Where Did the Processing Export Relocate to? An Optimization-Method-based Identification

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Abstract: The international relocation of processing exports is regarded as a bellwether of the global production reconfiguration. However, straightforwardly identifying the host economies of processing exports is challenging because of the lack of data. Thus, the paper first proved that the continuously decreasing Domestic value-added share in gross export (DVASHGE) is a sufficient condition for identifying the host economies of processing production. Then, a constrained weighted least squares optimization is proposed for unfolding the changes of DVASHGE in each specific economy during the recent past, overcoming the limitations of the mainstream input-output-based method. The empirical findings show that Vietnam and the Philippines in Southeast Asia, Colombia in South America, and Tunisia in North Africa are the host economies of processing production. The proposed optimization-method-based identification will provide an important reference for the global value chain studies centered on input-output-based indicators.

Keyword: Processing trade, Global industry relocation, Domestic value-added share in gross export, Input-output Analysis

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1. Introduction

In recent years, the world economy and the associated trade patterns have experienced sequential shocks generated by the Covid-19 crisis and the consequential supply chain disruptions, the increasing geopolitical tensions and uncertainties (e.g., the Russia-Ukraine war and the Brexit), the rising trade protectionism (e.g., the US-China trade war) and the associated policies. As a result, the global production location is likely to change profoundly in the coming years (Brakman et al., 2020; Gereffi, 2020). And how it will change is becoming an increasingly important but complicated question (Gao et al., 2022). Perhaps, capturing the international relocation of processing trade in the recent past would shed light on that question.

Processing trade refers to importing (all or part of the) raw and auxiliary materials, parts and components, accessories, and packaging materials from abroad and subsequently re-exporting the finished products following processing or assembly[1] (Yang et al., 2015; Manova and Yu, 2016). It is distinguished by two outstanding features compared with other production activities. First, processing trade takes advantage of the low production cost (e.g., labor cost, energy cost, etc.) and tax waiver (e.g., production tax, tariff, etc.) to offset the international transportation and communication cost and gain profit. It is very sensitive to the change(fluctuations) in production cost, which makes it more prone to relocating than other types of production activities when local costs rise. Second, processing trade is heavily dependent on the international supply chain since both its input and output relies on foreign market. It is typically dominated by the multi-national enterprises (82.0% of China's processing export is conducted by foreign invested enterprise) that is highly sensitive to geopolitical tensions and global economic uncertainties (Munasib et al., 2021), which makes it more likely to relocate when the relocation tendency appears.

The above-mentioned two features determine that the international relocation of processing trade is the bellwether of global production relocation. And thus, the prime aim of the paper is capturing the international relocation of processing trade. However, economies across the world rarely distinguish the processing trade from ordinary trade (to the best of our knowledge, only China and Mexico have separately recorded the processing trade data). This invalidates the approach that straightforwardly

[1] Note that the imported goods involved in processing trade (usually called processing imports) are only used to produce goods for processing exports.

identifying the international processing trade relocation through the official trade data and causes the lack of literature in this research area, which is the first challenge we met.

On the other hand, due to the high dependence on foreign intermediates, the domestic value-added generated by per unit of processing export is far less than other production activities. Such the "low value-added" attribute of processing trade is widely recognized in the literature on global value chains (GVC). For example, based on China's thorough data on processing trade, Lau et al. (2010), Chen et al. (2012), Koopman et al. (2012) and Yang et al. (2015) constructed the adapted China's non-competitive input-output table that distinguishes the production for processing trade. They found that China's domestic value-added share of gross export (DVASHGE) would be significantly overestimated while, its counterpart, China's vertical specialization (VS; Hummels et al., 2001) would be underestimated without capturing the heterogeneity of processing trade. Upward et al. (2013) arrived at a similar conclusion but based on the firm-level data. Chen et al. (2019) distinguished China's processing trade in the world input-output table (WIOT) and quantified how it biased the "Trade in Value-Added" (TiVA) indicators. Moreover, the "low value-added" attribute of processing trade also led to an "unexceptional exporter performance" in China that the productivity of export-oriented companies is even lower than the domestic-oriented companies (Dai et al., 2016), which is opposite to Melitz (2003) and Bernard et al (2003)'s theory. These facts inspired us whether it is rational to identify the host economies of processing trade (i.e., the economies to which the processing production relocates) through its decreasing DVASHGE? In next section, the paper theoretically proves that the continuously decreasing DVASHGE is a sufficient condition for identifying the host economies of processing production, overcoming the first challenge.

