Global Value Chains and Inequality with Endogenous Labor Supply*

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Abstract

We assess the role of global value chains in 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. 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 trade costs with the U.S., 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., specialization across stages, is critical to this outcome.

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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 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.

In this framework, a decline in trade costs facilitates specialization at the sector-level and at the production stage-level. 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. Even though workers observe the same change in wages for each sector and occupation, the individual worker's response will differ depending on his/her idiosyncratic productivity. There are general equilibrium feedback mechanisms at work, as well. Ultimately, the skill premia are affected.

To develop more intuition, we also study a "2^5" version of the model in terms of countries, worker types, sectors, stages, and occupations. 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. We find that the combined effect from sector and stage specialization on the skill premium is larger when the GVC intensity puts larger weights on a country's comparative advantage sector and stage.

We then calibrate the general version of our model for three countries, China, U.S., and constructed rest of the world (ROW); five worker types; three 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 mining sectors than in other sectors. 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 the U.S. When trade costs between China and the U.S. go down, all countries specialize further in their comparative advantage stages and sectors. In addition, we find that the skill premium rises in China by 1.8 percent and in the U.S. by close to 1 percent.[1] In both China and the U.S., the lower trade costs induce specialization to shift towards stages that use high-skilled-occupations more intensively. Thus, we have a "skill upgrading" mechanism which operates through stage specialization. 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 conduct a number of additional counterfactuals to understand our results better. Overall, we find that in the absence of GVCs, we would not get both China's and the U.S.'s skill premium to rise, and that our main explanation for the skill premium is correct.

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.

There are also other papers that propose alternative mechanisms to explain the effect of trade on inequality by departing from the standard Stolper-Samuelson effect: Bernard et al. (2007) show real wages can increase for both abundant and scarce factors; Parro (2013)

[1] For China this corresponds to about one-third of the increase in the college premium found in Ge and Yang (2014) during 2000-2007. For the U.S. it corresponds to about one-fifth of the increase during the 2000s.

shows that capital-skill complementarity can drive increase of the skill premium from trade in all countries; and Burstein and Vogel (2016) combine an HO framework in a model that features heterogeneous firms and skill-biased productivity. Our framework is in this vein.

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.

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. This is the skill upgrading story. These papers do not explicitly examine GVCs empirically or theoretically, i.e., employ a model with multiple sequential stages. Our paper builds, calibrates, and simulates a model with such a structure to examine quantitatively the importance of the GVC mechanism in transmitting changes in trade costs to changes in skill premia. Our framework in principle could have a skill upgrading channel, and we find that the calibrated model indeed does.

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. Lee (2017) introduces a more general setup for worker heterogeneity than our paper, where the degree of worker heterogeneity can vary even by country. Then the main focus of Lee (2017) is on quantifying the effect of changes in trade costs and changes in partner country's productivity on disaggregate labor market outcomes for a large number of countries. Lastly, the main counterfactual exercise of Lee (2017) is actual changes in trade costs between 2000 and 2007, as well as an increase in China's manufacturing productivity. In this paper, we do not introduce varying degree of worker heterogeneity across countries. Instead, 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. For quantification, we focus mainly on China and the U.S. to understand the core mechanisms.

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 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 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 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, $s = 1, \ldots, S$, there is a continuum of final goods over a set Ω^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 ω 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, $o = 1, \ldots, O$. 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, $i = 1, \ldots, N$, is exogenously endowed with $\bar{L}_{i,t}$ workers of type t, $t = 1, \ldots, T$. In our quantitative analysis, these types will be associated with observable worker characteristics, such as education. Each worker of each type "draws" a matrix of sector and occupation specific productivities, and on the basis of these productivities 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 ω 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 ω 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 ω by

$l(\omega) = (l^1(\omega), \ldots, l^J(\omega))$. At each stage j of the value chain for a product ω, firms use domestic labor, the stage $j-1$ good for ω, 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 ω in sector s is Cobb-Douglas:

$$f_i^{s,j}(x_i^{s,j}, L_i^{s,j,1}(\omega), \ldots, L_i^{s,j,O}(\omega), m_i^{s,j-1}(\omega))$$
$$= z_i^{s,j}(\omega)((x_i^{s,j})^{1-\alpha_i^s} \prod_o \left[L_i^{s,j,o}(\omega))^{\beta_i^{j,o}\alpha_i^s}\right]^{\gamma^{s,j}} (m_i^{s,j-1}(\omega))^{1-\gamma^{s,j}}.$$

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 ω 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 α_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.[2] More formally, as $\gamma^{s,j} \to 0$, the snake or value chain term dominates the roundabout and value-added terms, and vice versa for $\gamma^{s,j} \to 1$. α_i^s captures the relative importance of value-added and the composite intermediate with higher values of α_i^s corresponding to greater importance of value-added. This parameter varies across sectors and countries. We will call this parameter as value-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 $s = 1, \ldots, S$.

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 ω 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. ν 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 A_i^s, and is present across sectors. The HO channel operates through $\beta_i^{j,o}$, and

[2] 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.

is mainly present across stages. 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. Finally, note that our HO parameters are country-specific.

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.[3]

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').[4] Second, within-worker-type comparative advantage depends on the shape parameter θ_t. If workers' productivities are more dispersed within a type–i.e., lower θ_t–, then effects from the within-worker-type comparative advantage will be stronger than in the case of a larger θ_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 $\epsilon = (\epsilon^{1,1},\ldots,\epsilon^{s,o},\ldots,\epsilon^{S,O})$:

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

[3] Lee (2017) introduces a more general setup for worker productivity, where the distribution of worker productivity varies by country. Since the model is solved in proportional changes and the scale parameter is assumed to be fixed over time, Lee (2017) does not back out the scale parameter for each country. On the other hand, the shape parameter is estimated separately for four countries.

[4] In the next section we show that our main numerical result does not change when we uniformly scale up one country's productivity, as long as the relative magnitude of $T_t^{s,o}$ remains unchanged within the country.

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.[5]

We illustrate the worker and goods flows in Figure 1 below for a special case of the model with two countries, sectors, occupations (H and L), stages, and worker types (H and L).

