7    | 2.9           | 3.0     |

## 4.4 Estimation of the Roy Parameters

We estimate the Roy parameters,  $T_t^{s,o}$  and  $\theta_t$ , using the U.S. American Community Survey (ACS) for 2000 following the estimation method in Lee (2017). Workers draw sector- and occupation-specific idiosyncratic productivities from a Fréchet distribution  $G_t^{s,o}(\epsilon)$  as defined in Section 2. Different worker types have different productivity distributions. The scale parameter  $T_t^{s,o}$  governs the level of worker type  $t$ 's average productivity for sector  $s$  and occupation  $o$ . The shape parameter  $\theta_t$  is inversely related to within-type heterogeneity of productivity. Using the independence assumption between productivity draws and the characteristics of Fréchet distribution, we can derive the distribution of the equilibrium observed wage  $\tilde{w}$  for each worker type  $t$ <sup>6</sup>:

$$G_t^*(\tilde{w}) = \exp\left\{-\left[\sum_{s',o'} T_t^{s',o'} (w_i^{s',o'})^{\theta_t}\right] \tilde{w}^{-\theta_t}\right\}.$$

We use hourly wage profiles and individual's educational attainment in the U.S. ACS 2000 data to estimate the parameters of  $G_t^*(\tilde{w})$  for each worker type  $t$ . We jointly estimate  $\sum_{s',o'} T_t^{s',o'} (w_{us}^{s',o'})^{\theta_t}$  and  $\theta_t$  using the maximum likelihood.

The estimated  $\sum_{s',o'} T_t^{s',o'} (w_{us}^{s',o'})^{\theta_t}$ , the labor allocation  $\pi_{us,t}^{s,o}$  from the U.S. ACS 2000, and the expression for  $\pi_{us,t}^{s,o}$  from our model pin down individual  $T_t^{s,o}$ 's up to a normalization. Similarly to Hsieh et al. (2013), we normalize the scale parameter of high school dropouts, i.e.,  $T_1^{s,o} = 1$  for all  $(s, o)$ . Then, we back out  $T_t^{s,o}$  for  $t \neq 1$ . This normalization does not affect worker-level comparative advantage, because we compare ratios, not levels, of  $T_t^{s,o}$  to shape worker-level comparative advantage.

Table 4: ML Estimates of  $\theta_t$

|                  | High School<br>Dropouts | High School<br>Graduates | Some College<br>Education | College<br>Graduates | Advanced<br>Degrees |
|------------------|-------------------------|--------------------------|---------------------------|----------------------|---------------------|
| $\hat{\theta}_t$ | 1.972                   | 1.862                    | 1.735                     | 1.603                | 1.480               |
| S.E.             | (0.0043)                | (0.0055)                 | (0.0057)                  | (0.0015)             | (0.0005)            |

Table 4 reports the estimates of  $\theta_t$  and standard errors. The estimates show that better-educated workers have more dispersed productivity distributions within their type. Because

<sup>6</sup>The observed wage  $\tilde{w}$  is different from per-unit wage  $w_i^{s,o}$ . Wages we observe in data are not  $w_i^{s,o}$  but  $\tilde{w}$  which takes both per-unit wage and worker productivity into account.

$\theta_t$  is also the shape parameter of the distribution of equilibrium observed wages, this result also suggests that the wage distribution of high-skilled workers is more dispersed than that of low-skilled workers. This feature can be easily confirmed with individual wage profiles data as documented by Lee (2017).

Table 5: Sector- and Occupation-level Averages of Estimated  $T_t^{s,o}$

| (a) Sector-level Average |             |        |               |         |  |
|--------------------------|-------------|--------|---------------|---------|--|
|                          | Agriculture | Mining | Manufacturing | Service |  |
| High school graduates    | 0.91        | 1.67   | 1.83          | 1.85    |  |
| Some College Education   | 0.91        | 1.11   | 1.99          | 2.57    |  |
| College Graduates        | 0.87        | 1.30   | 3.67          | 4.85    |  |
| Advanced Degrees         | 0.77        | 0.70   | 2.72          | 5.91    |  |

| (b) Occupation-level Average |                              |                                    |  |                          |                                   |
|------------------------------|------------------------------|------------------------------------|--|--------------------------|-----------------------------------|
|                              | Low-skill<br>Service<br>Jobs | Assemblers<br>Machine<br>Operators | Precision<br>Produc-<br>tion<br>Crafters | Admin<br>Clerks<br>Sales | Managers<br>Prof Tech-<br>nicians |
| High school graduates        | 0.90                         | 0.84                               | 1.32                                     | 2.31                     | 2.47                              |
| Some College Education       | 0.47                         | 0.34                               | 0.94                                     | 2.23                     | 4.24                              |
| College Graduates            | 0.18                         | 0.12                               | 0.44                                     | 1.60                     | 11.03                             |
| Advanced Degrees             | 0.08                         | 0.05                               | 0.14                                     | 0.48                     | 11.88                             |

Table 5 summarizes the estimates of  $T_t^{s,o}$  for each type except for high school dropouts whose  $T_t^{s,o}$ 's are normalized to one. Worker-level comparative advantage is clearly identified across both sectors and occupations. While all worker types are more productive in absolute terms when they are in the service sector than in the agriculture sector, better-educated workers have a comparative advantage in the service sector. On the other hand, low-skilled workers have a comparative advantage in agriculture and mining sectors. Worker-level comparative advantage is much more clearly pronounced across occupations. While the average estimates of  $T_t^{s,o}$  range from 0.898 to 2.466 across five occupations for high school graduates, the average  $T_t^{s,o}$  of workers with advanced degrees for managerial and professional occupations is about 152 times larger than their average for low-skill service jobs. In other words, better educated workers have a much larger advantage for having high-skilled occupations

than for being in the service sector. In addition, the relative magnitudes of  $T_t^{s,o}$  show that, for better educated workers, having high-skilled occupations is much more beneficial if they are in the service sector than in other sectors.

