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TECHNOLOGY LEVEL AND THE GLOBAL VALUE CHAIN

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Technology Level and the Global Value Chain

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Abstract

This paper investigates the role of technology levels in shaping the structure of the global value chain (GVC) at the macro level. We incorporate Ricardian comparative advantage into the production of intermediate goods involving both snake- and spider–type supply chains to capture the overall GVC integration. We analytically find that the country with a higher technology level produces the intermediate inputs at production stages involving a higher degree of difficulty, which is consistent with the real data. Furthermore, we verify how well the model fits the observed data by executing the calibration procedure using data from the World Input–Output Database. Our findings indicate strong correlations between calibrated outcomes and the observed data, as high as 87.3% for the GVC participation value and 79.3% for the real wage, proving that our model is a plausible representation of the structure of the GVC.

JEL Classification Number: F12, F15, O33
Keywords: Global Value Chain, technology level, participation value, World

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1 Introduction

The global value chain (GVC) has been growing in importance in the world economy, and now accounts for about two-thirds of international trade. Production within the GVC is organized in multiple stages that take place in multiple countries to provide multiple intermediate goods, which are then incorporated into a final product. This process has been a focus of attention in recent studies from both theoretical and empirical perspectives.[1]

In this context, the main objective of this paper is to investigate the role of technology levels in shaping the structure of the GVC. We first impose a simple theoretical structure to explain the mechanism of GVC formation involving both snake- and spider-type production processes, with the technology level of all nations given. Then, we solve the model analytically and calibrate it to verify its fit to the data observed in reality.

In detail, our paper revisits the Ricardian framework proposed by Dornbusch, Fischer, and Samuelson (1977), introducing the production of intermediate goods to capture the overall GVC integration. Specifically, we develop a multi-country model of comparative advantage where countries are heterogeneous with respect to their technology level and labor force. Countries are involved in a GVC to produce a single final good through a variety of intermediate production stages. These production stages are not a sequence of processes taking place chronologically; each stage can be but is not necessarily part of other intermediate input production stages. In other words, GVC formation in this model involves both snake- and spider-type production processes. The terms "snake" and "spider" used here are from Baldwin and Venables (2013). In a "snake" production process, parts need to be performed sequentially, whereas in a "spider" production process, separate parts are assembled in no particular order. If we apply the example of "cotton to yarn to fabric to shirts" in Baldwin and Venables (2013) in our model, in-

[1] Chor (2019) provides a good review of theoretical modelling of the GVC, and Johnson (2018) summarizes the key empirical results.

stead of treating this process as a typical snake-type, we consider that one unit each of value added of cotton, yarn, or fabric contributes to one unit of the final shirt production. That is, regardless of whether the contribution to the final good is direct or indirect, the amount of intermediate goods used in the production is treated equivalently. Thus, the production process can be applied to both snake- and spider-type GVC configuration. Each intermediate good production stage, performed by a single country, has a degree of "difficulty," such that a country cannot produce at that stage unless its technology level is sufficiently high. We find that the country with a higher technology level produces the intermediate inputs at production stages involving a higher degree of difficulty, which is consistent with the real data.

Finally, we calibrate the model to verify how well the outcomes of the model fit the observed data. In the model, the participation value of a country in the GVC is measured in terms of the total value that the labor in the country contributes to the GVC. As the data counterpart of participation value, we use the share of value added of each country embodied in world final demand. To compute this, we rely on standard input-output analysis, using data from the World Input-Output Database (WIOD), which is prepared by the University of Groningen (Timmer et al., 2014). Our findings report a strong correlation between calibrated outcomes and observed data, as high as 87.3% for the GVC participation value and 79.3% for the real wage in our benchmark case, which proves that our model is a plausible representation of the structure of the GVC.

In recent work, Costinot et al. (2013) and Fally and Hillberry (2018) assume a continuum of production stages in the Ricardian framework to examine how countries specialize along the chain.[2] Another approach to modeling multistage production is represented in the recent works of Antràs and De Gortari (2020) and Johnson and Moxnes (2019) on the discrete number of

[2]These types of models were first introduced by Dixit and Grossman (1982) and Sanyal (1983).

stages. These authors introduce computational quantitative frameworks that rely on the idea of roundabout input-output linkages across sectors, implying that an output from a stage can serve as both an intermediate input and a final good, as in Caliendo and Parro (2012). The key departing point of these studies is that they regard the multistage production as a sequential rather than a coordinate process or, in other words, they focus on a snake- rather than a spider-type supply chain. Within such frameworks, one production stage is infeasible without the previous one. This assumption is appropriate for certain production processes, but not necessarily for all processes. In addition, although the use of the term "chain" in GVC analysis suggests a snake-type process, it has been documented that most supply chains are likely to be non-sequential spider-types (Diakantoni et al., 2017).

To the best of our knowledge, there has been limited focus on the spider-type supply chain in previous studies. Some key exceptions are Antràs et al. (2017) and Baldwin and Okubo (2019). Antràs et al. (2017) develop a multi-country sourcing model in which firms can self-select into importing based on their productivity and country-specific variables to examine the global sourcing strategy of a firm producing a final good. However, this setting only applies to firms producing final goods, not those producing intermediate inputs. Baldwin and Okubo (2019) introduce a model to investigate patterns of industrialization and deindustrialization of advanced and emerging economies. To achieve this goal, they avoid the assumption of a sequence of production processes and freely reorder intermediate inputs in their own way in the model. Accordingly, these studies are specific to the spider-type production processes and cannot be applied to the analysis of sequential supply chain in the snake-type production process.

In sum, previous studies develop frameworks that can consider either snake- or spider-type production process, but not both. Importantly, we present a setting in which we do not need to impose assumptions concerning how the intermediate goods enter into the GVC production process. Therefore, the key difference of our study from previous ones is that our model can incorporate both snake- and spider-type GVC configurations.