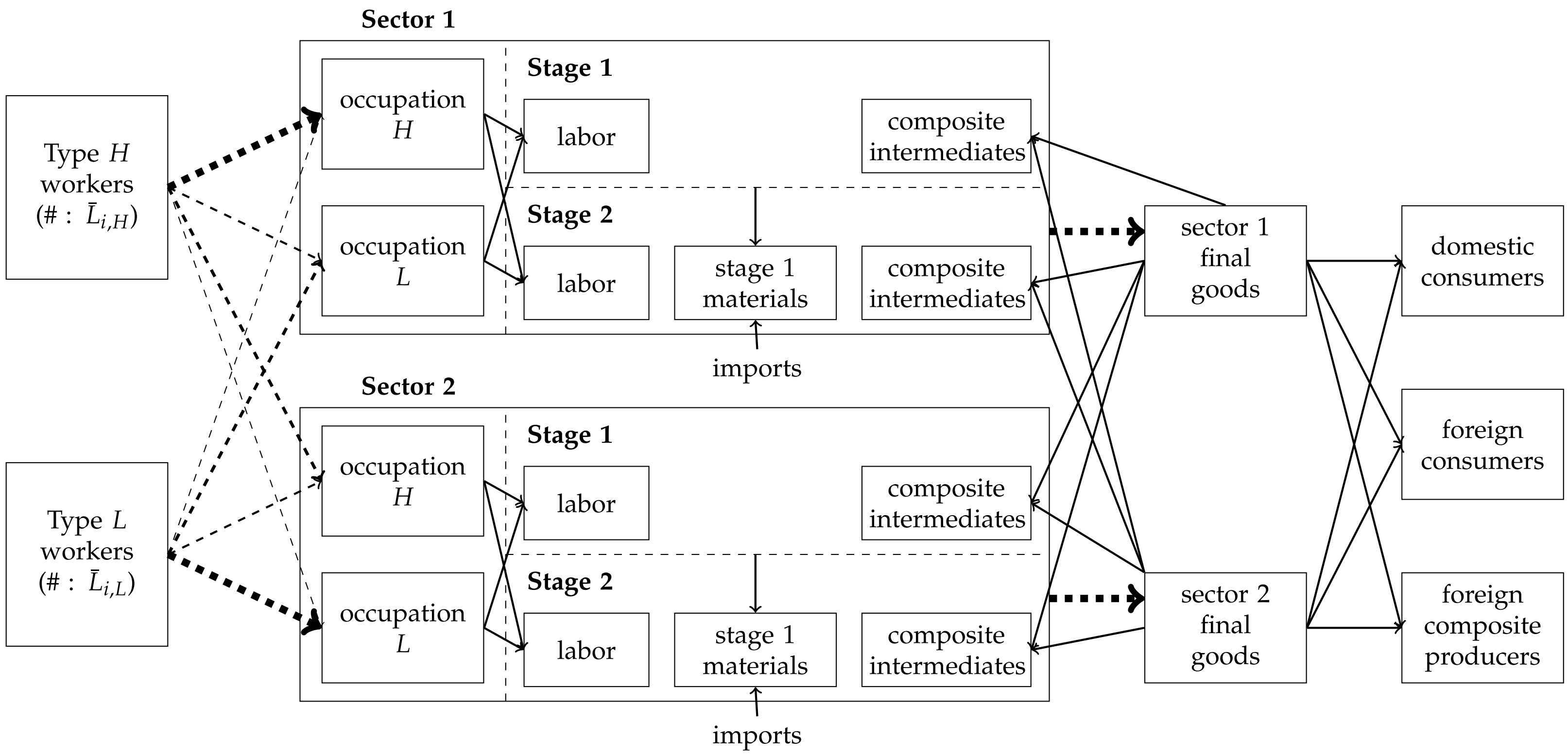
2.2 Equilibrium Sourcing Decision

In the above model, a final producer for ω 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. On the other hand, 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.

[5] The standard trade model with fixed, homogeneous, factors can be recovered via the following assumptions, which eliminate the Roy channel:

1. $\theta_t \to \infty$ 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. $T_t^{s,o} \to 0$ for every $o \neq t$ and $T_t^{s,t} = 1$ for all s and t.

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



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 ω by solving the following problem:

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

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:

$$\begin{aligned}
\Theta_i^{s,j}(x) &\equiv E_j[(p^{s,j}_{l_i^{s,j}(\omega)}(\omega)\tau^s_{l_i^{s,j}(\omega)i})^x] \\
&= E_j[(\frac{(c^{s,j}_{l_i^{s,j}(\omega)})^{\gamma^{s,j}}}{z^{s,j}_{l_i^{s,j}(\omega)}(\omega)})^x \times \Theta^{s,j-1}_{l_i^{s,j}(\omega)}(x(1-\gamma^{s,j})) \times (\tau^s_{l_i^{s,j}(\omega)i})^x].
\end{aligned}$$

We denote the optimal source for stage j materials of sector-s product ω 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 ω 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.

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

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

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

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

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

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 $j = 1, \ldots, J-1$, 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

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

for $j = 1, \ldots, J-1$. 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 monotonically 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 ω of sector s consumed in country i has followed a specific GVC path $l = (l^1, \ldots, l^J)$

is

$$\begin{aligned}
\lambda^s_{l,i} &= \Pr(l^{s,J}_i(\omega) = l^J | l^{s,J-1}_{l^J}(\omega) = l^{J-1}) \times \Pr(l^{s,J-1}_{l^J}(\omega) = l^{J-1} | l^{s,J-2}_{l^{J-1}}(\omega) = l^{J-2}) \times \dots \\
& \quad \dots \times \Pr(l^{s,1}_{l^2}(\omega) = l^1) \\
&= \frac{\prod_{j=1}^J A^s_{l^j}[(c^{s,j}_{l^j})^{\gamma^{s,j}}(\tau^s_{l^j l^{j+1}})]^{-\nu\tilde{\gamma}^{s,j}}}{\sum_{l'\in\mathbf{N}^J}\prod_{j=1}^J A^s_{l'^j}[(c^{s,j}_{l'^j})^{\gamma^{s,j}}(\tau^s_{l'^j l'^{j+1}})]^{-\nu\tilde{\gamma}^{s,j}}},
\end{aligned}$$

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:

$$\Pr(l^{s,J}_i(\omega) = n) = \frac{A^s_n (B^{s,J}_{ni})^{-\nu}}{\sum_{n'} A^s_{n'}(B^{s,J}_{n'i})^{-\nu}}.$$

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

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

$$\text{where } P^s_i = [\Gamma(\frac{\nu+1-\sigma}{\nu})]^{1/(1-\sigma)}(\sum_{l'\in\mathbf{N}^J}\prod_{j=1}^J A^s_{l'^j}[(c^{s,j}_{l'^j})^{\gamma^{s,j}}(\tau^s_{l'^j l'^{j+1}})]^{-\nu\tilde{\gamma}^{s,j}})^{-1/\nu}. \quad (1)$$

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 ϵ. In other words, worker's problem can be written as

$$\max_{s,o} w^{s,o}_i \epsilon^{s,o},$$

where $w^{s,o}_i$ is per-unit wage for workers in sector s of country i with occupation o. Workers take the per-unit wages as given. Since ϵ 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

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

where $\pi_{it}^{s,o}$ is the share of workers of type t in country i that work in occupation o and sector s. The shape parameter θ_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

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

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:

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

where we define

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

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 α, γ, and β 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 occupation, the individual worker's response will differ depending on his/her idiosyncratic productivity. The worker choices will then imply the change in the skill premium.