After that, the second challenge of the paper is to capture the accurate changes of DVASHGE for different economies. Although the mainstream method measuring the DVASHGE is the TiVA indicators calculated by the national or world input-output tables (WIOTs), due to the following reasons, such a method is not suitable for this paper. First, there is a significant time-lag for the publication of input-output tables [2]. Consequently, the TiVA indicators cannot unfold the international relocation of processing trade in the recent past, and thus, cannot serve as an leading indicator of global production

[2] In 2022, the most recent world input-output tables (WIOTs) are up to year 2018 (e.g., the 2021 edition of OECD inter-country input-output tables (OECD-ICIO)), while the other widely adopted WIOTs are only updated to year 2014 (e.g., 2016 release of world input-output database (WIOD)). For the national input-output tables, their publication time-lag is at least 2 years (and much longer than that in most economies).

relocation. Second, many developing economies neither possess official input-output data nor are included in the WIOTs. Therefore, measuring their DVASHGE based on input-output tables is extremely difficult, even though they may be potential destinations for processing production. Finally, the national or world input-output tables rarely distinguish the production of processing trade, which will seriously overestimate the DVASHGE and weaken its changes overtime, especially for the host economies of processing trade. For example, Yang *et al.* (2015) indicates that China's "real" DVASHGE in 2002 is 55% after distinguishing the processing trade, which is significantly lower than that calculated by traditional input-output table (72%, without distinguishing the processing trade). Thus, in order to overcome the second challenge, the paper put forward a constrained weighted least squares optimization model for capturing the changes of DVASHGE overtime based on the macro-economic data (i.e., GDP, consumption, capital formation, import, and export) for each specific economy, avoiding the above-mentioned shortcomings of TiVA indicators.

The paper is organized as follows: the next section provides the theoretical foundation of the changes of DVASHGE, and proves that the continuously decreasing DVASHGE is a sufficient condition for identifying the host economies of processing production. Then, the methodology section proposes a constrained weighted least squares optimization model for capturing the changes of DVASHGE overtime, which overcomes the shortcomings of the mainstream input-output method. In the empirical section, the paper introduces the selected economies as the candidates of host economy of processing production, and then, identifies the host economy of processing production among those candidates. Thereafter, the robustness check section proves the robustness of the proposed optimization-based identification. In the final section. the paper concludes with a discussion of the method and the associated empirical results.

2. Theoretical Foundation

2.1 The Domestic Value-Added Share of Gross Export (DVASHGE)

Table 1 presents a non-competitive input-output table with *N* sectors. Then, in Table 1, $\boldsymbol{Z}^d = \left(z_{ij}^d\right)_{N\times N}$ is an $N \times N$ matrix that denotes the domestic intermediate inputs from sector *i* to sector *j*; $\boldsymbol{Z}^m = \left(z_{ij}^m\right)_{N\times N}$ is an $N \times N$ matrix denoting the imported intermediate inputs from sector *i* to sector *j*; $\boldsymbol{c} = (c_i)_{N\times 1}$, $\boldsymbol{in} = (in_i)_{N\times 1}$, and $\boldsymbol{ex} = (ex_i)_{N\times 1}$ denote the $N \times 1$ vectors of domestic goods/services for final consumption, capital formation, and exports, respectively[3]; $\boldsymbol{M}^F = \left(m_{ik}^F\right)_{N\times 3}$ denotes the $N\times 3$ matrix of imported final products; $\boldsymbol{v} = \left(v_j\right)_{N\times 1}$ denotes an $N\times 1$ vector of the sectoral value added while $'$ denotes the transposition of a vector; $\boldsymbol{m} = (m_i)_{N\times 1}$ is an $N\times 1$ vector giving the gross import; $\boldsymbol{x} = (x_i)_{N\times 1}$ is an $N\times 1$ vector giving the gross output, which equals its total input.

Table 1: Non-competitive Input-output Table with N Sectors.

Output / Input		Intermediates	Final Demand			Gross Output/Import
		$1 \quad 2 \quad \cdots \quad n$	Consumption	Capital Formation	Exports	
Domestic Intermediates	1, 2, $\vdots$, n	$\boldsymbol{Z}^d = \left(z_{ij}^d\right)_{N\times N}$	$\boldsymbol{c} = (c_i)_{N\times 1}$	$\boldsymbol{in} = (in_i)_{N\times 1}$	$\boldsymbol{ex} = (ex_i)_{N\times 1}$	$\boldsymbol{x} = (x_i)_{N\times 1}$
Imported Intermediates	1, 2, $\vdots$, n	$\boldsymbol{Z}^m = \left(z_{ij}^m\right)_{N\times N}$	$\boldsymbol{M}^F = (m_{ik}^F)_{N\times 3}$			$\boldsymbol{m} = (m_i)_{N\times 1}$
Value Added		$\boldsymbol{v}' = (v_i)_{N\times 1}$				
Total Input		$\boldsymbol{x}' = (x_i)_{N\times 1}$				