All things considered, the novelty of our work is as follows. First, this is one of the first comprehensive attempts to examine how the technology levels of countries shape the structure of their participation in the GVC at the macro level. Second, in contrast to previous studies, our model incorporates both snake- and spider-type production processes in the GVC configuration. Third, we quantitatively demonstrate that the mechanism of comparative advantage explains not only trade in the final good, but also the GVC formation. We believe that our work contributes to the recent debate on the importance and effect of the global economy on GVC participation.

The remainder of the paper is organized as follows. Section 2 constructs a model with a multi-country framework to characterize the effect of technology levels on GVC formation. Section 3 presents data construction using the WIOD and describes the calibration procedure used to quantify the model's performance. Section 4 discusses the findings, including how the real-world data support our model. Section 5 concludes.

2 The model

In this section, we present a quantitative general equilibrium model with a multi-country framework. The model builds on the Ricardian model by Dornbusch et al. (1977), with two new aspects. First, we introduce the production of an intermediate good, incorporating both snake- and spider-type production processes, to represent the formation mechanism of the GVC. Second, we explicitly specify all functions in the model to allow for the subsequent calibration exercise that we perform.

The basic assumptions of the model are as follows. There is a world in which there are K countries, differing from each other in their technology levels and labor endowments.[3] The technology level of country k, where $k = 1, \ldots, K$, is T_k. T_k is measured by the level of the country's most advanced science and technology. We label countries in order of increasing technology levels, i.e., $T_k < T_{k+1}$ for all k. Following this assumption, country K is the country that has the highest technology level, T_K. All the countries are endowed with different quantities of labor, the sole factor of production. The labor endowment of country k is L_k, and its labor wage is w_k.

K countries are involved in a GVC to produce a single final good. The final good is the numeraire. One unit of the final good is produced from one unit of value added of each intermediate good produced by a single country.[4] Each intermediate good can be but is not necessarily part of other intermediate goods. Regardless of whether the contribution to the final good is direct or indirect, the amount of value added of the intermediate goods used in the production is treated equivalently and, thus, the production process can be applied to both snake- and spider-type production processes in the GVC configuration. An important difference between our GVC and traditional trade models, related to how the setting affects the determination of production volume, should be mentioned here. In the Ricardian model of trade introduced by Dornbusch et al. (1977), the production volume of each final good is determined by preferences. However, in our setting, once the volume of the final good is decided, the production volume of each intermediate input is automatically determined. For example, if we decide to produce an automobile as a final good, it automatically follows that we need certain intermediate goods produced; that is, we need the tire production stage to provide a set of four tires, the wiper production stage to provide a set of two windshield wipers, and the engine production stage to provide one engine.

[3]Although countries also differ in other aspects, such as capital endowments or geographical location, this paper's focus is only on the technology level and labor endowment.

[4]Note that an intermediate good is produced by a single country, but a country is in charge of producing multiple intermediate goods. Later in this section, we discuss which single countries are in charge of producing which intermediate goods.

The cost to produce the final good from the intermediate goods is zero.

Each intermediate good production stage is different in terms of its level of difficulty. For example, an engine production stage involves a higher level of difficulty than does a windshield wiper production stage. The degree of difficulty in producing an intermediate good j involves a technology threshold $D(j)$, such that a country cannot produce the good unless its technology level is at least equal to or higher than the threshold, i.e., $T_k \geq D(j)$. For example, it is not feasible for a country with a low technology level to produce complex high-technology goods, such as a complete automobile engine, or pharmaceutical products. Without loss of generality and for simplicity, we assume that the degree of difficulty, $D(j)$, equals j, where $j \in [0, T_{max}]$ and where T_{max} is the highest degree of difficulty in the GVC. That is, we refer to the stage of producing an intermediate good by its degree of difficulty. As an example, stage j is required to produce intermediate good j with the degree of difficulty $D(j)$. As a result, stages in the GVC are ordered to match the order of the degrees of difficulty. That is, the GVC in our model contains a variety of separate stages, which are not a sequence of chronological processes. Using the example of automobile production again, the engine production stage requires a considerably high level of technology and, thus, the degree of difficulty of this stage means that it is in the highest place in the GVC. In second place is tire production and in third place is windshield wiper production. Thus, the sequence of the windshield wiper, tier, and engine production stages in the GVC follows an increasing order in terms of the degree of difficulty.

At each intermediate input production stage, the amount of labor required for one unit of value-added production is assumed to be inversely proportional to the difference between the technology level of the country, T_k, and the degree of difficulty of the stage, $D(j)$. That is, the unit labor requirement decreases in the technology level of the country, but increases in the degree of difficulty of the stage; this assumption is very natural. In relation to the former point, if a country's technology level is high, it does not need much labor to produce one unit of good. Concerning the latter point, a production stage with a higher degree of difficulty requires more production inputs. As labor is the sole production input factor, production at a higher stage in the GVC requires more labor because the degree of difficulty is higher. Furthermore, these two factors do not affect the unit labor requirement independently; the interaction between them also matters. More precisely, the difference between the technology level of the country and the degree of difficulty of the production stage also plays an important role. The higher the technology level of a country compared with the degree of difficulty of a production stage, the less labor that country requires to produce one unit of value added of a good at that stage. Letting $a_{j,k}$ denote the unit labor requirement of country k at stage j, this assumption is shown as follows:

$$a_{j,k} = \frac{1}{T_k - D(j)} = \frac{1}{T_k - j}. \tag{1}$$

Under the definition of the degree of difficulty, the unit labor requirement, $a_{j,k}$, is guaranteed to be positive. From this setting, we have the following simple proposition: *in the GVC, the higher the country's technology level, the more difficult the stages at which it produces.*