We now discuss how particular parameters of the model map into comparative advantage and their skill premium. 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, i.e., the Ricardian channel. Under typical circumstances, Ricardian 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.

Relative factor endowments also indirectly shape sector-level comparative advantage of countries through $\bar{L}_{i,t}$ and $T^{s,o}_{i,t}$, because sectors also use different occupations with different intensities based on $\beta^{j,o}_i \alpha^s_i \gamma^{s,j}$. Note that if both α^s_i and $\gamma^{s,j}$ are the same across sectors, then relative factor endowments do not affect sector-level comparative advantage channel.

A country's stage-level comparative advantage is driven primarily from the HO channel. Owing to our assumption that the occupation intensity coefficients $\beta^{j,o}_i$ do not vary by sector, the textbook HO channel is not present. However, there are two other sources of HO forces. The first is that the occupation intensity coefficients $\beta^{j,o}_i$ vary by stage, so this variation across stages, in conjunction with differences in supplies of the types of labor, $\bar{L}_{i,t}$, as well as their productivities, $T^{s,o}_{i,t}$, 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 $1-\alpha^s_i$, and/or GVC intensity $1-\gamma^{s,j}$ 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. However, since occupational intensities vary also by country, this variation by country, in conjunction with variation across sectors in the GVC intensity, $1-\gamma^{s,j}$ can also generate changes in skill premia that potentially go in the same direction in both skill-abundant and skill-scarce countries.

The Ricardian channel also shapes the stage-level comparative advantage through the interaction between A^s_i 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.

It should be clear from the above discussion that the Roy channel, building from worker type endowments $\bar{L}_{i,t}$ and workers productivities, $T^{s,o}_t$, is closely tied to the Ricardian channel (primarily at the sector level) and the HO channel (primarily at the stage level). The combination of $\bar{L}_{i,t}$ and $T^{s,o}_t$ determines the effective labor endowment. When trade costs decline, the effective labor endowment affects specialization patterns, which in turn affects the fundamental wages $w^{s,o}_i$.

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 $\gamma^{s,j} \to 1$. In the extreme case where $\gamma^{s,j} = 1$ for all $j = 1, \ldots, J$, 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 $\gamma^{s,j} \to 0$, 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.

It should be clear from the above discussion that it is not obvious that there is a monotonic relationship between higher GVC intensity, i.e., higher $1-\gamma^{s,j}$, and a higher change in the skill premium in one or both countries induced by lower trade barriers. 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 provide two key equations, the one governing equilibrium GVCs, and the labor market clearing condition. Each country has an exogenous supply of two types of workers. Worker's optimization problem is the same as in the baseline model.

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. To further simplify the model, we assume that the occupation intensity $\beta^{j,o}$ does not vary by country in this simple "Two" model. 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, and its intensity γ^s determines the GVC intensity for sector s , $1-\gamma^s$. The production process is illustrated in the boxes in the middle of Figure 1.

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.

Again, following 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:

$$\lambda^s_{l,i} = \frac{A^s_{l^1}(c^{s,1}_{l^1}\tau^s_{l^1l^2})^{-\nu(1-\gamma^s)} \times A^s_{l^2}[(c^{s,2}_{l^2})^{\gamma^s}\tau^s_{l^2i}]^{-\nu}}{\sum_{l'\in\mathbf{N}^2} A^s_{l'^1}(c^{s,1}_{l'^1}\tau^s_{l'^1l'^2})^{-\nu(1-\gamma^s)} \times A^s_{l'^2}[(c^{s,2}_{l'^2})^{\gamma^s}\tau^s_{l'^2i}]^{-\nu}},$$

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:

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

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.

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.[6]

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 productions 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, $\theta_t = 1.5$ 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 γ^s for both aggregate and distributional effects of reduction in trade costs, we will experiment with different values of γ^s and with a sector-level variation in γ^s later in this section.

Results We first discuss the effects of lower trade costs on aggregate prices and the pattern of GVCs $\lambda_{l,i}^s$. 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 90% in country 2.

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

[6] 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.

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 0.8 percent under high trade costs to 26.5 under free trade (for final consumers of sector 1 goods in country 1).

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 1: Changes in $\lambda^s_{l,i}$ from the Benchmark Simulation

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

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

		(1) $\tau_{in}^{s}=2$		(2) $\tau_{in}^{s}=1$		(3) change (pp)	
	$\pi_{i,t}^{s,o}$	$o=1$	$o=2$	$o=1$	$o=2$	$o=1$	$o=2$
Country 1, Type H	$s=1$	0.081	0.255	0.085	0.261	0.3	0.6
	$s=2$	0.138	0.525	0.138	0.516	0.03	-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	0.2445	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	0.139	0.516	0.138	-0.8	-0.02
	$s=2$	0.256	0.081	0.261	0.085	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.

In our exercise, the worker productivity distributions are the same across countries. What would be the effect of lower trade costs if the distributions were different? We consider a special case in which we uniformly scale up one country's labor productivity $T_t^{s,o}$ holding its relative magnitude across sectors, occupations, and types fixed. For example, if we multiply every $T_t^{s,o}$ by two so workers in country 2 are twice as much productive on average, then the skill premium decreases by -1.29% in country 1 and increases by 1.06% in country 2. As long as worker's comparative structure remains unchanged, uniform increase of the average productivity does not change our main result, because labor market outcomes of interest such as labor allocation and relative average wage all depend on worker's comparative advantage, not on their absolute advantage.

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. 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 γ^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 $1 - \gamma^s$, we repeat the exercise of a reduction in trade costs from $\tau_{in}^s = 2$ to $\tau_{in}^s = 1$ with all the parameters the same as above, except for the values of γ^s, which range from 0 to 1 in each sector.

Figure 2 shows that domestic sourcing (both stages are produced in the consuming country) declines as trade costs decline for all values of γ^s. The key point is that in panel (a), with lower values of γ^1, i.e., higher values of GVC intensity, the decrease in domestic sourcing in sector 1 is larger, and similarly for sector 2 in panel (b). Again, the intuition is that with higher values of $1 - \gamma^1$, the "elasticity" of domestic sourcing in sector 1 with respect to trade costs is larger, because more of the good-in-process crosses multiple borders. In addition, the magnitude of changes in the probability of domestic sourcing in a certain sector depends only on its own GVC intensity, and not on the GVC intensity of the other sector.