Then, the row equation of domestic production can be presented as:

$$\boldsymbol{Z}^d\boldsymbol{e} + \boldsymbol{c} + \boldsymbol{in} + \boldsymbol{ex} = \boldsymbol{x} \tag{1}$$

Where $\boldsymbol{e} = (1)_{N\times 1}$ is the summation vector comprised of 1. Calculating the domestic direct input coefficients matrix as $\boldsymbol{A}^d = \boldsymbol{Z}^d\hat{\boldsymbol{x}}^{-1} = \left(\frac{z_{ij}^d}{x_j}\right)_{N\times N}$, then the equation (1) can be converted to:

$$\boldsymbol{A}^d\boldsymbol{x} + \boldsymbol{c} + \boldsymbol{in} + \boldsymbol{ex} = \boldsymbol{x} \tag{2}$$

$$\left(\boldsymbol{I} - \boldsymbol{A}^d\right)^{-1}(\boldsymbol{c} + \boldsymbol{in} + \boldsymbol{ex}) = \boldsymbol{x} \tag{3}$$

Equation (3) is the key equation of non-competitive Leontief input-output model (Miller and Blair, 2009), where $\boldsymbol{I}$ is the N×N identity matrix, $\boldsymbol{B}^d = (I - \boldsymbol{A}^d)^{-1} = \left(b_{ij}^d\right)_{N\times N}$ is the well-known domestic Leontief inverse (or domestic total requirement coefficients). b_{ij}^d denotes the domestic inputs by sector *i* required (directly and indirectly) in order to deliver one unit of sector *j*'s output to final demand. Next,

[3] Hereinafter, the final consumption, capital formation and exports denote that of domestic goods/services. All the imported final products are excluded.

by calculating the direct value-added coefficient vector as $\boldsymbol{a}_v = \boldsymbol{v}'\hat{\boldsymbol{x}}^{-1} = \left(\frac{v_j}{x_j}\right)_{1\times N}$, the gross domestic production (*GDP*) can be measured as:

$$GDP = \sum_j v_j = \boldsymbol{a}_v \cdot \boldsymbol{x} = \boldsymbol{a}_v\left(\boldsymbol{I} - \boldsymbol{A}^d\right)^{-1}(\boldsymbol{c} + \boldsymbol{in} + \boldsymbol{ex}) = \boldsymbol{b}_v(\boldsymbol{c} + \boldsymbol{in} + \boldsymbol{ex}) \tag{4}$$

Where $\boldsymbol{b}_v = \boldsymbol{a}_v\boldsymbol{B}^d = (b_{v,j})_{1\times N}$ is the total value-added coefficients vector, $b_{v,j}$ denotes the domestic value-added generated (directly and indirectly) by one unit of sector *j*'s output to final demand. Set $\bar{c} = \sum_i c_i$, $\overline{in} = \sum_i in_i$, $\overline{ex} = \sum_i ex_i$ as the gross final consumption, the gross capital formation, and the gross export, respectively. Then, $\boldsymbol{cs} = \left(\frac{c_i}{c}\right)_{N\times 1}$, $\boldsymbol{ins} = \left(\frac{in_i}{in}\right)_{N\times 1}$, and $\boldsymbol{exs} = \left(\frac{ex_i}{ex}\right)_{N\times 1}$ denote the sectoral share of the final consumption, the capital formation, and the exports, respectively. And the equation (4) can be converted to:

$$GDP = (\boldsymbol{b}_v \cdot \boldsymbol{cs})\bar{c} + (\boldsymbol{b}_v \cdot \boldsymbol{ins})\overline{in} + (\boldsymbol{b}_v \cdot \boldsymbol{exs})\,\overline{ex} = \alpha\bar{c} + \beta\overline{in} + \gamma\overline{ex} \tag{5}$$

Where $\alpha = \boldsymbol{b}_v \cdot \boldsymbol{cs}$, $\beta = \boldsymbol{b}_v \cdot \boldsymbol{ins}$, and $\gamma = \boldsymbol{b}_v \cdot \boldsymbol{exs}$ correspond to the domestic value-added share of gross final consumption, gross capital formation, and gross export. The equation (4) indicates that the GDP comprises three parts, i.e., the domestic value-added driven by final consumption, by capital formation, and by export.