The estimated  $\theta_t$  and  $T_t^{s,o}$  shape worker-level comparative advantage within and across types, which is the Roy channel in our model. Because workers have different productivities across sectors and occupations, the same trade shocks can generate different sector- and occupation-level responses among workers, as we showed in the previous section. In addition, the relative magnitude of  $T_t^{s,o}$ , along with the type-level labor supply  $\bar{L}_{i,t}$ ,  $T_t^{s,o}$ , affects the effective occupation-level labor endowment, which shapes the Heckscher-Ohlin comparative advantage across sectors and production stages.

## 4.5 Calibration of the Production Parameters

After we calibrate the trade costs, the common trade elasticity, the type-level labor supply, the Roy parameters, and the demand parameters, we calibrate the remaining production side parameters,  $\gamma^s$ ,  $\alpha_i^s$ ,  $A_i^s$ , and  $\beta_i^{j,o}$  for the year 2000. Calibration of the first three sets of parameters follows the approach in AG by targeting similar sets of moments. Because our model has multiple sectors, we target sector-specific moments. Each set of targeted moments discussed below can be linked to each parameter. However, the relationship between targeted moments and parameters is not one-to-one, of course. All of the calibrated parameters are jointly related to all of the targeted moments through the general equilibrium.

First, we calibrate the expressions for domestic absorption of final goods and intermediate goods from the corresponding WIOD 2000 data. The model expression for bilateral trade flows of final goods is  $\tilde{\lambda}_{in}^{F,s}$  as derived above. Intermediate trade flows can be a part of the roundabout structure or a part of the GVC structure. We denote bilateral trade flows of intermediate goods from each structure by  $\tilde{\lambda}_{ik}^{1,s}$  for the roundabout structure and  $\tilde{\lambda}_{ik}^{2,s}$  for the GVC structure. The model expressions of these two variables are:

$$\tilde{\lambda}_{ik}^{1,s} = \tilde{\lambda}_{ik}^{F,s} b^s \sum_{s'} \frac{1 - \alpha_k^{s'}}{\alpha_k^{s'}} \sum_o \sum_t \bar{w}_{k,t} \pi_{k,t}^{s',o} \bar{L}_{k,t}$$

$$\tilde{\lambda}_{ik}^{2,s} = \sum_{j=1}^{J-1} \tilde{\gamma}^{s,j} \sum_n \sum_{l \in A_{ik}^j} \lambda_{l,n}^s b^s \left[ \sum_t \bar{w}_{n,t} \bar{L}_{n,t} + \sum_{s'} \frac{1 - \alpha_n^{s'}}{\alpha_n^{s'}} \sum_o \sum_t \bar{w}_{n,t} \pi_{n,t}^{s',o} \bar{L}_{n,t} \right],$$

where  $A_{ik}^j \equiv \{l = (l^1, \dots, l^J) \in \mathbf{N}^J | l^j = i \text{ and } l^{j+1} = k\}$  is a set of all GVC paths that cross country  $i$  at stage  $j$  and country  $k$  at stage  $j + 1$ . Taking both roundabout and GVC production structures into account, bilateral trade flows of intermediate goods between

country  $i$  and country  $k$  in our model are given by  $\tilde{\lambda}_{ik}^{I,s} = \frac{\tilde{\lambda}_{ik}^{1,s} + \tilde{\lambda}_{ik}^{2,s}}{\sum_{i'} [\tilde{\lambda}_{i'k}^{1,s} + \tilde{\lambda}_{i'k}^{2,s}]}$ . As in AG, the diagonal entries of  $\tilde{\lambda}_{in}^{F,s}$  and  $\tilde{\lambda}_{ik}^{I,s}$  matrices help identify the GVC intensity  $\gamma^s$ . Unlike in AG, we also exploit sector-level variation in domestic absorption to obtain the sector-specific GVC intensity.

The WIOD also reports value-added and gross output in each industry and each country. We aggregate the tables to three countries and four sectors. We then compute the ratio of value-added to gross output in each sector and each country. We use this moment to help calibrate the country- and sector-specific value-added shares  $\alpha_i^s$ . We also calibrate the Ricardian productivity parameters  $A_i^s$  by targeting the share of GDP of each sector and each country in total world GDP.

The occupation intensity  $\beta_i^{j,o}$  at each production stage in each country is identified from a combination of the diagonal entries of the  $\tilde{\lambda}_{in}^{F,s}$  and  $\tilde{\lambda}_{ik}^{I,s}$  matrices, the share of value-added to gross output, and the share of wage payment to a particular occupation within each sector in each country. This last moment is obtained from the ILOSTAT database from the International Labor Organization (ILO.)

Summarizing, we jointly calibrate  $\gamma^s$ ,  $\alpha_i^s$ ,  $A_i^s$ , and  $\beta_i^{j,o}$  to match as closely as possible the model moments to their data counterparts. Table A1 and Table A2 in the Appendix report the calibration results for  $\gamma^s$ ,  $\alpha_i^s$ ,  $A_i^s$ , and  $\beta_i^{j,o}$  for the year 2000. The model-generated moments fit the targeted moments reasonably well. The correlation between these two sets of moments is 0.82. Our model fits the diagonal entries of final and intermediate goods matrices and GDP shares the best; the correlation between these targeted moments and the model-generated moments is about 0.9. Our model also fits several non-targeted moments well. For example, the correlation coefficients between the model-predicted off-diagonal entries of the  $\tilde{\lambda}_{in}^{F,s}$  and  $\tilde{\lambda}_{ik}^{I,s}$  matrices and their data counterparts range from 0.82 to 0.88.

We highlight several features of our calibrated parameters. First, there is variation in  $\gamma^s$  across sectors. The range is from 0.12 for agriculture to 0.5 for mining, with 0.4 and 0.48 for manufacturing and services, respectively. As a reminder, lower values of  $\gamma^s$  imply a greater share of stage-two production is coming from the stage-one good. For example, agriculture stage-two production depends greatly on its stage-one input.