Figure 2: Changes in Domestic Sourcing Probability with Different Values of γ (%)

(a) Country 1, sector 1

(b) Country 1, sector 2

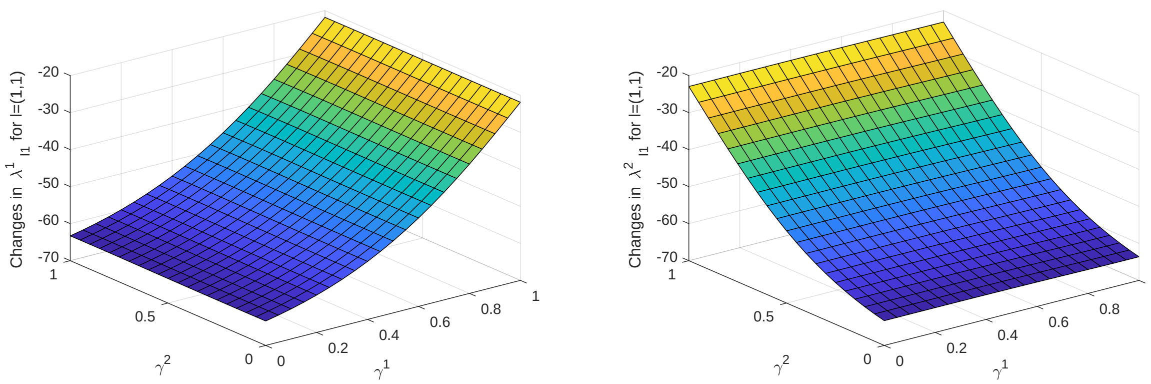
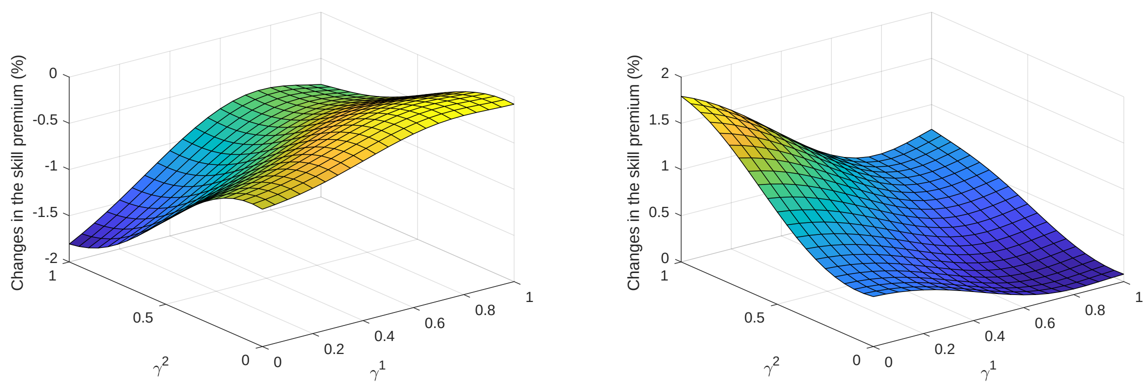


Figure 3 shows that the change in the skill premium from a decline in trade costs is not monotonic in the values of γ^1 and γ^2. Our interpretation is that the GVC intensity, i.e., $1 - \gamma^s$, interacts with other factors to influence the skill premium. Indeed, note that the skill premium change in country 1 is maximized when $\gamma^1 = 0$ and $\gamma^2 = 1$, i.e., the greatest value-added weight is placed on country 1's comparative advantage sector and stage (sector 1 and stage 1), and similarly for country 2. In other words, the skill premium change is larger if a country has a great deal of value-added in the sector and stage in which it has a comparative advantage. More broadly, 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 the skill premium response to changes in trade costs.

In summary, the results from our numerical exercises show how GVC intensities and the Roy mechanism interact with standard HO comparative advantage. First, 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. Fifth, the distributional effects

Figure 3: Changes in the Skill Premium with Different Values of γ (%)

(a) Country 1 (b) Country 2



of the reduction in trade costs are not monotonic in the GVC intensity. The effects on the skill premium are larger, when GVCs put larger value-added 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, worker types, occupations, and 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 the GVC intensity.

Following the calibrated framework, we turn to the parameters. Some parameters are assigned, some are directly estimated from the data, and some are set to match moments in the data. Specifically, the trade elasticity ν , the elasticity of substitution of product varieties σ are assigned; type-level labor supply $\bar{L}_{i,t}$, final good expenditure shares b^s, and trade costs τ^s_{in} are estimated from the data; the Roy worker productivity parameters are assigned and calibrated based on Lee (2017); and the production function parameters - the sector-specific GVC intensity γ^s, the value-added share α^s_i, Ricardian productivities A^s_i, and country- and stage-specific occupation intensity $\beta^{j,o}_i$, - are set to match moments in the data.

4.1 Countries, Worker Types, Occupations, and Production Stages

We calibrate the model to three countries–China, U.S., 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., and the ROW, and with three sectors ($S = 3$): agriculture and 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, $J = 2$.[7]

4.2 Assigned Parameters, Labor Supply and Expenditure Shares

We assign $\nu = 4$ from Simonovska and Waugh (2014) for the common stage-invariant part of trade elasticity. Conditional on the assigned value of ν, we calibrate bilateral trade costs for each country pair and each sector using bilateral trade flows of final goods in the WIOD 2000. We set $\sigma = 2$ for the elasticity of substitution between within-sector product varieties. 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.

4.3 Calibration of Bilateral Trade Costs

Our model delivers a mapping from the GVC probability $\lambda^s_{l,n}$ to bilateral trade flows of goods. Similarly to AG, trade flows of final goods from country i to country n are defined by $\tilde{\lambda}^{F,s}_{in} = \sum_{l \in \Lambda^J_i} \lambda^s_{l,n}$, where Λ^J_i 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

[7] In a more general version of calibration, J can be also jointly calibrated with other parameters of the model.

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 ν, and these two identifying assumptions, we can back out bilateral trade costs τ_{in}^s by following the Head and Ries (2001) method:

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

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 τ_{in}^s

Country pair	Agriculture and Mining	Manufacturing	Service
China - U.S.	5.9	2.6	7.8
China - ROW	2.6	2.1	1.8
U.S.- ROW	3.1	2.9	3.0

4.4 Calibration of the Roy Parameters

Our framework for heterogeneous worker productivities yield the same analytic form of the equilibrium wage distribution as that of Lee (2017). 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[8]:

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

Lee (2017) estimates $\sum_{s',o'} T_t^{s',o'}(w_t^{s',o'})^{\theta_t}$ and θ_t for four countries including the U.S. In our paper, we assume that the productivity distribution of workers does not vary by country.