2.2 The Processing Export and DVASHGE

Considering the significant "low value-added" attribute of processing export, Yang *et al.* (2015) constructed the adapted China's non-competitive input-output table that distinguishes the production for processing trade. In this table, each sector is divided into three types of production. They are 1) the production of domestic enterprises for domestic final use (indicated by superscript *D*); 2) the production of processing export (indicated by superscript *P*); and 3) the combination of production of non-processing exports and production by foreign-invested enterprises for domestic use (indicated by superscript *N*). Thus, this adapted input-output table is also referred to as the DPN table, of which the structure is shown in table 2.

Table 2: The structure of the DPN input-output table.

Output / Input		Intermediates: D	Intermediates: P	Intermediates: N	Final Demand: Consumption	Final Demand: Capital Formation	Final Demand: Exports	Gross Output/ Import
Domestic Intermediates	D	$\boldsymbol{Z}_{DD}^d$	$\boldsymbol{Z}_{DP}^d$	$\boldsymbol{Z}_{DN}^d$	$\boldsymbol{c}_D$	$\boldsymbol{in}_D$	$\boldsymbol{0}$	$\boldsymbol{x}_D$
	P	$\boldsymbol{0}$	$\boldsymbol{0}$	$\boldsymbol{0}$	$\boldsymbol{0}$	$\boldsymbol{0}$	$\boldsymbol{ex}_P$	$\boldsymbol{x}_P$
	N	$\boldsymbol{Z}_{ND}^d$	$\boldsymbol{Z}_{NP}^d$	$\boldsymbol{Z}_{NN}^d$	$\boldsymbol{c}_N$	$\boldsymbol{in}_N$	$\boldsymbol{ex}_N$	$\boldsymbol{x}_N$
Imported Intermediates		$\boldsymbol{Z}_D^m$	$\boldsymbol{Z}_P^m$	$\boldsymbol{Z}_N^m$	$\boldsymbol{M}^F$			$\boldsymbol{m}$
Value Added		$\boldsymbol{v}_D'$	$\boldsymbol{v}_P'$	$\boldsymbol{v}_N'$				
Total Input		$\boldsymbol{x}_D'$	$\boldsymbol{x}_P'$	$\boldsymbol{x}_N'$				

In Table 2, the domestic intermediate flow matrix $\boldsymbol{Z}^d = \begin{pmatrix} \boldsymbol{Z}_{DD}^d & \boldsymbol{Z}_{DP}^d & \boldsymbol{Z}_{DN}^d \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{Z}_{ND}^d & \boldsymbol{Z}_{NP}^d & \boldsymbol{Z}_{NN}^d \end{pmatrix}$ is a $3N \times 3N$ matrix, where the $N \times N$ sub-matrix $\boldsymbol{Z}_{IJ}^d$ $(I, J \in \{D, P, N\})$ denotes the domestic intermediate inputs from I type of production to J type of production. Since the processing production is only used for export, $\boldsymbol{Z}_{PJ}^d = \boldsymbol{0}$ $(J \in \{D, P, N\})$. In addition, the $N \times 3N$ imported intermediate flow matrix is $\boldsymbol{Z}^m = (\boldsymbol{Z}_D^m \quad \boldsymbol{Z}_P^m \quad \boldsymbol{Z}_N^m)$; the $3N \times 1$ vectors of final consumption and capital formation correspond to $\boldsymbol{c} = \begin{pmatrix} \boldsymbol{c}_D \\ 0 \\ \boldsymbol{c}_N \end{pmatrix}$ and $\boldsymbol{in} = \begin{pmatrix} \boldsymbol{in}_D \\ 0 \\ \boldsymbol{in}_N \end{pmatrix}$, respectively; the $3N \times 1$ vectors of export is $\boldsymbol{ex} = \begin{pmatrix} 0 \\ \boldsymbol{ex}_P \\ \boldsymbol{ex}_N \end{pmatrix}$, where the $N \times 1$ sub-vector $\boldsymbol{ex}_P$ and $\boldsymbol{ex}_N$ correspond to the processing export and non-processing export, respectively; the $3N \times 1$ vector of the sectoral value added is $\boldsymbol{v} = \begin{pmatrix} \boldsymbol{v}_D \\ \boldsymbol{v}_P \\ \boldsymbol{v}_N \end{pmatrix}$ and the $3N \times 1$ vector of the gross output is $\boldsymbol{x} = \begin{pmatrix} \boldsymbol{x}_D \\ \boldsymbol{x}_P \\ \boldsymbol{x}_N \end{pmatrix}$. Then, similar with the derivation from equation (1) to (4), when distinguishing the processing production:

$$GDP = \boldsymbol{b}_v(\boldsymbol{c} + \boldsymbol{in} + \boldsymbol{ex}) = \boldsymbol{b}_v(\boldsymbol{c} + \boldsymbol{in}) + \boldsymbol{b}_v^P \boldsymbol{ex}_P + \boldsymbol{b}_v^N \boldsymbol{ex}_N \tag{6}$$