Second, the calibrated value-added shares  $\alpha_i^s$  vary a great deal across countries and sectors with a mean of 0.50 with a standard deviation of 0.22. Third, the Ricardian productivity parameters  $A_i^s$  suggest that China has a comparative advantage in the manufacturing sector, and the U.S. has a comparative advantage in the services sector. This Ricardian comparative advantage will shape the sector-level specialization patterns, while the endowment-based comparative advantage from the Roy channel will mainly determine stage-level specialization pattern.

Fourth, the calibrated occupation intensities  $\beta_i^{j,o}$  indicate that a production stage has different interpretations across countries in terms of occupation intensity. In relative terms, stage one uses high-skilled occupations more intensively in the U.S., but the same stage uses less-skilled occupations more intensively in China. If the United States specializes in stage 1 and China specializes in stage 2 following a trade liberalization, this pattern in  $\beta_i^{j,o}$  will be consistent with the skill upgrading story of [Feenstra and Hanson \(1995\)](#), [Zhu and Trefler \(2005\)](#), and [Costinot and Vogel \(2010\)](#). This is one implication of our model that goes beyond that of [Lee \(2017\)](#). In addition, in our model, with its explicit vertical production structure, occupation intensities carry different weights based on the GVC intensity for each sector. In previous research on offshoring without a vertical production structure, factor intensities essentially carry the same weight in the entire value chain. From the lens of our GVC structure, the calibrated  $\gamma^s$  shows that the condition of the same weight across stages is not satisfied. In other words, the role of occupation intensity is more or less important across stages and sectors depending on the magnitude of  $\gamma^s$ . We will further discuss this mechanism in the next section.

## 5 Counterfactuals

Based on the calibrated and estimated parameters from Section 4, we perform counterfactual exercises in order to quantitatively assess the aggregate and distributional impacts of trade liberalization. We solve the model with bilateral trade costs and other model parameters calibrated to the year 2000. We then introduce exogenous changes in bilateral trade costs to the model. The main counterfactual scenario we look at is a 50% decline in trade costs for China-U.S.A. and China-ROW. The goal of this counterfactual is to quantitatively assess the aggregate and distributional effects of China’s integration into world economy in an explicit GVC setting.

This shock is especially relevant for our paper, because since China joined the WTO in 2001, it has had an enormous impact on the global economy, and, as part of that impact, it has heavily specialized in global value chains. Our model should capture the multiple facets in which the China shock affects labor demand and labor supply in different countries through sector- and stage-level specialization, interaction between country- and worker-level comparative advantages, and the relative GVC intensity across sectors.

Another form of the China shock studied in recent research is an increase in China’s productivity—e.g., [Autor et al. \(2013\)](#). In our model, this would show up as an exogenous increase in  $A_{CHN}^s$ . However, we focus only on the effect of a decline in trade costs with China in this paper, because trade costs have a direct relationship with the effective trade

elasticity, which relies on our main GVC mechanism. Lee (2017) introduces both types of China shocks separately and shows that the quantitative magnitude of distributional effects is much larger from the trade-cost-related China shock.

We then study the role of our GVC channel in explaining distributional effects of the China shock by running alternative counterfactuals where the GVC channel does not operate or magnifies country-level comparative advantage. Our main counterfactual results are also robust to alternative values of the elasticity of substitution ( $\sigma$ ) or the common part of the trade elasticity ( $\nu$ ).

We note that all of the results presented below are quantitative, not qualitative. They depend on the general equilibrium interaction of all the mechanisms we have discussed in our paper, with the specific magnitude of each mechanism dictated by the calibrated values of the parameters.

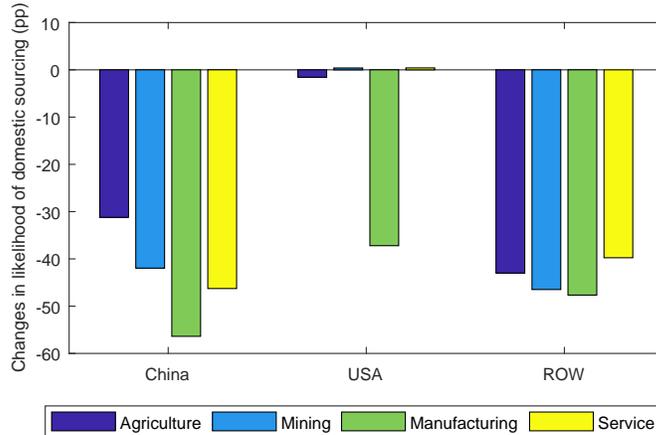
## 5.1 Baseline Counterfactual Results

In our baseline counterfactual exercise, we use our model calibrated to the year 2000 and then reduce the trade costs involving China. We first show the impact on the goods specialization patterns, and then we turn to the distributional impacts. Our primary measure of distributional impact will be the skill premium, which we defined earlier in the data as the wage premium of workers who have at least some college education over workers without any college education. The model counterpart of the skill premium is  $\bar{w}_{i,H}/\bar{w}_{i,L}$ , where worker types  $H$  and  $L$  are defined as they are in the data.

Figure 5 shows the implied changes in the prevalence of domestic sourcing  $\lambda_{(i,i),i}^s$ . The figure shows that all three countries, and especially China and the ROW, are less likely to source both production stages from domestic producers. Of the four sectors, the manufacturing sector has the largest decline in the prevalence of domestic sourcing in all countries; the declines range from -37 percentage points (pp) to -56 pp. This result is related to the fact that China has a comparative advantage in the manufacturing sector and also to the relatively high GVC intensity—lower  $\gamma^s$ —in the manufacturing sector. The magnification of aggregate outcomes, including the aggregate effective trade elasticity, is larger in the sector with a higher GVC intensity.