[8]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.

Thus, we take the estimates for the U.S. from Lee (2017) and assume that China and ROW have the same parameter values. The estimates of θ_t range from 1.48 to 1.97 and are lower for more educated worker types. These estimates suggest that better-educated workers have more dispersed productivity distributions within their type. Because θ_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).

The estimated $\sum_{s',o'} T_t^{s',o'}(w_t^{s',o'})^{\theta_t}$ from Lee (2017), the labor allocation $\pi_{us,t}^{s,o}$ from the U.S. American Community Survey 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: Sector- and Occupation-level Averages of Calibrated $T_t^{s,o}$

(a) Sector-level Average

	Agriculture and Mining	Manufacturing	Service
High School Graduates	1.16	1.86	1.88
Some College Education	1.01	2.00	2.57
College Graduates	1.12	3.66	4.83
Advanced Degrees	0.86	2.68	5.83

(b) Occupation-level Average

	Low-skill Service Jobs	Assemblers Machine Operators	Precision Production Crafters	Admin Clerks Sales	Managers Prof Technicians
High School Graduates	0.87	0.85	1.37	2.36	2.72
Some College Education	0.50	0.37	0.99	2.38	5.05
College Graduates	0.20	0.14	0.47	1.86	13.34
Advanced Degrees	0.09	0.06	0.16	0.59	14.70

Table 4 summarizes the calibrated values 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 values of $T_t^{s,o}$ range from 0.87 to 2.72 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 155 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.

θ_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, γ^s, α_i^s, A_i^s, and $\beta_i^{j,o}$ for the year 2000. This is a total of 45 parameters, because $\sum_o \beta_i^{j,o} = 1$ for every (i, j). We calibrate these parameters to match data moments as closely as possible. For the first three sets of parameters, we follow 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 for the case of two stages. The model expressions of these two variables are:

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

$$\tilde{\lambda}_{ik}^{2,s} = (1-\gamma^s) \sum_{n} \lambda_{(i,k),n}^{s} b^s [\sum_{t} \bar{w}_{n,t} \bar{L}_{n,t} + \sum_{s'} \frac{1-\alpha_n^{s'}}{\alpha_n^{s'}} \sum_{o} \sum_{t} \bar{w}_{n,t} \pi_{n,t}^{s',o} \bar{L}_{n,t}].$$

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 γ^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 three 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 α_i^s. We also calibrate the Ricardian productivity parameters A_i^s by targeting the share of GDP of each sector within each country and the share of each country's aggregate GDP 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 γ^s, α_i^s, A_i^s, and $\beta_i^{j,o}$ to match as closely as possible the model moments to their data counterparts. There are 75 data moments in total, as the occupation payment share adds up to 1 for each country and sector. Table A1 and Table A2 in the Appendix report the calibration results for γ^s, α_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 0.91. Our model is moderately successful at matching non-targeted moments. For example, the correlation coefficient 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 is 0.56.

We highlight several features of our calibrated parameters. First, there is variation in γ^s across sectors. The range is from 0.13 for agriculture and mining, with 0.80 and 0.65 for manufacturing and services, respectively. As a reminder, lower values of γ^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 α_i^s vary a great deal across countries and sectors with a mean of 0.38 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.[9] 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 than stage two in the U.S. In China, stage two uses high-skilled occupations more intensively than stage one. If the U.S. 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 γ^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 γ^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. only. The goal of this counterfactual is to quantitatively assess the aggregate and distributional effects of China's integration into world economy – focusing on its trade with the U.S. – in an explicit GVC setting.

This shock is especially relevant for our paper, because following China's entry into the

[9] They also suggest China has a comparative advantage in agriculture.

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.

We then perform several counterfactual exercises designed to understand the main mechanisms, as well as the role of our GVC parameter γ^s, behind our results. We also conduct three robustness exercises with alternative specifications for the production function coefficients α, β and γ. 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 between China and the U.S. We briefly review some of the aggregate implications, and then we turn to the specialization patterns, and 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 some college education and higher, and high school graduates and lower, respectively.[10]

Owing to the lower trade costs between China and the U.S. real wages, and hence, welfare, increases for each type of worker in each country. The increases across types in China range from 15% to 18%. In the U.S., the welfare increases range from 4% to 5% across types. The welfare gains in ROW are all less than 0.2%, because ROW is not experiencing a direct trade shock in our counterfactual. In addition, not surprisingly, trade shares of output increase. We find, for example, that China's export share of gross output in the manufacturing sector increases (in log terms) by 22%. The U.S. export share of gross output in manufacturing increases (in log terms) by 34%.

We now turn to the sector and stage specialization patterns. Table 5 below shows the baseline changes in the share of each sector's value-added out of the aggregate value added of

[10] We can compute other measures of inequality, such as the Theil index, the 90th-50th percentile wage gap, and/or the 50th-10th percentile wage gap. However, owing to our estimates of θ_t, which are all < 2, the variance of the wage distribution is technically ∞. Hence, measures of inequality that are related to variances, such as all the measures mentioned above, will likely not yield meaningful numbers.

a country. This table shows that China's manufacturing value-added share increases. In the United States, the services value-added share increases. This is the sense in which China's comparative advantage is in manufacturing, and the U.S.'s is in services.

To illustrate the importance of stage-level specialization in response to the decline in trade costs between China and the U.S., 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. Looking at Tables 5 and 6, note that the U.S. comparative advantage in stage 1 of services dominates its disadvantage in stage 2 of services, so that, in total, the U.S. service sector value-added share rises. Similarly, China's comparative advantage in stage 2 of manufacturing dominates its disadvantage in stage 1 of manufacturing, so that in total, China's manufacturing sector value-added share rises.

Table 5: Baseline Changes in Sectoral Value-Added Shares (%)

	Agriculture and Mining	Manufacturing	Service
China	-1.98	2.61	-0.63
USA	-0.11	-1.45	1.56
ROW	0.03	-0.12	0.09

Table 6: Baseline Changes in Share of Stage 1 Output (%)

	Agriculture and Mining	Manufacturing	Service
China	-0.77	-18.89	-7.45
USA	3.4	30.38	2.94
ROW	1.1	1.16	0.44

Our model also yields the labor reallocation patterns within each worker type in response to the China trade integration shock. Figure 4 shows the labor reallocation across sectors and occupations for high school dropouts and workers with advanced degrees in China and the U.S. Each country's comparative advantage across sectors is a major factor that determines workers' reallocation across sectors. In China, both worker types tend to reallocate to the manufacturing sector. In the U.S., both worker types are likely to move to the service 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, less educated workers are moving to low-skill service occupations, while higher educated workers are more likely to move into managerial and professional occupations in the service sector. Lastly, our model predicts more reallocation for less educated workers, which is related to their larger labor allocation elasticity θ_t from our estimation.