To prove this proposition, we consider two arbitrary countries and two arbitrary production stages in the GVC. We refer to the two countries as North (N) and South (S). The North and the South can be any two countries with different technology levels. The North is assumed to have a higher level of technology than the South, i.e., $T_N > T_S$. The two arbitrary production stages are i and j, where stage i is assumed to be more difficult compared with stage j, i.e., $D(i) > D(j)$ or $i > j$. To identify which of the two countries has a comparative advantage in producing at stage i relative to stage j, we need to compare $\frac{a_{i,N}}{a_{j,N}}$ and $\frac{a_{i,S}}{a_{j,S}}$. By the definition of $a_{j,k}$ in equation (1), we find that $\frac{a_{i,N}}{a_{j,N}} = \frac{T_N - j}{T_N - i} < \frac{T_S - j}{T_S - i} = \frac{a_{i,S}}{a_{j,S}}$. This is because rearranging the inequality, we have $(T_N - T_S)(i - j) > 0$, which is always true. This means that among any two stages in the GVC, the North always has a comparative advantage over the South in producing at stages with a higher degree of difficulty or, in other words, the country with the higher technology level operates at a higher stage of the GVC.

To explore the GVC formation, we need to clarify which country is in charge of which stage in the GVC. Following the proposition, the GVC is joined by K countries, with technology levels that are increasing in order, in line with the increasing order of the degrees of difficulty of each stage of the GVC. Thus, there exists a cutoff stage j_k^* separating the production stages of two countries, country k and country $k+1$, so that country k only produces at a stage lower than j_k^* and country $k+1$ only produces at a stage higher than j_k^*. Thus, country k is in charge of producing intermediate goods from stage j_{k-1}^* to stage j_k^*. Note that, j_{k-1}^* is smaller than j_k^* because of the increasing order of countries in the GVC according to their technology levels. Furthermore, j_k^* must be smaller than T_k under the assumption that a country can only produce an intermediate good if its technology level is at least equal to or higher than the degree of difficulty to produce the good. At the cutoff stage j_k^*, there is no difference in the marginal cost of production between country k and country $k+1$, that is:

$$w_k a_{j_k^*,k} = w_{k+1} a_{j_k^*,k+1}.$$

We can rewrite this equation using the definition of $a_{j,k}$ in equation (1) as follows:

$$\frac{w_k}{w_{k+1}} = \frac{a_{j_k^*,k+1}}{a_{j_k^*,k}} = \frac{T_k - j_k^*}{T_{k+1} - j_k^*}. \tag{2}$$

The final good is the numeraire and, thus, the budget constraint for each agent in country k is:

$$c_k = w_k, \tag{3}$$

where c_k is the volume of the final good consumed by each agent in country k.

At the equilibrium of the goods market, net output of the final good must equal the total consumption of all individuals in all K countries. Thus, we have the following goods market clearing condition:

$$y = \sum_k L_k c_k, \tag{4}$$

where y is the output volume of the final good.

Now, let us consider the labor market in each country. Country k participates in the GVC from production stage j^*_{k-1} to stage j^*_k, where each stage requires an amount of labor equal to $a_{j,k}$. Thus, to produce y units of the final good, the total labor demand of country k is $y \int_{j^*_{k-1}}^{j^*_k} a_{j,k} dj$. We assume the full employment of labor and, thus, the labor market clearing condition in country k is given by:

$$y \int_{j^*_{k-1}}^{j^*_k} a_{j,k} dj = L_k.$$

By the definition of $a_{j,k}$ in equation (1), this equation is rewritten as:

$$y \ln \frac{T_k - j^*_{k-1}}{T_k - j^*_k} = L_k.^5 \tag{5}$$

The full employment conditions in equation (5) are applied to country 2 to country $K - 1$. With the same explanation, the conditions for country 1 and country K, respectively, are as follows:

$$y \int_0^{j^*_1} a_{j,1} dj = L_1 \Leftrightarrow y \ln \frac{T_1}{T_1 - j^*_1} = L_1, \tag{6}$$

[5] The sign of the logarithm is positive because j^*_{k-1} is smaller than j^*_k, as mentioned in the discussion of the cutoff stage, meaning that the argument of the logarithm is larger than one.

$$y \int_{j^*_{K-1}}^{T_{max}} a_{j,K} dj = L_K \Leftrightarrow y \ln \frac{T_K - j^*_{K-1}}{T_K - T_{max}} = L_K.^6 \quad (7)$$

After putting all countries in order of increasing technology levels and combining equations (2) to (7), we have a system of equations consisting of $2 \times K$ equations with $2 \times K$ unknowns. In particular, the equations are the cost indifference conditions at the cutoff stages in equation (2), the goods market clearing condition in equation (4) in combination with the budget constraints for agents in each country in equation (3), and the labor market clearing conditions from equations (5) to (7) for all K countries. The exogenous variables are the technology level and the labor force of each country and the degree of difficulty associated with each industry. These exogenous variables can be generated from the data, as described in the next section. The unknowns determined in the equilibrium are the cutoff stages j^*_k, where $k = 1, \ldots, K-1$, the real wages w_k, where $k = 1, \ldots, K$, and the amount of final output y. To solve for the equilibrium, we use the calibration method presented in Section 3.2.

Note that we also need to confirm the following conditions after solving the model. The first condition guarantees the possibility of production by a country; that is, a country's technology level must be at least equal to or higher than the degree of difficulty of the highest stage at which it produces, $T_k \geq j^*_k$. This is because we assume that a country can only produce an intermediate good if its technology level is at least equal to or higher than the degree of difficulty required to produce the good. The second condition guarantees that the sequence of degrees of difficulty of the cutoff stages along the GVC is monotonic increasing, i.e., $j^*_{k+1} \geq j^*_k$ for all k.