The counterfactual also implies that the likelihood of domestic sourcing in the service sector increases slightly—0.52 pp—in the United States. Based on the calibrated Ricardian productivity  $A_i^s$ , the United States has a comparative advantage in the services sector. When China’s trade costs are lowered, there are two offsetting effects on the U.S. services sector.

Figure 5: Counterfactual Changes in the Prevalence of Domestic Sourcing  $\lambda_{(i,i),i}^s$



First, the lower trade barriers will mean that China can start producing and exporting the downstream part of services to the U.S., which reduces the prevalence of sourcing both stages domestically. Second, China’s specialization in manufacturing facilitates the U.S. specializing more in both stages of services.

To illustrate the importance of stage-level specialization in response to the decline in trade costs, Table 6 shows for each country-sector pair the percentage change in stage 1 output as a share of total output across both stages. The table shows that China specializes in stage 2 in all sectors and the United States specializes in stage 1 in all sectors, but agriculture. The small increase in the stage 1 output share in the U.S. service sector (compared to other sectors) is related to the result for domestic sourcing in Figure 5. The U.S. comparative advantage in the service sector dominates its comparative disadvantage in stage 2, which makes it more likely to source both stages of the service sector from itself.

Table 6: Counterfactual Changes in the Share of Stage 1 within Sectors (%)

|       | Agriculture | Mining | Manufacturing | Service |
|-------|-------------|--------|---------------|---------|
| China | -10.9       | -94.3  | -57.4         | -91.4   |
| USA   | -5.0        | 13.7   | 19.5          | 2.2     |
| ROW   | -43.8       | 15.8   | -8.6          | 19.9    |

The changing sector- and stage-level specialization patterns change the relative demand for labor and finally change the skill premium. Our model implies that decline in China’s

trade costs leads to an increase the skill premium in all three countries, China, U.S., and ROW, by 0.25%, 0.94%, and 1.09%, respectively. This parallel increase in skill premia is consistent with the previously mentioned skill upgrading story in the literature.

The increase in the U.S. is driven by sector-level and stage-level specialization forces, both of which go in the same direction. The U.S. has a comparative advantage in the service sector. Moreover, highly educated workers in the U.S. have a comparative advantage in the services sector. Hence, the sector level channel leads to an increase in the skill premium. The U.S. also has a comparative advantage in stage 1 production. Stage 1 production in the U.S. is high-skilled occupation intensive; moreover, higher educated workers have a comparative advantage in high-skilled occupations. Hence, the stage-level channel also leads to an increase in the skill premium.

The increase in the skill premium in China reflects two offsetting forces. At the sector level, China has a comparative advantage in manufacturing. Less educated workers in China have a comparative advantage in the manufacturing sector. Hence, the sector level leads to a decrease in the skill premium in China. On the other hand, at the stage level, China has a comparative advantage in stage 2 production. Stage 2 production in China is high-skilled occupation intensive; moreover, higher educated workers have a comparative advantage in high-skilled occupations. Hence, the stage level channel leads to an increase in the skill premium. The skill upgrading story in the literature holds through stage-level specialization introduced by our GVC structure. Overall, our model predicts that the stage-level specialization dominates the sector level specialization, leading to an increase in China's skill premium.

In addition, the magnitude of the skill premium change should depend on the exact level of the GVC intensity, because our calibration results for  $\gamma^s$  show that sectors differ in GVC intensity. Therefore, how strongly the skill upgrading story holds under the context of GVC depends on how much each sector depends on GVCs.

According to our calibrated model, the U.S. has a comparative advantage in stage 1 and in the service sector. However, compared to agriculture and manufacturing sectors, the service sector is where stage 1 has relatively lower weight. Therefore, the increase of the skill premium is limited in magnitude in the U.S. Similarly, because  $\gamma^s$  is relatively small in the manufacturing sector, where China has a comparative advantage, the fact that stage 2 uses high-skilled occupations more intensively does not drive up the labor demand for better educated workers very much. This limits the increase in China's skill premium. The actual GVC structure calibrated to the data translates only a part of specialization effects into wage responses, thus it limits the magnitude of distributional effects of the China shock.

In order to better understand the role of our GVC structure, we run the same coun-

terfactual exercise with  $\gamma^s = 0.999$  for all  $s$ .<sup>7</sup> This extreme case shuts down the GVC channel because all value-added comes from stage 2. In this case, there is only sector-level comparative advantage through the Ricardian channel, and better educated workers have a comparative advantage in the service sector through the Roy channel. In this exercise, our model implies that the skill premium increases by 0.17% in the U.S., and it decreases by 1.16% in China. This result highlights the importance of the GVC as a transmission mechanism increasing the skill premium in both countries.