In equation (6), $\boldsymbol{b}_v = (\boldsymbol{b}_v^D, \boldsymbol{b}_v^P, \boldsymbol{b}_v^N)$ is the total value-added coefficients vector, where the $1 \times N$ sub-vectors $\boldsymbol{b}_v^D$, $\boldsymbol{b}_v^P$ and $\boldsymbol{b}_v^N$ correspond to the total value-added coefficients for *D*, *P*, *N* type of production, respectively. Moreover, due to the "low value-added" attribute of processing export, $\boldsymbol{b}_v^P \ll \boldsymbol{b}_v^N$, $\boldsymbol{b}_v^P \ll \boldsymbol{b}_v^D$, (Upward et al., 2013; Yang et al., 2015). Again, set $\bar{c} = \sum_i c_i^D + \sum_i c_i^N$, $\overline{in} = \sum_i in_i^D + \sum_i in_i^N$, $\overline{ex}_P = \sum_i ex_i^P$, $\overline{ex}_N = \sum_i ex_i^N$ as the gross final consumption, the gross capital formation, the gross processing export, and the gross non-processing export respectively ($\overline{ex} = \overline{ex}_P + \overline{ex}_N$). Then, $\boldsymbol{cs} = \begin{pmatrix} \frac{\boldsymbol{c_D}}{\bar{c}} \\ 0 \\ \frac{\boldsymbol{c_N}}{\bar{c}} \end{pmatrix}$, $\boldsymbol{ins} = \begin{pmatrix} \frac{\boldsymbol{in_D}}{\overline{in}} \\ 0 \\ \frac{\boldsymbol{in_N}}{\overline{in}} \end{pmatrix}$, $\boldsymbol{exs}_P = \frac{\boldsymbol{ex_P}}{\overline{ex}_P}$, and $\boldsymbol{exs}_N = \frac{\boldsymbol{ex_N}}{\overline{ex}_N}$ denote the sectoral share of final consumption, capital formation, the processing export, and the non-processing export, respectively. And the equation (6) can be converted to:

$$GDP = (\boldsymbol{b}_v \cdot \boldsymbol{cs})\bar{c} + (\boldsymbol{b}_v \cdot \boldsymbol{ins})\overline{in} + (\boldsymbol{b}_v^P \cdot \boldsymbol{exs}_P)\overline{ex}_P + (\boldsymbol{b}_v^N \cdot \boldsymbol{exs}_N)\overline{ex}_N \tag{7}$$

$$GDP = (\boldsymbol{b}_v \cdot \boldsymbol{cs})\bar{c} + (\boldsymbol{b}_v \cdot \boldsymbol{ins})\overline{in} + \left[(\boldsymbol{b}_v^P \cdot \boldsymbol{exs}_P)\frac{\overline{ex}_P}{\overline{ex}} + (\boldsymbol{b}_v^N \cdot \boldsymbol{exs}_N)\frac{\overline{ex}_N}{\overline{ex}}\right]\overline{ex} \tag{8}$$

Then, comparing equation (5) and (8):

$$\begin{aligned} \gamma &= (\boldsymbol{b}_v^P \cdot \boldsymbol{exs}_P)\frac{\overline{ex}_P}{\overline{ex}} + (\boldsymbol{b}_v^N \cdot \boldsymbol{exs}_N)\frac{\overline{ex}_N}{\overline{ex}} \\ &= (\boldsymbol{b}_v^P \cdot \boldsymbol{exs}_P)\frac{\overline{ex}_P}{\overline{ex}} + (\boldsymbol{b}_v^N \cdot \boldsymbol{exs}_N)\left(1 - \frac{\overline{ex}_P}{\overline{ex}}\right) \\ &= \boldsymbol{b}_v^N \cdot \boldsymbol{exs}_N + (\boldsymbol{b}_v^P \cdot \boldsymbol{exs}_P - \boldsymbol{b}_v^N \cdot \boldsymbol{exs}_N)\frac{\overline{ex}_P}{\overline{ex}} \end{aligned} \tag{9}$$