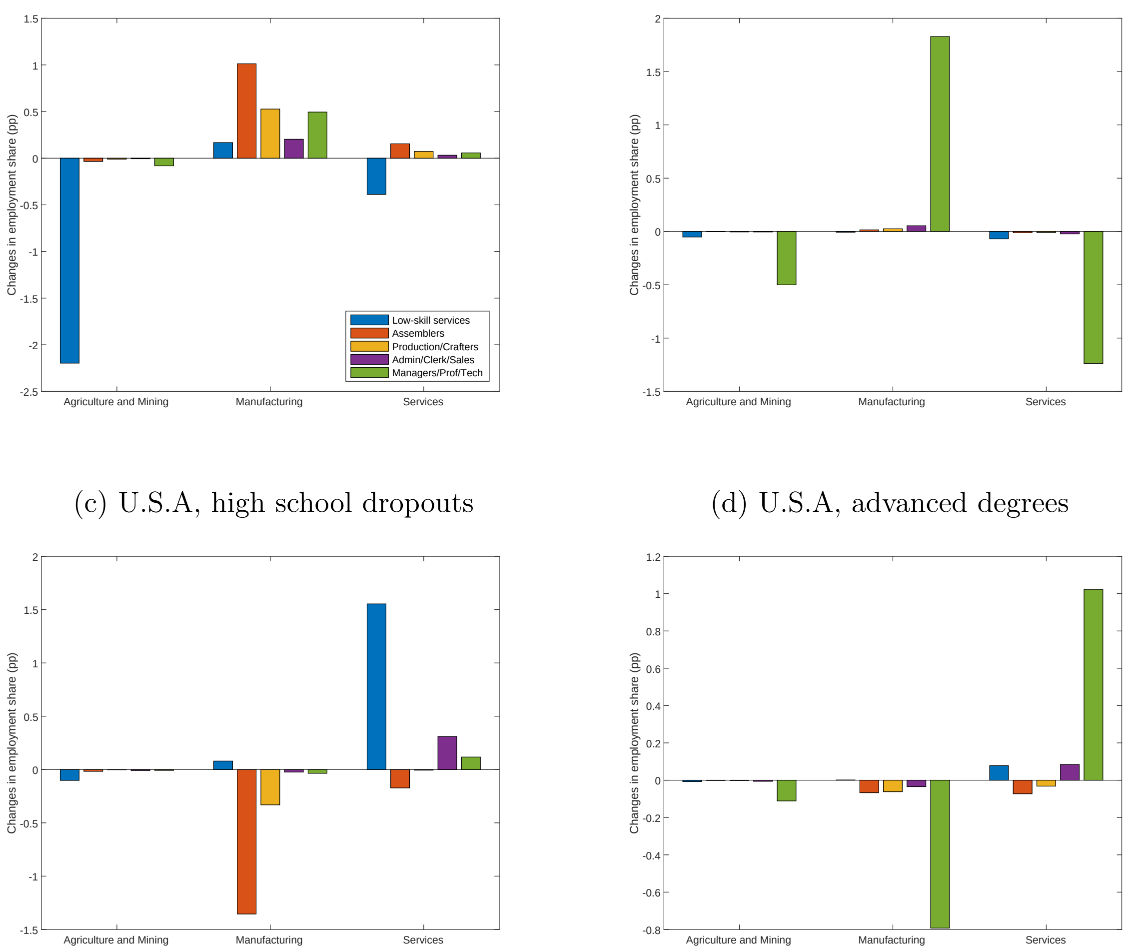
Figure 4: Within-worker-type Reallocation of Labor

(a) China, high school dropouts

(b) China, advanced degrees

(c) U.S.A, high school dropouts

(d) U.S.A, advanced degrees



How do all the changing specializations and reallocations show up in the skill premium? The first row of Table 7 shows the skill premium results for each country. Our model implies that decline in China's trade costs with the U.S. leads to an increase of the skill premia in China and the United States by 1.81% and 0.95%, respectively. The ROW has a slight decline in its 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. In other words, the stage specialization introduced by our GVC structure delivers the skill upgrading story from the literature. Overall, our model predicts that the stage specialization dominates the sector specialization, leading to an increase in China's skill premium.

The increase in the U.S. is driven by sector and stage 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 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 channel also leads to an increase in the skill premium.

Table 7: Baseline and Other Counterfactual Changes in the Skill Premium (%)

	China	USA	ROW
Baseline	1.81	0.95	-0.08
No Ricardian	2.64	-2.74	2.83
Standard HO	0.54	-0.38	-0.04
Restricted Roy	6.38	0.68	-0.17
No GVC	0.42	-5.38	0.49

To provide support for our above intuition, as well as to further understand our results, we conduct several additional counterfactuals in which we remove the transmission channels, one at a time.[11] In these counterfactuals, we do not re-calibrate the other parameters; we

[11] We thank an anonymous referee for suggesting most of the following counterfactuals.

are focusing on understanding the transmission channels.

In the first additional counterfactual, we remove the Ricardian trade mechanism by setting the Ricardian productivity parameters for each country-sector pair to be the geometric mean across the countries within the sector, i.e., $\bar{A}^s = \left(\Pi_{i=1}^{I} A_i^s\right)^{1/I}$. The second row of Table 7 provides the effects of the lower Chinese trade costs with the U.S. on the skill premium in each country. The skill premium in China increases by more than in the baseline case, while the skill premium in the U.S. now declines.

With the Ricardian channel removed, our model generates sector specialization patterns that are opposite to what we observe in the data. The lower trade costs now allow China to specialize in manufacturing and services. As discussed above in the Roy parameter estimation results, highly educated worker types like to sort into services. Hence, the increase in demand for Chinese services leads to increased demand for highly educated Chinese workers, which then leads to an increase in the skill premium that is larger than in the baseline case. Put differently, China's Ricardian comparative advantage in manufacturing allows China to specialize only in manufacturing when trade costs decline, which has a dampening effect on its skill premium owing to the forces described above. Turning to the U.S., in this counterfactual, the U.S. specializes in agriculture and mining – its value-added shares in both manufacturing and services decline. On the worker side, from Table 4 it can be seen that less educated workers have a comparative advantage in agriculture and mining. Hence, the U.S. skill premium declines. Overall, this counterfactual shows the central importance of sector specialization in understanding our results.