[6] Under the definition of T_{max} as the highest degree of difficulty in the GVC, all cutoff stages are smaller than T_{max}, that is $j^*_k < T_{max}$ for all k. Thus, the sign of the logarithm is positive.

3 Data construction and calibration

In this section, we present the data used in this study, the procedure used to solve for the equilibrium of the model numerically, and the approach to measure GVC participation by different countries.

We use World Input-Output Database (WIOD) release 2016, which covers 28 European Union countries and 15 other major countries (a total of 43 countries) for the period from 2000 to 2014 (Timmer et al., 2015). The WIOD provides data for the 56 sectors that we use in our analysis.[7] We conjecture that industries in the WIOD capture the key properties of stages in the GVC, and thus serve as a good case to verify how our model fits the real data. The WIOD provides information on global linkages between countries' industries in the form of World Input-Output Tables (WIOT) making it a suitable database to define GVC participation. We assume that an industry is identical to a stage as defined in our theoretical model. The more disaggregated level at which a sector in the WIOD is split (as indicated by an increase in ISIC code digits), the more accurate our assumption would become. Several previous studies for instance, Miller and Temurshoev (2017) and Antràs and Chor (2018), which examine upstreamness and downstreamness measures of GVC using WIOD imply that an industry represents a stage in the GVC and define GVC using global linkages across industries.[8]

Below, we explain how we compute our key indicators. We use both WIOT and the Socio-economic accounts that are published in the 2016 release of the WIOD.[9]

[7] The 2016 release of the WIOD follows the ISIC rev. 4 classification.

[8] It is true that the output of a stage in our theoretical model is one intermediate good, whereas a sector in WIOT produces more than one intermediate good as well as final goods. However, given data availability, we are not able to make a weaker assumption.

[9] In what follows, we omit the time superscript to avoid notational ambiguity.

3.1 Exogenous variables

Labor force

The labor force in country k, L_k, is measured as the number of persons engaged in economic activity in this country. Labor force in an industry, $L_{j,k}$, is measured as the number of persons engaged in the economic activity in the industry j of country k. These data are retrieved from the Socio-economic accounts and the unit is thousands of people.

Technology level

The technology level is defined as the level of the most advanced science and technology of a country. First, we compute labor productivity as the value added of each industry j in country k per persons engaged in economic activity in the same industry and country. That is:

$$LP_{j,k} = \ln \frac{VA_{j,k}}{L_{j,k}}, \tag{8}$$

where $VA_{j,k}$ is the value added of industry j in country k. We obtain this value from a row vector of value added in WIOT. It is measured in constant millions of US dollars.[10] After computing all data at the industry level, we define the technology level of country k as the maximum labor productivity within the industries of the country as follows:

$$T_k = \max_j LP_{j,k}. \tag{9}$$

There are two reasons for using this measure. First, our goal is to find

[10]To obtain real value added, we deflate its nominal values using the country-level GDP deflator. GDP deflator data are obtained from the World Bank World Development Indicators (WDI) database. For Taiwan, the GDP deflator is obtained from the Statistics Bureau of Taiwan (https://eng.stat.gov.tw). The natural logarithm is used to normalize the distribution.

the closest counterpart to the technology level in the model. Given that labor is the only factor of production in our theoretical setting, it is natural to regard value added per person engaged as a close measure of physical productivity.[11] Second, as suggested by the model, T_k should represent the maximum difficulty level at which the country can produce; thus, *maximum* labor productivity within the industries of the country would serve this objective.

Industries' degree of difficulty and the highest degree of difficulty in the GVC

First, we identify the degree of difficulty of each industry (stage) in the WIOD. We take this degree to be the weighted average technology level of a set of the highest producing countries in each industry. We select these countries based on their value added share in the total value added of the industry worldwide. First, we sort countries from the highest to the lowest value added share. Then, we add their value added shares until we reach a certain ratio; in the benchmark case, this ratio is set at 70%.[12] That is, we define the set of the highest producing countries Θ as the countries for which the combined value added share reaches 70% of the worldwide industry value added. This approach is similar to the market concentration definition of firms in the industry. Next, we compute the weighted average technology

[11]Note that productivity measurement could be also proxied by total factor productivity (TFP), and approached by a conventional productivity growth equation. However, we do not choose TFP because it would require us to use other factors of production, such as capital, which are not the focus of our paper.

Furthermore, value added per worker has been used in the trade and growth literature as a counterpart of theoretical model productivity (Connolly & Yi, 2015). In regard to the proxy for the technology level, other factors may need to be considered, such as industry specifics and level of competition. Nevertheless, we believe that our proxy of the technology level has the advantage of being sufficiently simple to serve as a counterpart of T_k in the model.

[12]We used alternative ratios of 50%, 60%, and 80% and did not observe any significant changes in the tracking results. Hereafter, we refer to ratios 60% and 80% when reporting the results. The full results are available upon request.

level of countries in set Θ. The weight is the share of these countries in the industry's total value added. Thus, the degree of difficulty of industry j is as follows:

$$D(j) = \sum_{k \in \Theta} \frac{VA_{j,k}}{VA_j} LP_{j,k}. \tag{10}$$

Now, we can easily define the highest degree of difficulty in the GVC, T_{max}, as the maximum degree of difficulty among all industries:[13]

$$T_{max} = \max_j \{D(j)\}. \tag{11}$$

3.2 Calibration

In this section, we describe the procedure used to solve for the equilibrium of the model using the data for 43 countries' technology levels and labor forces.