According to equation (9), the DVASHGE is determined by three components. They are 1) the sectoral total value-added coefficients for the processing export and the non-processing export ($\boldsymbol{b}_v^P$ and $\boldsymbol{b}_v^N$), 2) the sectoral share of the processing export and the non-processing export ($\boldsymbol{exs}_P$ and $\boldsymbol{exs}_N$), and 3) the proportion of the processing export in the gross export ($\frac{\overline{ex}_P}{\overline{ex}}$). Since $\boldsymbol{b}_v^P \ll \boldsymbol{b}_v^N$, $\boldsymbol{b}_v^P \cdot \boldsymbol{exs}_P - \boldsymbol{b}_v^N \cdot \boldsymbol{exs}_N < 0$. Thus, a continuing decline in DVASHGE leads to at least one of the three following conditions, as shown in figure 1. First, the total value-added coefficients ($\boldsymbol{b}_v^P$ and $\boldsymbol{b}_v^N$) are decreasing, denoting a higher dependence on the imported intermediates. Second, the sectors with low total value-added coefficients occupy more percentages in the processing and the non-processing export, denoting the competitive advantage is becoming increasingly concentrated in those sectors. Third, the proportion of the processing export in the gross export is rising. Obviously, if the third condition holds, then the economy is, of course, the host economy of processing production. On the other hand, if the first or second condition holds, then it means the economy's dependence on the international supply chain is increasing. If that economy is a low-cost developing economy, then it satisfies the two significant features of processing trade, and thus, is probably the host economy of processing production. As a conclusion, **the continuously decreasing DVASHGE is a sufficient condition for identifying the host economies of processing production, especially for those low-cost developing economy.**

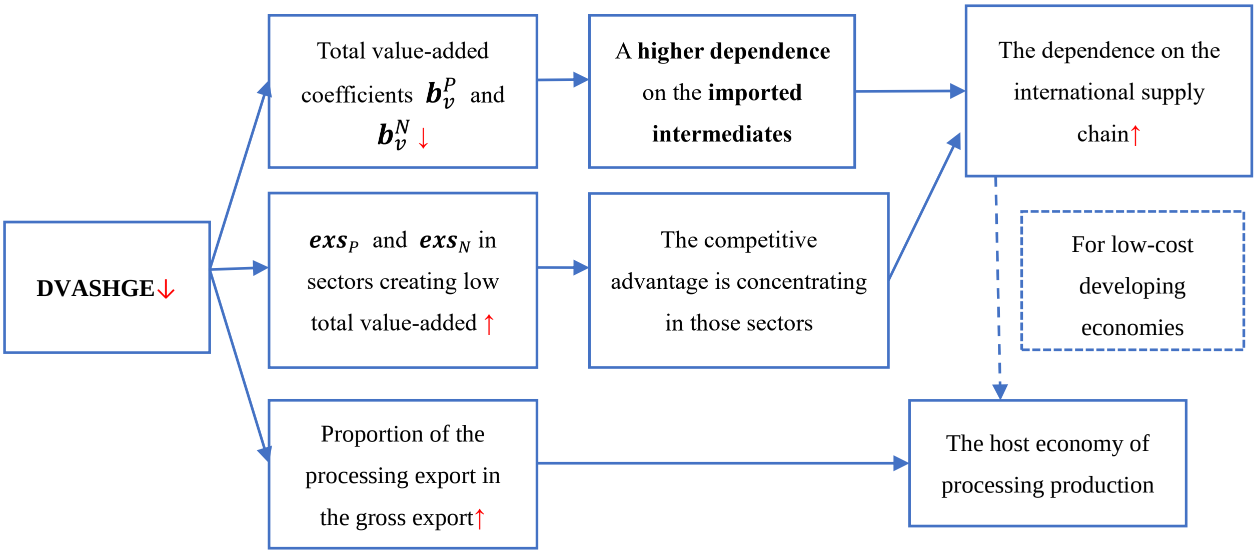
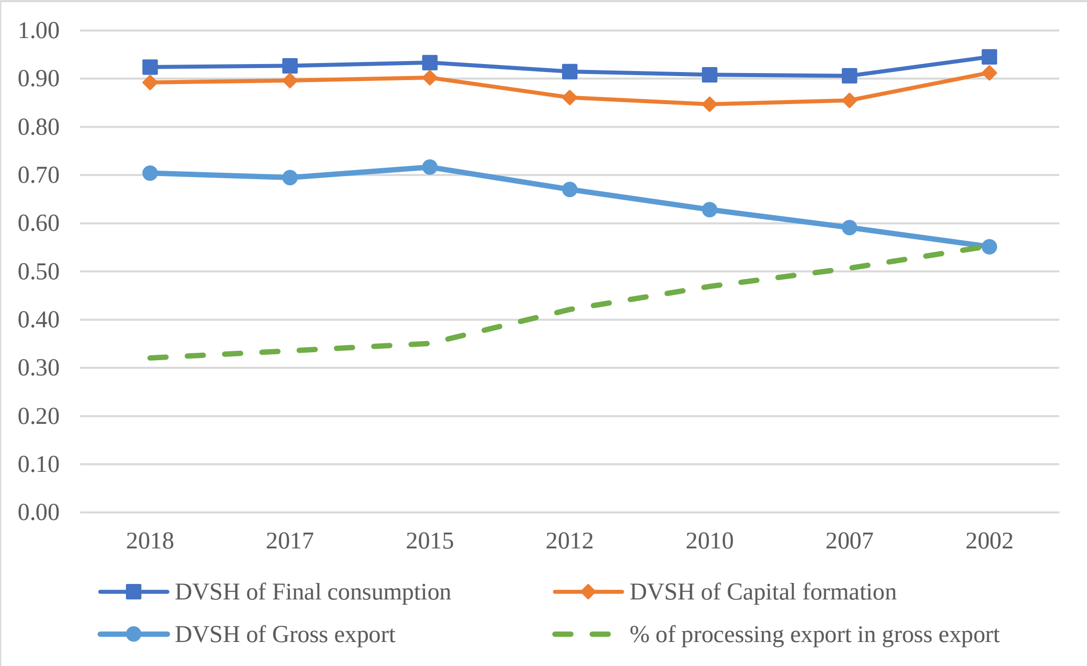