In the second additional counterfactual, we remove the country-specific feature of the production function occupation coefficients by setting $\beta_i^{j,o}$ equal to the arithmetic mean across countries, i.e., $\bar{\beta}^{j,o} = \sum_{i=1}^{I} \beta_i^{j,o}$. In other words, in this counterfactual, we will have the usual HO mechanism operating across stages, and nothing more. Thus, the skill upgrading story plays no role. The third row of Table 7 shows that, in response to the lower trade costs, China's skill premium rises by less than in the baseline, and the U.S. has a decline its skill premium, again the opposite sign of the baseline result.

In this counterfactual, the sector specialization pattern, which is determined largely by the Ricardian productivity parameters, is similar to that of the baseline. Moreover, the stage specialization pattern is also similar to that of the baseline. Recall that China's stage 2 occupation coefficients were overall more skill intensive than in stage 1. The arithmetic means across countries of the stage 2 occupation coefficients are similar to China's stage 2 coefficients. However, the arithmetic means across countries of the stage 1 occupation coefficients are more skill-intensive than China's stage 1 occupation coefficients. This means the gap in China's skill intensity between stage 1 and stage 2 is much smaller in this counterfactual (than in the baseline). Hence, the same changes in specialization patterns will result in a smaller change in the skill premium. Turning to the U.S., we have a similar argument. The arithmetic means of the stage 2 occupation coefficients are similar to those of the U.S. However, the arithmetic means of the stage 1 occupation coefficients are less skill-intensive than those of the U.S. Hence, to the extent that the U.S. still specializes in stage 1 goods, this is going to reward less-skilled labor and lead to a decline in the skill premium. Why does the U.S. continue to specialize in stage 1 when the trade costs decline? This is because the U.S. specializes in services, owing to Ricardian comparative advantage, and, because γ^s for services is lower than γ^s for the manufacturing, this means the U.S. will focus relatively more on stage 1 in services than in the manufacturing.

In the third additional counterfactual, we restrict the Roy mechanism. Specifically, starting from the initial high trade cost equilibrium, we impose the restriction that the share of type t workers in country i in occupation o remains fixed when trade costs are lowered. In other words, the share of Chinese college educated workers working as managers does not change when trade costs decline. Note that these workers can still switch sectors. The fourth row of Table 7 shows that China's skill premium increases by much more than in the baseline, while the U.S. skill premium increases by less than in the baseline.

The U.S. result may seem counterintuitive from a perspective that Roy forces, by facilitating labor reallocation across occupations, mitigate wage changes, and hence, lead to small changes in the skill premium; removing such forces, then, should lead to larger changes in the skill premium. To understand this result, it is useful to start from the baseline simulation. When trade costs decline, highly educated workers tend to switch sectors, but not occupations. However, less educated workers switch both sectors and occupations. In China, it turns out that the less educated workers upgrade from very low-skilled occupations in agriculture to less low-skilled occupations in manufacturing. This tends to raise the return to the less educated workers, thus mitigating the increase in the skill premium. Hence, when workers are not allowed to switch occupations, this effect is absent, thus leading to a larger increase in the skill premium than in the baseline scenario. In the United States baseline scenario, the occupation switch involves the less educated workers downgrading from medium skilled occupations in manufacturing to low skilled jobs in services. This tends to increase the skill premium. Hence, when workers are not allowed to switch occupations, this effect is absent, thus leading to a smaller increase in the skill premium than in the baseline scenario.

In the fourth additional counterfactual, we restrict the GVC mechanism by setting $\gamma_s = 0.999 \quad \forall s$. Now, all (but a small share of) value-added is from stage 2. This case is essentially a one-stage model with no GVC mechanism in effect. The final row of Table 7 shows that in China the skill premium increase is smaller than in the baseline, 0.42%, and in the

U.S. the skill premium declines by 5.38%. In this counterfactual, the absence of stage-level specialization, which, as we discussed above, is essential for the skill premium to rise in both countries, it is not surprising that the change in the skill premium is less positive for both countries. However, why does the skill premium decline in the U.S.? With all value-added coming from stage 2, it turns out that the U.S. comparative advantage is now in agriculture. The share of value-added rises in this sector, and falls in manufacturing and services, which is again the opposite to what we observe in the data. As mentioned above, less educated workers have a comparative advantage in agriculture. Hence, the shift to agriculture leads to these workers' wages rising, and a fall in the skill premium.

To summarize, there are a number of intricate mechanisms underlying our results. But, our counterfactuals serve to reinforce and support our primary story, which is that the stage-level specialization facilitates increases in the skill premium in both China and the U.S., and, for China, the effect is large enough to offset the skill premium reducing effect of from its specialization in the manufacturing sector. The stage level specialization is the key mechanism that enables the skill-upgrading in both countries to be realized when trade costs decline.

5.2 Additional Counterfactuals

We now conduct four further sets of counterfactuals. Our focus continues to be understanding our main results, so we do not re-calibrate the parameters. First, we seek to further understand why in China the stage specialization dominates the sector specialization to yield a skill premium increase. The top row of Table 8 gives the change in the skill premium in response to the baseline trade cost decline when all the occupational coefficients in the stage 1 and stage 2 production functions for China are set to 0.2. Hence, China's comparative advantage in stage 2 is weaker than before; moreover, any labor demand shift across stages will be equally distributed across occupations in China. We indeed see that China's skill premium increase is much smaller than in the baseline, while that of the U.S. is virtually unchanged.

In a related exercise, we set China's occupational coefficients to be equal to that of the U.S. in both stages. The results are shown in the second row of Table 8. Now, China's skill premium declines slightly. Clearly, the coefficients matter in driving both the extent of stage specialization and the impact of that specialization on wages and the skill premium. As discussed above, it is the relatively high skill occupational intensity of stage 2 and the relatively low skill occupational intensity of stage 1 that drives China's skill premium increase.

We also examine the effect of a broader trade cost decline, one in which China's trade costs with the U.S. and the ROW both decline by 50%. The third row of Table 8 presents the results. The skill premium in China and the U.S. rise by more than in the baseline exercise. This is partly because the ROW has a large weight in the global economy, and the forces that applied to China and the U.S. now apply to China and the ROW.

Finally, we examine the effects of a 10% increase in China's overall TFP, i.e., a 10% increase of A^s_{CHN} for all s. We conduct this exercise to contrast it with our primary trade cost decline exercise. The table shows that the TFP increase leads to an increase in the skill premium in China of roughly the same magnitude as the trade cost decline. However, there are very small spillover effects to the U.S. and the ROW.