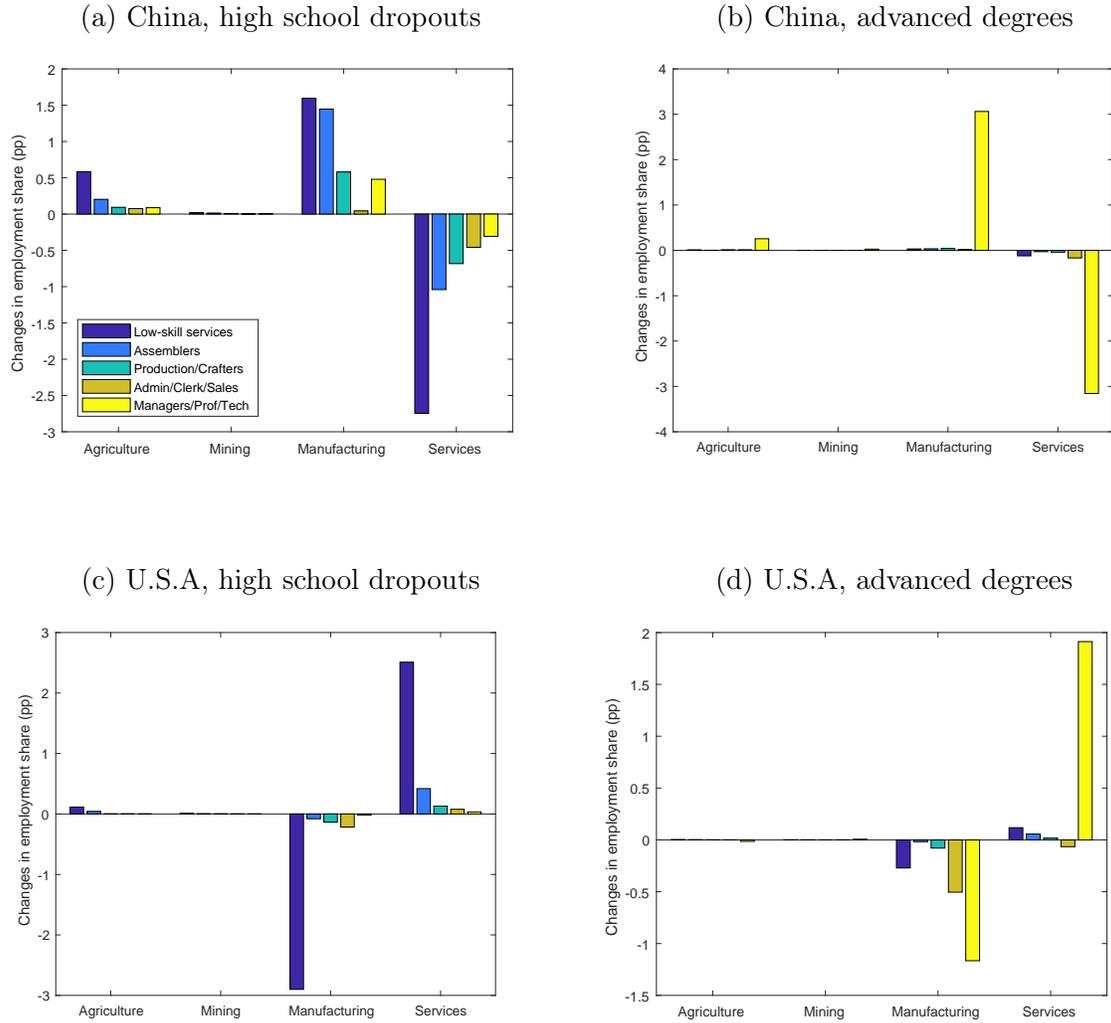
Combining our calibration results with the counterfactual results, we conclude that in the absence of the GVC channel, the skill upgrading in both China and the U.S. could not occur. Both countries specialize in relatively high-skilled-occupation-intensive production stages through GVCs, and therefore, the skill premium increases in both countries. However, conditional on the GVCs, our calibrated values of the GVC intensity show that there is lower intensity, or weight, on each country's comparative advantage stage and sector combination. This limits the magnitude of the increases in the skill premium for both countries. If there was a larger weight on each country's comparative advantage sector and stage combination, then the GVC effect on the skill premium would be even larger. We discuss this alternative case in the next subsection.

Our model also shows the labor reallocation patterns within each worker type in response to the China trade integration shock. Figure 6 shows the labor reallocation across sectors and occupations for high school dropouts and workers with advanced degrees in the U.S. and China. Each country's comparative advantage across sectors is a major factor that determines workers' reallocation across sectors. In the U.S., both worker types are likely to move to the service sector. In China, both types tend to reallocate into the manufacturing sector. While sector-level reallocation is similar between worker types, different worker types tend to choose different occupations even when they are moving into the same sector. This occupation-level labor reallocation is determined by the relative magnitude of  $T_t^{s,o}$  across occupations. For example, in the U.S., even though both worker types are likely to move into the service sector, low-skilled workers are going there for low-skill service occupations, while better educated workers are much more likely to have managerial and professional occupations in the service sector. Lastly, our model predicts more reallocation within less educated worker types, which is related to their larger labor allocation elasticity  $\theta_t$  from our estimation.

---

<sup>7</sup>We keep the calibrated values for the other parameters the same without re-calibrating the model to focus only on the mechanism. Results from the re-calibrated model are discussed in the next section, Section 5.2.

Figure 6: Within-worker-type Reallocation of Labor



We conduct sensitivity analysis with respect to two key elasticities, the elasticity of substitution ( $\sigma$ ) and the common part of the trade elasticity ( $\nu$ ). We first run the same counterfactual with  $\sigma = 1$  (Cobb-Douglas) and  $\sigma = 4$ , respectively.<sup>8</sup> The skill premium increases in both China and the U.S. with these alternative parameter values, and the magnitudes are very similar to the baseline result  $-0.34\%$  and  $0.16\%$  for China, and  $0.94\%$  and  $0.94\%$  for the U.S., respectively. We then run the counterfactual with  $\nu = 5.5$  and  $\nu = 8.28$  (EK), respectively. The signs again remain unchanged, but the skill premium increases more with these alternative common trade elasticities which are larger than the baseline value  $\nu = 4$ . The skill premium increases by  $2.04\%$  and  $3.62\%$  in China and by  $1.42\%$  and  $2.10\%$  in the

<sup>8</sup>For these exercises, we did not recalibrate the other parameters.

U.S. for each  $\nu = 5.5$  and  $\nu = 8.28$ . Overall, we conclude that varying these two elasticities does not change the results by much.

## 5.2 Alternative Counterfactuals with Different GVC Intensities

In order to investigate the role of the GVC intensities on the distributional impacts of the China shock, we run the same counterfactual exercise (50% decline in bilateral trade costs with China) with alternative values of  $\gamma^s$ . We conduct two alternative counterfactuals.