Figure 1: The continuously decreasing DVASHGE and the host economies of processing production

2.3 The reversed timeline evidence from China

Based on China's time-series DPN input-output tables, the paper measures the domestic value-added share of different final demand. These reversed timeline evidence from China supports our theoretical foundation presented in section 2.2. As shown in figure 2, when tracing from 2018 back to 2002, China's DVASHGE is continuously decrease with its increasing processing production intensity (indicated by the proportion of the processing export in the gross export). In addition, the relocation of processing export leads to the greater variation in China's domestic value-added share of gross export than that of final consumption or capital formation. During 2002-2017, the interval of DVASHGE is (0.55, 0.72), of which the range is more than twice as much as final consumption (0.91, 0.95) or capital formation (0.85, 0.91).



Note: The X-axis is an inverse timeline for giving expression to the increasing processing production intensity

Figure 2: China's domestic value-added share of different final demand and the processing production intensity

3. Methodology

The theoretical section has proved that the continuously decreasing DVASHGE is a sufficient condition for identifying the host economies of processing production, especially for those low-cost developing economies. Thus, the subsequent task is to capture the changes of DVASHGE for each specific economy. However, due to the three limitations presented in the introduction section, the TiVA indicator based on the input-output table is not an ideal approach for the paper. Hence, the paper adopts the constrained weighted least squares optimization method for estimating the changes of DVASHGE.

3.1 The constrained weighted least squares optimization

Weighted least squares optimization is a widely used method that estimates the parameters by minimizing the sum of squared residuals/variations (Fabozzi et al., 2017). In practical applications, Weighted Least Squares Optimization often needs to satisfy specific constraints, and thus, is referred to as the constrained weighted least squares optimization. This method has wide applications in various research fields such as statistics, finance, economics, etc. For example, Hao et al. (2020) use a robust weighted least squares approach to estimate the real prices of crude oil, which improves forecasting performance by down-weighting the variation of extreme observations through using a class of kernel functions. Wang et al. (2020) use a weighted least squares method to forecast stock returns, assigning greater weights to more recent observations for declining their variations between the true value and the fitting value. This approach yields better predictive performance compared to estimates obtained using ordinary least squares.

$$\min y = \begin{array}{c} \varphi_\alpha^0(\alpha_0-\overline{\alpha_0})^2+\varphi_\beta^0\left(\beta_0-\overline{\beta_0}\right)^2+\varphi_\gamma^0(\gamma_0-\overline{\gamma_0})^2+ \\ \sum_{t=1}^{n}\left[\varphi_\alpha^t(\alpha_t-\alpha_{t-1})^2+\varphi_\beta^t(\beta_t-\beta_{t-1})^2+\varphi_\gamma^t(\gamma_t-\gamma_{t-1})^2\right] \end{array} \tag{10}$$

$$\text{s.t.} \quad \forall t \quad \alpha_t\bar{c}_t+\beta_t\overline{in}_t+\gamma_t\,\overline{ex}_t=GDP_t \tag{11}$$