Theoretically, we have to solve the simultaneous equations system of 86 equations for 86 unknown variables, which are the real wages of 43 countries, 42 cutoff stages, and the output volume of the final good. However, we can simplify the process by solving a smaller system as follows. First, we find that dividing the equation of the labor market clearing condition of a country (equations (5)-(7)) by the corresponding equation of any other country, results in the output volume of the final good, y, being canceled out. Thus, the new equation now contains only the variables of the cutoff stages. Doing this division by combining any two countries pairwise, we can form a new simultaneous equations system of 42 equations to solve for 42 cutoff stages, j_k^*. To solve this simultaneous equations system with data for 43 countries' technology levels and labor forces, we use the Gauss-Seidel method, which is a well-known iterative method used to solve the large-scale systems of nonlinear algebraic equations.[14]

[13] With this T_{max}, the positivity of the argument of the logarithm in equation (7) is guaranteed.

[14] This is a technique for solving n equations of a system one at a time in sequence, and

Next, with the cutoff stages, j_k^*, solved from the new simultaneous equations above, we can easily calculate the output volume of the final good, y, from the labor market clearing condition of any country using equations (5)–(7). Finally, to solve for the real wage of all 43 countries, we combine the cost indifference conditions at the cutoff stages in equation (2), the budget constraint conditions for agents in each country in equation (3), and the goods market clearing condition in equation (4) to obtain the following:

$$\begin{aligned} y &= \sum_k L_k c_k \text{ (equation (4))} \\ &= \sum_k L_k w_k \text{ (by equation (3))} \\ &= w_1 \left(L_1 + \sum_{k=2}^{K} L_k \prod_{\tilde{k}=2}^{k} \frac{w_{\tilde{k}}}{w_{\tilde{k}-1}} \right) \\ &= w_1 \left(L_1 + \sum_{k=2}^{K} L_k \prod_{\tilde{k}=2}^{k} \frac{T_{\tilde{k}} - j_{\tilde{k}-1}^*}{T_{\tilde{k}-1} - j_{\tilde{k}-1}^*} \right) \text{ (by equation (2)).} \end{aligned}$$

The output volume of the final good, y, and all the cutoff stages are already known. Thus, we can calculate the real wage of country 1, w_1. As we know w_1 and all cutoff stages, we use the cost indifference conditions at the cutoff stages in equation (2) to calculate the real wages of all other countries.

Our final goal is to obtain a comprehensive understanding of the GVC formation. The calculation of the cutoff stages allows us only to verify which country is in charge of which production stages. Thus, we also need to examine the participation value of each country. The participation value of country k is defined as the total value that labor in country k contributes

it uses previously computed results as a new guess for the next iteration round as soon as they are available. For details, see Judd (1998).

to the GVC, i.e., $w_k L_k$. With all the real wages solved above, we can easily calculate the participation values of all countries in the GVC.

3.3 Observed data on real wages and participation values

To verify the fit of our model to the data, we need to identify the real wages and participation values of each country that we observe in the data.

Real wage

We proxy wages, $w_{j,k}$, using employee compensation which is available in Socio-economic accounts of the WIOD (in millions of national currency) for each industry j of country k. We first denominate employee compensation in US dollars using exchange rates provided by the WIOD. Then, we find the country-level wages by adding together the compensation for all industries and dividing the sum by the total labor force of these industries in the same country:[15]

$$w_k = \frac{\sum_j w_{j,k}}{\sum_j L_{j,k}}. \tag{12}$$

Participation value

The participation value is proxied by a country's value added in world final demand. The calculation proceeds as follows.[16] Given the global input–

[15] To determine real compensation, we deflate nominal compensation using the GDP deflator. To maintain consistency of data sources, we used the Socio-economic accounts of the WIOD to derive the real wage. We conducted a robustness check using country-level real compensation of employees and adjusted net income per capita in constant prices provided in the World Bank WDI database as well.

[16] We follow the standard approach for input–output analysis (Miller & Blair, 2009). The calculation of value added in world final demand is discussed in OECD (2019).

output table (WIOT) as provided in the WIOD, the gross output of each industry is:

$$\mathbf{x} = \mathbf{Z}\mathbf{e_1} + \mathbf{F}\mathbf{e_2}, \tag{13}$$

where $\mathbf{x}$ is a vector (of dimension 2464×1) of gross output for each country and industry (gross output = total use), $\mathbf{Z}$ is a matrix (2464×2464) of intermediate supply and use, $\mathbf{e_1}$ and $\mathbf{e_2}$ are column summation vectors $\mathbf{1}$ of dimensions 2464×1 and 44×1, respectively, and $\mathbf{F}$ is a matrix (2464×44) of the each country's final use of each country–industry's production.[17] The WIOD provides data on final use disaggregated into final consumption expenditure by households, final consumption expenditure by nonprofit organisations serving households, final consumption expenditure by government, gross fixed capital formation, and changes in inventories and valuables. We sum the final use categories to obtain a column vector of country k's final use of each country–industry production. Matrix $\mathbf{F}$ represents a set of 44 column vectors of final use. From equation (13), we obtain:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{F}\mathbf{e_2}, \tag{14}$$

where $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{\mathbf{-1}}$ is a technical input coefficients matrix, and $\hat{\mathbf{x}}^{\mathbf{-1}}$ is an inverse of a diagonal matrix $\hat{\mathbf{x}}$ (2464×2464) with the elements of the gross output vector $\mathbf{x}$ strained along the main diagonal. A typical element of matrix $\mathbf{A}$ is defined as $A_{ij} = Z_{ij}/x_j$, where Z_{ij} is a typical element of matrix $\mathbf{Z}$ denoting intermediate supply from industry i to industry j, and x_j is gross output of industry j. Solving for $\mathbf{x}$, we obtain:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{F}\mathbf{e_2} = \mathbf{B}\mathbf{F}\mathbf{e_2}, \tag{15}$$

[17] WIOT provide data for the "rest of the world," in addition to our 43 countries of interest; thus, we have 44 regions. In addition, in our computation of value added in world final demand, we use the full set of 56 industries; thus, we obtain the 2464 dimension.