Table 8: Additional Counterfactuals (%)

	China	USA	ROW
$\beta^{j,o}_C = 0.2$	0.31	0.93	-0.08
$\beta^{j,o}_C = \beta^{j,o}_U$	-0.14	0.96	-0.08
Broader Trade Cost Decline	6.50	1.32	-1.08
China TFP Increase	1.83	0.06	-0.14

In summary, the first two additional counterfactual exercises show that differences in occupational intensities across stages and countries matter for our skill premium results. Of course, without our GVC channel, we could not have differences across stages. The latter two additional counterfactuals show that a wider set of forces could be driving China's and the U.S.'s skill premium increase in the 2000s. We offer one additional point. It would be very useful to be able to have a result like "y% of the skill premium increase in China is because of channel x" and "z% of the skill premium increase in China is because of channel w". However, the complicated non-linear forces in our model preclude doing this.

5.3 Counterfactuals with Re-calibrated Parameters

As a way to further understand the transmission channels of our model, all of the preceding counterfactuals did not involve re-calibrating the model. In this sub-section, we now change parameters, and re-calibrate the other production parameters – the Ricardian productivites, A^s_i, the value-added shares, α^s_i, and the occupational coefficients $\beta^{j,o}_i$ – to ensure as close a fit as possible to the data moments. We then conduct our 50% China-U.S. trade cost decline counterfactual.

Table 9: Re-Calibrated Model Counterfactual Changes in the Skill Premium (%)

	China	USA	ROW
No GVC	-0.03	0.04	0.002
No Roundabout	0.25	-0.22	0.04
Sector-specific Beta's	0.47	-0.53	-0.01

We first consider the case where the GVC channel is shut down by setting $\gamma^s = 0.999$ for all sectors s; virtually all value-added comes only from stage 2 production. The first row of Table 9 shows that in the absence of GVCs, and with the rest of the production parameters re-calibrated, the effects on the skill premium from the China-U.S. trade cost decline are considerably smaller than in our baseline. These results again point to the importance of explicitly modeling GVCs to obtain an appropriate measure of the effect of trade cost declines on the skill premium. We then consider a case in which the value-added shares $\alpha_i^s = 0.999$. In other words, those intermediate goods involved in roundabout production are essentially eliminated. When the model is re-calibrated and the trade costs decline, the second row of Table 9 shows that the effect of the trade cost shock on the skill premium is considerably less positive, and the effect becomes even negative for the U.S. Thus, we conclude that both the GVC and the roundabout mechanisms are important to quantify the effect of trade shocks on skill premia.

A key part of our calibration is calibrating country-specific production function occupational coefficients. In our final re-calibration, we calibrate sector-specific production function occupational coefficients. That is, instead of calibrating $\beta_i^{j,o}$, we calibrate $\beta^{s,j,o}$.[12] This framework is closer to the traditional HO framework. The calibrated parameters suggest that stage 2 of both manufacturing and services is very high skill-intensive, while stage 1 of these two sectors is very low skill-intensive. In addition, the intensity of production-related occupations is very high in stage 1, which is not consistent with usual task intensities in upstream and downstream stages. Thus, our model with sector-specific occupational coefficients is not able to capture the way that tasks are usually thought to be spread over stages, at least in manufacturing. The third row of Table 9 shows that China's skill premium increases, and the U.S. skill premium decreases, by about one-half percent. One reason the absolute magnitudes are smaller in response to the trade cost decline is because the change in special-

[12] In principle, we could have calibrated a production function with sector and country-specificity, i.e., $\beta_i^{s,j,o}$. However, this would imply calibrating 93 parameters, instead of the 45 in our baseline calibration. We would need to add many more data moments to the 75 that we already have. Our goal with the baseline framework is to have the minimal framework that allows for both sector and stage specialization.

ization (value-added shares) is smaller. In addition, the U.S. continues to specialize in stage 1 across all sectors; this is mainly low skill intensive; hence, the U.S. skill premium declines. We conclude from this exercise that allowing for country-specific occupational coefficients is essential to have skill upgrading.

6 Conclusion

The increasing prevalence of vertical specialization through global value chains has attracted a great deal 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. We study the effect of a decline in trade costs between China and the U.S. to capture the effect of China's entry into the WTO on the U.S., China's largest trade partner in 2000, and China. When trade costs are lowered, each country specializes in their comparative advantage sectors and stages. In particular, the trade shock leads both China and the U.S. 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 both China and the U.S. Therefore, the skill premium increases in both countries. Thus, GVCs allow our model to generate the skill upgrading story from the trade literature. In addition to governing the direction of the change in the skill premium, the GVC channel governs the magnitude of the change in the skill premium. Our calibrated model shows that the sector-specific GVC intensity determines how much of the specialization effect from trade liberalization translates into relative wage responses.

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.

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A Additional Tables

Table A1: Calibrated γ^s, α_i^s, and A_i^s for the Year 2000

(a) GVC Intensity, γ^s

	Agriculture and Mining	Manufacturing	Service
γ^s	0.13175	0.79556	0.65362

(b) Roundabout Intensity, α_i^s

	Agriculture and Mining	Manufacturing	Service
China	0.44	0.18087	0.06256
U.S.	0.09273	0.36946	0.61382
ROW	0.62241	0.4672	0.57775

(c) Ricardian Productivity, A_i^s

	Agriculture and Mining	Manufacturing	Service
China	13.565	1.219	1.8031
U.S.	0.66043	4.9561	142.08
ROW	4.3494	12.207	98.355

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

(a) China

	Low-skill Service Jobs	Assemblers Machine Operators	Precision Production Crafters	Admin Clerks Sales	Managers Professionals Technicians
Stage 1	0.8694	0.01685	0.01002	0.01002	0.093713
Stage 2	0.13422	0.25258	0.15533	0.10491	0.35258

(b) U.S.

	Low-skill Service Jobs	Assemblers Machine Operators	Precision Production Crafters	Admin Clerks Sales	Managers Professionals Technicians
Stage 1	0.31334	0.01002	0.01002	0.21823	0.4484
Stage 2	0.02996	0.4165	0.16099	0.07742	0.31512

(c) ROW

	Low-skill Service Jobs	Assemblers Machine Operators	Precision Production Crafters	Admin Clerks Sales	Managers Professionals Technicians
Stage 1	0.57411	0.06475	0.05704	0.05839	0.24669
Stage 2	0.03145	0.2685	0.07639	0.12502	0.49963