In the first alternative counterfactual, we put extreme weights on each country’s comparative advantage sector and stage. We set  $\gamma^s = 1$  for the manufacturing sector and  $\gamma^s = 0$  for the service sector. This puts the maximum weight on stage two for manufacturing, which is China’s comparative advantage, and the maximum weight on stage 1 for the services sector, which is the U.S. comparative advantage. We set  $\gamma^s = 0.5$  for the remaining two sectors, so that both stages are equally important in those sectors. We keep the values of the occupation intensity  $\beta_i^{j,o}$  from our baseline calibration. Given these values, we then re-calibrate the Ricardian productivity  $A_i^s$  and the value-added share  $\alpha_i^s$ .<sup>9</sup>

In response to the China trade integration shock, the skill premium in China and the U.S. increase, as before. However, the magnitude of the increase is almost twice as high as in the baseline exercise – 0.58% increase in China and 1.47% increase for the U.S. This result suggests that if GVC intensities are weighted towards each country’s comparative advantage sector and stage, then changes in labor demand based on the relative occupation intensity will be larger. And these larger changes in labor demand will translate into larger wage changes, especially for the highly educated workers in both countries, and ultimately larger changes in the skill premia. Our result mirrors our second simulation of the simple 2<sup>5</sup> case. In the simulation, when we put larger weights on each country’s comparative advantage sector and stage (by varying the gap between  $\gamma^s$  across two sectors), the effect of decline in trade costs on the skill premium is larger.

In the second alternative counterfactual exercise, we consider the case where the GVC channel is shut down by setting  $\gamma^s = 0.999$  for all sectors  $s$ . In the previous subsection, we studied this alternative specification without re-calibrating the model. Now, we re-calibrate the Ricardian productivity  $A_i^s$  and the value-added share  $\alpha_i^s$  (and keep the values of  $\beta_i^{j,o}$  from the baseline calibration). All value-added comes only from stage 2 production, country-level comparative advantage is defined only across sectors based on the relative magnitude of  $A_i^s$ . Hence, when the China integration shock occurs, China specializes in the manufacturing sector, and the U.S. specializes in the service sector. Because occupation intensities vary by

---

<sup>9</sup>We re-calibrated these parameters to match the same set of moments as in the baseline calibration.

stage, not by sector, the sector-level specialization changes the fundamental wage variable  $w_i^{s,o}$  primarily across sectors. The Roy channel of our model shows that better-educated workers have a comparative advantage in the service sector. Therefore, increased labor demand in the service sector in the U.S. increases the skill premium in the U.S. (+0.02%.) In contrast, higher labor demand in the manufacturing sector of China decreases the skill premium in China (-0.39%.) without the GVC channel.

The key role of the GVC channel in our model is that each country's specialization in relatively high-skilled production operates through GVCs. If the GVC mechanism does not operate, the skill upgrading argument in the literature does not hold. The skill premium in the U.S. still increases in response to the China shock even in the no-GVC counterfactual but by a much smaller amount, because GVCs add one more layer of country-level comparative advantage across production stages based on stage-specific occupation intensities.

In summary, two alternative counterfactual exercises show that the GVC channel makes the skill upgrading mechanism work by making each country specialize in production stages that are relatively intensive in high-skilled occupations. Given that the GVC channel is operative, the actual GVC intensity governs how much of the specialization effect translates into changes in relative wages. The baseline and alternative counterfactuals show that the skill premium in each country responds more the greater the value-added in each country's comparative advantage sector originating from its comparative advantage stage.

## 6 Conclusion

The increasing prevalence of vertical specialization through global value chains has attracted a lot of attention in the literature. However, the role of GVCs as a propagating mechanism of distributional impacts of trade shocks has been surprisingly understudied. In this paper, we provide new insight on the effect of GVCs on aggregate outcomes, such as trade flows and prices, and more importantly, on the skill premium, by introducing a new quantitative general equilibrium model of GVCs with Ricardian and Heckscher-Ohlin motives for trade, and with Roy heterogeneous worker mechanisms.

Our model shows how country-level comparative advantage and worker-level comparative advantage interacts with each other through GVCs. When trade shocks are transmitted through GVCs, countries specialize in sectors and stages where they have a comparative advantage. Different sectors depend differently on each production stage, and different production stages have different occupation intensities. Therefore, the effect on relative labor demand varies by sector and occupation. Workers respond to this change in labor demand by reallocating their labor based on their own comparative advantage in sector and occupation.

We calibrate our model to the U.S., China, and the rest of the world in 2000, and study the effect of a decline in trade costs with China, to capture China’s entry into the WTO. The trade shock leads each country to specialize in stages where high-skilled occupations are used more intensively. As a consequence, the relative demand for high-skilled occupations for which high-skilled workers have a comparative advantage increases in all countries. Therefore, the skill premium increases everywhere. The skill upgrading argument in the trade literature operates in our model through GVCs.

The GVC channel governs the direction of changes in the skill premium, and also its magnitude. Our model shows that the sector-specific GVC intensity determines how much of the specialization effect from trade liberalization translates into relative wage responses. Our calibrated model shows that each country’s comparative advantage sector and stage in fact has a relatively small contribution to the entire value chain, and therefore the increase in the skill premium from the trade shock is not large.

Our model can serve as a good toolkit to quantify the distributional impacts of changes in trade environment through global value chains. While our model features a rich interaction between country-level comparative advantage, worker-level comparative advantage, and global value chains, it does not have varying length of value chains across sectors or a more general sectoral input-output linkage structure for the composite intermediate good. We leave these two features for future research.