where $\mathbf{B} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ is the well-known Leontief inverse (2464×2464), and $\mathbf{I}$ is an identity matrix (2464×2464). Typical element B_{ij} gives the (extra) output in industry i needed to satisfy one (extra) dollar of final use in industry j. The Leontief inverse at the global level shows how much output from each country and industry is required to produce a given vector of final goods (Johnson & Noguera, 2017). We measure the GVC participation value as country k's domestic value added component in world final demand $\mathbf{VFD_k}$. $\mathbf{VFD_k}$ vector (56×1) includes both the direct and indirect contributions of country k's industries to world final demand via all global input–output linkages. That is:

$$\mathbf{VFD_k} = \widehat{\mathbf{V'_k}} \mathbf{B_{k,global}} \mathbf{f_{k,global}}, \tag{16}$$

where $\widehat{\mathbf{V'_k}}$ is a diagonal matrix (56×56) with the value added to output ratio for country k's industries on the main diagonal, $\mathbf{B_{k,global}}$ is the row block of the global Leontief inverse matrix corresponding to country k (56×2464), and $\mathbf{f_{k,global}}$ is a vector of country k's global final demand for goods and services from each industry in other countries (2464×1). $\mathbf{f_{k,global}}$ is found by summing the elements of each row of final demand matrix $\mathbf{F}$ except the element of country k's final demand. Each element of the vector $\mathbf{VFD_k}$ represents the value added of an industry j in world final demand. We define a matrix $\mathbf{VFD}$ (56×44) as a set of 44 column vectors $\mathbf{VFD_k}$, with each vector corresponding to a country.[18] Note that the $\mathbf{VFD_k}$ calculation is consistent with both snake and spider GVC production processes, as in our theoretical model setting, and thus, we do not need to make any additional assumptions about the way intermediate goods are embodied in the final good. Finally, we find the *participation value* of country k as the total value added in world final demand of the industries of country k, FFD_DVA_k by summing the elements of the vector $\mathbf{VFD_k}$ that correspond to all industries

[18]The 44^{th} column vector corresponds to the rest of the world.

in the WIOD:[19]

$$FFD\_DVA_k = \sum_j VFD_{j,k}, \tag{17}$$

Table 1 presents the summary statistics for technology levels, degrees of difficulty, participation values, and real wages.

Table 1: Summary statistics.

	Mean	Std.Dev.	Min	Max
T_k	6.31	1.02	3.53	8.63
$D(j)$	4.22	1.06	0.83	6.69
FFD_DVA_k	216, 751.80	300, 397.60	1, 050.81	1, 923, 552.00
w_k	29, 185.18	21, 777.76	456.92	91, 886.38

Notes: The calculation is based on 645 observations for T_k, FFD_DVA_k, and w_k, and on 840 observations for $D(j)$. FFD_DVA_k is measured in millions of US dollars, and w_k is in dollars per person engaged. $D(j)$ is reported for the benchmark case of the ratio 70%. For details, see Section 3.1.

4 Findings

The goal of this section is twofold. First, we present some evidence of the proposition derived from equation (1). Second, we discuss how our model fits the real-world data.

4.1 Technology level, degree of difficulty, and GVC participation

The proposition derived from equation (1) states that in the GVC, the higher the country's technology level, the more difficult the stages at which it produces. Therefore, the key implication of the proposition is that countries

[19] We work with real values of FFD_DVA_k; thus, we deflate the nominal values using the GDP deflator.

with a higher technology level are expected to have a higher share in production for global final demand in the industries associated with a higher degree of difficulty, i.e., higher $D(j)$. Although this conclusion is intuitive in its nature, we attempt to provide evidence from the data. First, we find the country–industry contribution to the industry's world GVC production by dividing country k's industry j value added in world final demand by industry j's total value added in world final demand:

$$S_{j,k} = \frac{VFD_{j,k}}{\sum\limits_{k} VFD_{j,k}}. \tag{18}$$

Second, in accordance with equation (1), we derive the difference between the technology level and the industry's degree of difficulty in the following way:

$$\frac{1}{a_{j,k}} = T_k - D(j). \tag{19}$$

The fraction $\frac{1}{a_{j,k}}$ is a proxy for countries' productivity at different stages of the GVC. Next, we estimate the following simple equation:

$$S_{j,k,t} = \beta \frac{1}{a_{j,k,t}} + \delta_t + \gamma_k + \sigma_j + \varepsilon_{j,k,t}, \tag{20}$$

where t is the time index, k is the country index, and j is the industry index. Our hypothesis derived from the proposition that there is a positive correlation between $S_{j,k}$ and $\frac{1}{a_{j,k}}$, meaning that we expect a positive coefficient β. We estimate equation (20) by ordinary least squares with different types of fixed effects. Table 2 presents the results of the estimation.

The coefficient β is positive and significant in all specifications. Thus, we observe a robust positive relationship between GVC participation $S_{j,k}$ and $\frac{1}{a_{j,k}}$. The interpretation of this observation is that a high technology level of a country is associated with a high level of production at stages of high difficulty, i.e., high complexity. This interpretation implies that the

Table 2: GVC participation, technology level and industry's degree of difficulty.

	(1)	(2)	(3)
$\frac{1}{a_{j,k}} = T_k - D(j)$	0.001***	0.001***	0.002***
	(0.001)	(0.0001)	(0.0001)
Constant	0.021***	0.015***	0.032***
	(0.001)	(0.005)	(0.001)
Observations	36,034	36,034	36,034
R^2	0.001	0.402	0.949
Year FE	Yes	Yes	Yes
Industry FE	No	Yes	No
Country FE	No	Yes	No
Industry-Country FE	No	No	Yes

Notes: The table shows the correlation between $S_{j,k}$ and $\frac{1}{a_{j,k}}$. The dependent variable is $S_{j,k}$. The symbols ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are shown in parentheses. Standard errors are clustered at the industry level.

proposition derived from equation (1) is a plausible inference about the real-world GVC production. Therefore, in the next section we proceed by testing how well our model fits the data.

4.2 Participation value and labor: Model vs. data

Table 3 reports the correlation between calibrated outcomes and the observed data. In particular, the top part of the table reports the correlation between the calibrated participation values from the model and the observed participation values, $\ln FFD\_DVA_k$. The lower part of the table reports the correlation between calibrated and observed wages, $\ln w_k$. We report the results for the three ratios that we use to identify the set of the highest producing countries, Θ. As mentioned in Section 3.1, we select this set of countries by their value added contribution to the worldwide value added of the industry, which allows us to compute the degree of difficulty of each industry, $D(j)$, and the highest degree of difficulty in GVC, T_{max}, that we use to calibrate outcomes from the model. In Table 3, the selected ratios are 60%, 70%, and 80% of the industry's worldwide value added, with 70% being the benchmark case.[20] We observe a strong relationship between the calibrated and observed data. For the participation value, the correlation is 0.873 for 2000–2014 in the benchmark case. The probability shown in parentheses indicates that the correlation is significant at the $p < 0.001$ level. The result is robust for all alternative ratios. These findings show that our theoretical model correctly captures the modern production of the GVC. We believe that its simple structure provides a better understanding of the mechanism determining countries's participation in the GVC given their level of technological development and labor force. Furthermore, note that participation value is not limited to any specific type of production process and could be a proxy for both spider and snake GVC participation, as in our theoretical model setting.

In respect to real wages, we observe a significant correlation of the calibrated and real data. The magnitude of the correlation is 0.793 for 2000–2014 in the benchmark case. Again, this confirms the good fit of our model to the data.[21]

To reinforce this point, we plot the calibrated values against the real data for the year 2014 for the benchmark case. Figure 1 reports the calibrated participation value against value added in world final demand. Figure 2 reports calibrated wages against compensation per person engaged. The positive correlation can be observed clearly for both cases.

[20]For details, see Section 3.1.

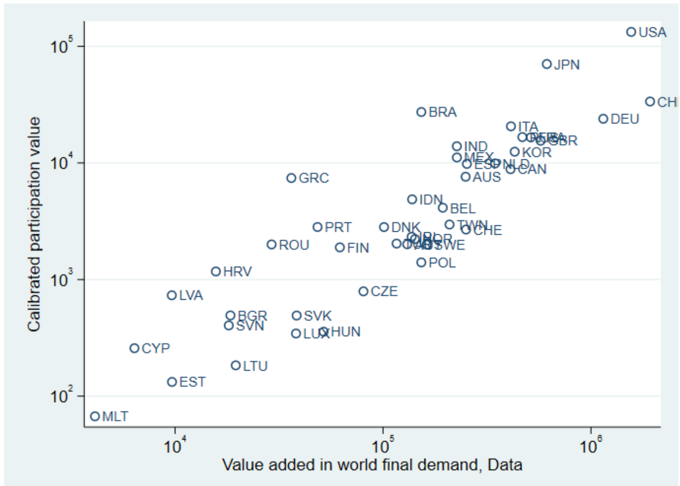
[21]As a robustness check, we computed the correlation of the calibrated real wage with the real compensation of employees and adjusted net income per capita in constant prices provided by the World Bank WDI database. The overall correlation with the former and latter (in the benchmark case) were 0.672 and 0.789, respectively.

Table 3: Correlation between calibrated and observed data.

Participation value			
Year	Ratio 60%	Ratio 70% (benchmark)	Ratio 80%
2000	0.808*** (0.000)	0.808*** (0.000)	0.808***(0.000)
2001	0.803*** (0.000)	0.803*** (0.000)	0.803***(0.000)
2002	0.777*** (0.000)	0.777*** (0.000)	0.777***(0.000)
2003	0.831*** (0.000)	0.864*** (0.000)	0.864***(0.000)
2004	0.832*** (0.000)	0.885*** (0.000)	0.893*** (0.000)
2005	0.816*** (0.000)	0.882*** (0.000)	0.887*** (0.000)
2006	0.844*** (0.000)	0.902*** (0.000)	0.908*** (0.000)
2007	0.902*** (0.000)	0.902*** (0.000)	0.904*** (0.000)
2008	0.907*** (0.000)	0.911*** (0.000)	0.913*** (0.000)
2009	0.903*** (0.000)	0.900*** (0.000)	0.902*** (0.000)
2010	0.904*** (0.000)	0.902*** (0.000)	0.902*** (0.000)
2011	0.911*** (0.000)	0.906*** (0.000)	0.910*** (0.000)
2012	0.904*** (0.000)	0.896*** (0.000)	0.901*** (0.000)
2013	0.905*** (0.000)	0.901*** (0.000)	0.901*** (0.000)
2014	0.891*** (0.000)	0.886*** (0.000)	0.886*** (0.000)
2000-2014	**0.856***(0.000)**	**0.873***(0.000)**	**0.876***(0.000)**
Wage			
Year	Ratio 60%	Ratio 70% (benchmark)	Ratio 80%
2000	0.780***(0.000)	0.780***(0.000)	0.780***(0.000)
2001	0.792***(0.000)	0.792***(0.000)	0.792***(0.000)
2002	0.809***(0.000)	0.809***(0.000)	0.809***(0.000)
2003	0.813***(0.000)	0.813***(0.000)	0.813***(0.000)
2004	0.814***(0.000)	0.814***(0.000)	0.813***(0.000)
2005	0.804***(0.000)	0.802***(0.000)	0.801***(0.000)
2006	0.803***(0.000)	0.799***(0.000)	0.797***(0.000)
2007	0.781***(0.000)	0.781***(0.000)	0.779***(0.000)
2008	0.805***(0.000)	0.803***(0.000)	0.800***(0.000)
2009	0.828***(0.000)	0.830***(0.000)	0.829***(0.000)
2010	0.803***(0.000)	0.805***(0.000)	0.805***(0.000)
2011	0.830***(0.000)	0.834***(0.000)	0.832***(0.000)
2012	0.815***0.000)	0.820***(0.000)	0.818***(0.000)
2013	0.816***(0.000)	0.821***(0.000)	0.821***(0.000)
2014	0.820***(0.000)	0.824***(0.000)	0.824***(0.000)
2000-2014	**0.775***(0.000)**	**0.793***(0.000)**	**0.786***(0.000)**