## References

- ALVAREZ, F. AND R. E. LUCAS (2007): “General Equilibrium Analysis of the Eaton–Kortum Model of International Trade,” *Journal of Monetary Economics*, 54, 1726–1768. [1.1](#), [2.4](#), [3.2](#)
- ANTRÀS, P. AND D. CHOR (2013): “Organizing the Global Value Chain,” *Econometrica*, 81, 2127–2204. [1.1](#)
- ANTRÀS, P. AND A. DE GORTARI (2017): “On the Geography of Global Value Chains,” *NBER Working Paper Series*, 23456. [1](#), [1.1](#), [2](#), [2.1](#), [2.2](#), [3.1](#)
- AUTOR, D. H., D. DORN, AND G. H. HANSON (2013): “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review*, 103, 2121–68. [1](#), [1.1](#), [5](#)
- (2015): “Untangling Trade and Technology: Evidence from Local Labour Markets,” *The Economic Journal*, 125, 621–646. [1.1](#)

- BARRO, R. J. AND J. W. LEE (2013): “A New Data Set of Educational Attainment in the World, 1950–2010,” *Journal of Development Economics*, 104, 184–198. 4.2
- BURSTEIN, A., E. MORALES, AND J. VOGEL (2015): “Accounting for Changes in Between-Group Inequality,” *NBER Working Paper Series*, 20855. 1.1
- BURSTEIN, A. AND J. VOGEL (2016): “International Trade, Technology, and the Skill Premium,” *Journal of Political Economy* (forthcoming). 1.1
- CALIENDO, L. AND F. PARRO (2015): “Estimates of the Trade and Welfare Effects of NAFTA,” *The Review of Economic Studies*, 82, 1–44. 2.1, 3.1
- COSTINOT, A. AND J. VOGEL (2010): “Matching and Inequality in the World Economy,” *Journal of Political Economy*, 118, 747–786. 1.1, 4.5
- (2015): “Beyond Ricardo: Assignment Models in International Trade,” *Annual Review of Economics*, 7, 31–62. 1.1
- DAO, M., M. DAS, Z. KOCZAN, W. LIAN, AND OTHERS (2017): “Why is Labor Receiving a Smaller Share of Global Income? Theory and Empirical Evidence,” *IMF Working Papers*, 17. 1.1
- DE GORTARI, A. (2017): “Disentangling Global Value Chains,” *Working Paper*. 1, 1.1, 2.1, 3.1, 4.1
- DORN, D. (2009): “Essays on Inequality, Spatial Interaction, and the Demand for Skills,” Ph.D. thesis, University of St. Gallen. 4.1
- EATON, J. AND S. KORTUM (2002): “Technology, Geography, and Trade,” *Econometrica*, 70, 1741–1779. 1.1, 2, 2.1
- EBENSTEIN, A., A. HARRISON, M. MCMILLAN, AND S. PHILLIPS (2014): “Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys,” *Review of Economics and Statistics*, 96, 581–595. 1.1
- FEENSTRA, R. C. AND G. H. HANSON (1995): “Foreign Investment, Outsourcing and Relative Wages,” *NBER Working Paper Series*, 5121, doi: 10.3386/w5121. 1.1, 4.5
- (1999): “The Impact of Outsourcing and High-Technology Capital on Wages: Estimates For the United States, 1979–1990,” *The Quarterly Journal of Economics*, 114, 907–940. 1.1

- GALLE, S., A. RODRÍGUEZ-CLARE, AND M. YI (2017): “Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade,” *NBER Working Paper Series*, 23737. 1.1
- GOLDBERG, P. K. AND N. PAVCNİK (2007): “Distributional Effects of Globalization in Developing Countries,” *Journal of Economic Literature*, 45, 39–82. 1.1
- GROSSMAN, G. M., E. HELPMAN, AND P. KIRCHER (2015): “Matching, Sorting, and the Distributional Effects of International Trade,” *Working Paper*. 1.1
- GROSSMAN, G. M., E. HELPMAN, E. OBERFIELD, AND T. SAMPSON (2017): “The Productivity Slowdown and the Declining Labor Share: A Neoclassical Exploration,” *NBER Working Paper Series*, DOI: 10.3386/w23853. 1.1
- HARRIGAN, J., A. RESHEF, AND F. TOUBAL (2016): “The March of the Techies: Technology, Trade, and Job Polarization in France, 1994—2007,” *NBER Working Paper Series*, 22110. 1.1
- HEAD, K. AND J. RIES (2001): “Increasing Returns Versus National Product Differentiation as an Explanation for the Pattern of Us-Canada Trade,” *American Economic Review*, 91, 858–876. 4.3
- HELPMAN, E. AND O. ITSKHOKI (2010): “Labour Market Rigidities, Trade and Unemployment,” *The Review of Economic Studies*, 77, 1100–1137. 1.1
- HELPMAN, E., O. ITSKHOKI, M.-A. MUENDLER, AND S. J. REDDING (2016): “Trade and Inequality: From Theory to Estimation,” *The Review of Economic Studies*, 0, 1–49. 1.1
- HSIEH, C.-T., E. HURST, C. I. JONES, AND P. J. KLENOW (2013): “The Allocation of Talent and U.S. Economic Growth,” *NBER Working Paper Series*, 18693. 1.1, 4.4
- HUMMELS, D., J. ISHII, AND K.-M. YI (2001): “The Nature and Growth of Vertical Specialization in World Trade,” *Journal of International Economics*, 54, 75–96. 1.1
- JOHNSON, R. C. AND A. MOXNES (2016): “Technology, Trade Costs, and the Pattern of Trade with Multi-Stage Production,” *Working Paper*. 1.1
- JOHNSON, R. C. AND G. NOGUERA (2012): “Accounting for Intermediates: Production Sharing and Trade in Value Added,” *Journal of International Economics*, 86, 224–236. 1.1, 2.5
- KATZ, L. F. AND K. M. MURPHY (1992): “Changes in Relative Wages, 1963–1987: Supply and Demand Factors,” *The Quarterly Journal of Economics*, 107, 35–78. 1.1

- KOOPMAN, R., Z. WANG, AND S.-J. WEI (2014): “Tracing Value-Added and Double Counting in Gross Exports,” *American Economic Review*, 104, 459–494. 1.1
- KRUGMAN, P. (1995): “Growing World Trade: Causes and Consequences,” *Brookings Papers on Economic Activity*, 1995, 327–377. 1.1
- KRUGMAN, P. R. (2008): “Trade and Wages, Reconsidered,” *Brookings Papers on Economic Activity*, 2008, 103–137. 1.1
- KRUSELL, P., L. E. OHANIAN, J.-V. RÍOS-RULL, AND G. L. VIOLANTE (2000): “Capital-skill Complementarity and Inequality: A Macroeconomic Analysis,” *Econometrica*, 68, 1029–1053. 2.1
- LAGAKOS, D. AND M. E. WAUGH (2013): “Selection, Agriculture, and Cross-Country Productivity Differences,” *American Economic Review*, 103, 948–80. 1.1
- LAWRENCE, R. Z. AND M. J. SLAUGHTER (1993): “International Trade and American Wages in the 1980s: Giant Sucking Sound or Small Hiccup?” *Brookings Papers on Economic Activity. Microeconomics*, 1993, 161–226. 1.1
- LEE, E. (2017): “Trade, Inequality, and the Endogenous Sorting of Heterogeneous Workers,” *Working Paper*. 1, 1.1, 2, 2.1, 2.3, 2.5, 4.4, 4.4, 5
- OHNSORGE, F. AND D. TREFLER (2007): “Sorting It Out: International Trade with Heterogeneous Workers,” *Journal of Political Economy*, 115, 868–892. 1.1
- PARRO, F. (2013): “Capital-Skill Complementarity and the Skill Premium in a Quantitative Model of Trade,” *American Economic Journal: Macroeconomics*, 5, 72–117. 2.1
- PIERCE, J. R. AND P. K. SCHOTT (2016): “The Surprisingly Swift Decline of US Manufacturing Employment,” *American Economic Review*, 106, 1632–1662. 1.1
- ROY, A. D. (1951): “Some Thoughts on the Distribution of Earnings,” *Oxford economic papers*, 3, 135–146. 1.1
- SIMONOVSKA, I. AND M. E. WAUGH (2014): “The Elasticity of Trade: Estimates and Evidence,” *Journal of International Economics*, 92, 34–50. 4.2
- TEULINGS, C. N. (2005): “Comparative advantage, relative wages, and the accumulation of human capital,” *Journal of Political Economy*, 113, 425–461. 1.1
- TRAIBERMAN, S. (2016): “Occupations and Import Competition Evidence from Danish Matched Employee-Employer Data,” *Working Paper*. 1.1

YI, K.-M. (2003): “Can Vertical Specialization Explain the Growth of World Trade?” *Journal of Political Economy*, 111, 52–102. 1.1, 2.1, 2.5

——— (2010): “Can Multistage Production Explain the Home Bias in Trade?” *American Economic Review*, 100, 364–393. 1.1, 2.5

ZHU, S. C. AND D. TREFLER (2005): “Trade and inequality in developing countries: a general equilibrium analysis,” *Journal of International Economics*, 65, 21–48. 1.1, 4.5

## A Tables and Figures

Table A1: Calibrated  $\gamma^s$ ,  $\alpha_i^s$ , and  $A_i^s$  for the Year 2000

(a) GVC Intensity,  $\gamma^s$

|            | Agriculture | Mining | Manufacturing | Service |
|------------|-------------|--------|---------------|---------|
| $\gamma^s$ | 0.1213      | 0.5007 | 0.3999        | 0.4475  |

(b) Roundabout Intensity,  $\alpha_i^s$

|        | Agriculture | Mining | Manufacturing | Service |
|--------|-------------|--------|---------------|---------|
| China  | 0.2893      | 0.5140 | 0.3747        | 0.5405  |
| U.S.A. | 0.2347      | 0.2788 | 0.3847        | 0.4668  |
| ROW    | 1           | 0.8272 | 0.5900        | 0.5001  |

(c) Ricardian Productivity,  $A_i^s$

|        | Agriculture | Mining | Manufacturing | Service |
|--------|-------------|--------|---------------|---------|
| China  | 36.748      | 66.968 | 94.982        | 63.733  |
| U.S.A. | 44.031      | 52     | 51.938        | 162.62  |
| ROW    | 74.875      | 150.38 | 199.97        | 100     |

Table A2: Calibrated  $\beta_i^{j,o}$  for the Year 2000

(a) China

|         | Low-skill<br>Service<br>Jobs | Assemblers<br>Machine<br>Operators | Precision<br>Production<br>Crafters | Admin<br>Clerks<br>Sales | Managers<br>Professionals<br>Technicians |
|---------|------------------------------|------------------------------------|-------------------------------------|--------------------------|--|
| Stage 1 | 0.4271                       | 0.1391                             | 0.1390                              | 0.1549                   | 0.1389                                   |
| Stage 2 | 0.2969                       | 0.2871                             | 0.1250                              | 3.27E-17                 | 0.2900                                   |

(b) U.S.A.

|         | Low-skill<br>Service<br>Jobs | Assemblers<br>Machine<br>Operators | Precision<br>Production<br>Crafters | Admin<br>Clerks<br>Sales | Managers<br>Professionals<br>Technicians |
|---------|------------------------------|------------------------------------|-------------------------------------|--------------------------|--|
| Stage 1 | 0.5581                       | 0.0703                             | 0.0351                              | 0.0505                   | 0.2851                                   |
| Stage 2 | 0.6250                       | 1.53E-06                           | 0.0625                              | 0.3130                   | 1.53E-06                                 |

(c) ROW

|         | Low-skill<br>Service<br>Jobs | Assemblers<br>Machine<br>Operators | Precision<br>Production<br>Crafters | Admin<br>Clerks<br>Sales | Managers<br>Professionals<br>Technicians |
|---------|------------------------------|------------------------------------|-------------------------------------|--------------------------|--|
| Stage 1 | 0.8398                       | 1.53E-06                           | 1.53E-06                            | 0.1602                   | 1.53E-06                                 |
| Stage 2 | 5.55E-17                     | 0.2788                             | 0.1332                              | 1.91E-04                 | 0.5889                                   |