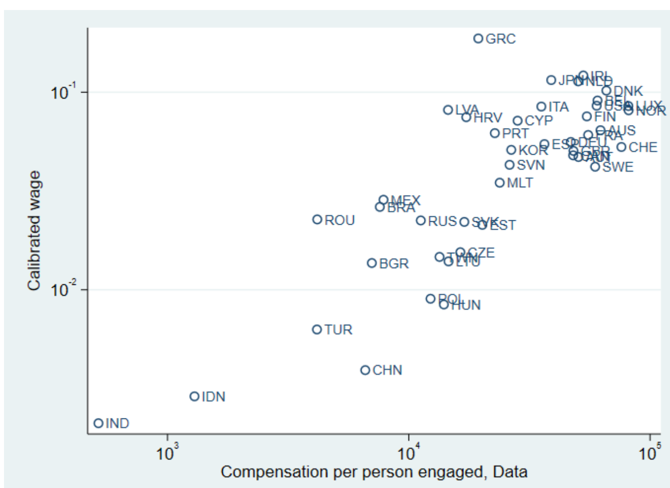
Notes: Pairwise correlation. The symbols ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively. The p-value for a two-tailed test is given in parentheses. We report the correlation with the calibrated participation value and wages based on three different ratios used to compute the industry's degree of difficulty and T_{max}, 60%, 70%, and 80%. For details, see Section 3.1.

Figure 1: Calibrated participation value versus observed data



Notes: Axes are log-scale. The x-axis reports value added in world final demand in millions of US dollars in 2014. The y-axis reports the participation value calibrated from our model using T_{max} given by the industries' degree of difficulty computed using ratio 70%. For details, see Section 3.1.

Figure 2: Calibrated wage versus observed data



Notes: Axes are log-scale. The x-axis reports compensation per number of persons engaged in 2014, the y-axis reports the wages calibrated from our model using T_{max} given by the industries' degree of difficulty computed using ratio 70%. For details, see Section 3.1.

Finally, table 4 reports the moments of the observed and calibrated participation values and real wages. The values of moments show a close match. The strong positive correlations and good fit of our model are not surprising,

Table 4: Moments. Calibrated and observed data.

Participation value	Observed	Ratio 60%	Ratio 70%	Ratio 80%
Std. dev.	1.58	1.89	1.84	1.84
P90-P10	4.22	4.98	4.64	4.58
Real wage	Observed	Ratio 60%	Ratio 70%	Ratio 80%
Std. dev.	1.09	1.36	1.24	1.22
P90-P10	2.54	3.22	2.94	2.93
N	645	645	645	645

Notes: The table shows moments of the observed and calibrated participation value and wages based on three different ratios used to compute the industry's degree of difficulty and T_{max}, 60%, 70%, and 80%. For details, see Section 3.1. N is number of observations.

given that our model is built on a standard Ricardian framework, which is known to explain well the amount of trade between countries. However, the manner in which we introduce the production of intermediate goods into the framework helps to prove that the concept of comparative advantage holds for the GVC as well. Moreover, countries with a higher technology frontier face a choice between performing most tasks necessary to produce the final good within their own borders or moving the production stages involving lower technological difficulty to less developed countries. In this paper, we show that the important factors determining the outcome of this decision are the technology level and the labor endowment of the country.

5 Conclusion

Most recent studies attempting to understand the GVC have approached the problem by exploring multistage production within various frameworks.

These frameworks assume either a snake-type GVC, which depicts the production process as a sequence of stages, or a spider-type GVC, which regards production process as an assembly of distinctly produced intermediate inputs; however, no existing studies incorporate both frameworks. By contrast, this paper attempts to relax these assumptions and view the production process as a set of intermediate production stages that form the production of the final good.

To achieve our goal, we developed a simple multi-country model where countries are heterogeneous with respect to their technology level and labor force endowments. The model is a simple reconsideration of the Ricardian comparative advantage framework of Dornbusch et al. (1977) applied to the GVC production structure. The framework does not impose limits on how the production process is regarded and, thus, we can consider both snake-type and spider-type GVC and examine the role of the technology level in shaping the structure of the GVC.

The paper yields some interesting results. First, we show analytically that the country with a higher technology level focuses on the production stage involving a higher degree of difficulty. This finding is consistent with the real data. Second, we calibrate the model and compare the results with the real data. For this purpose, we rely on the World-Input Output Database. Participation values in the GVC are calibrated from the model using data on the technology level and labor. In the real data, this value is proxied by the countries' value added embodied in the world final demand, which is computed using a standard input–output analysis approach. Interestingly, the correlation between calibrated outcome and observed data is found to be high as 87.3% for the participation value and 79.3% for the real wage. Therefore, we conclude that our model is a plausible representation of the real world.

Given our findings, we believe that more consideration should be given to the production process and trade in the GVC. A theoretical model that considers both snake- and spider-type GVCs could bring new and interesting insights into the global production structure. We believe that our model is a first step in developing such an understanding, and we aim to explore further extensions in future research.

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