Equation (10) and (11) constitute a constrained weighted least squares optimization problem for solving the changes of DVASHGE in a specific economy. Equation (10) is the objective function, where α_t, β_t, and γ_t are the **unknown variables** denoting the domestic value-added share of gross final consumption, gross capital formation, and gross export at year *t*, respectively. $\overline{\alpha_0}$, $\overline{\beta_0}$, and $\overline{\gamma_0}$ are the reference value (given coefficients, see section 4.2 for details) of α_0, β_0, and γ_0, and 0 denotes the start year. φ_α^t, φ_β^t, and φ_γ^t are the weights of the variation of α, β, and γ between year *t* and *t*-1, which are set according to 3.2 and 3.3. Equation (11) is the constraints theoretically derived from equation (5), where $\bar{c}_t$, $\overline{in}_t$, $\overline{ex}_t$, and GDP_t correspond to the gross final consumption, the gross capital formation, the gross export, and GDP of that specific economy at year *t*, respectively.

The economic intuition of the model is that the domestic value-added share of different final demand should satisfy the following three conditions. First, their value at the start year should be as close to the reference value as possible. Second, their value at adjacent years should also be as close as possible. Third, their value should hold the GDP identity equation as shown in equation (5). The model is based on two fundamental assumptions. First, the variation of domestic value-added share of each specific final demand between adjacent years should be slight and smooth. This is because the production techniques and supply chain in a specific economy should be stable between adjacent years. Otherwise, sharp changes would require expensive management or equipment costs, which are not practical. Second, the variation of domestic value-added share of gross export should be wider than that of final consumption and capital formation, considering the high dependence on the international supply chain for the processing export. This is embodied in the weights setting as presented in section 3.3.[4]

[4] These two assumptions are supported by the empirical results of China that distinguishing the heterogeneity of processing export, as indicated in figure 2.

3.2 Weights Setting Stage-1: the magnitude of different final demand

Simplifying the model in a two-year situation (year 0 and *t*) and giving $\overline{\alpha_0}\bar{c}_0 + \overline{\beta_0}\overline{in}_0 + \overline{\gamma_0}\overline{ex}_0 = GDP_0$, then the basic model (equation (10) and (11)) can be converted to:

$$min\, y = \varphi_\alpha^t(\alpha_t - \overline{\alpha_0})^2 + \varphi_\beta^t\left(\beta_t - \overline{\beta_0}\right)^2 + \varphi_\gamma^t(\gamma_t - \overline{\gamma_0})^2 \tag{12}$$

$$\text{s.t.}\quad \alpha_t\bar{c}_t + \beta_t\overline{in}_t + \gamma_t\overline{ex}_t = GDP_t \tag{13}$$

Define $\Delta\alpha_t = (\alpha_t - \overline{\alpha_0})$, $\Delta\beta_t$=$\left(\beta_t - \overline{\beta_0}\right)$, and $\Delta\gamma_t = (\gamma_t - \overline{\gamma_0})$, calculate $\overline{\alpha_0}\bar{c}_t + \overline{\beta_0}\overline{in}_t + \overline{\gamma_0}\overline{ex}_t = GDP_t'$. Then the simplified model is further converted to:

$$min\, y = \varphi_\alpha^t{\Delta\alpha_t}^2 + \varphi_\beta^t{\Delta\beta_t}^2 + \varphi_\gamma^t{\Delta\gamma_t}^2 \tag{14}$$

$$\text{s.t.}\ \ \Delta\alpha_t\bar{c}_t + \Delta\beta_t\overline{in}_t + \Delta\gamma_t\overline{ex}_t = GDP_t - GDP_t' \tag{15}$$

Using Lagrange multiplier method to solve this problem, then

$$min\, y = \varphi_\alpha^t{\Delta\alpha_t}^2 + \varphi_\beta^t{\Delta\beta_t}^2 + \varphi_\gamma^t{\Delta\gamma_t}^2 - \lambda(\Delta\alpha_t\bar{c}_t + \Delta\beta_t\overline{in}_t + \Delta\gamma_t\overline{ex}_t - GDP_t + GDP_t') \tag{16}$$

$$\begin{cases} 2\varphi_\alpha^t\Delta\alpha_t - \lambda\bar{c}_t = 0 \\ 2\varphi_\beta^t\Delta\beta_t - \lambda\overline{in}_t = 0 \\ 2\varphi_\gamma^t\Delta\gamma_t - \lambda\overline{ex}_t = 0 \end{cases} \tag{17}$$

$$\begin{cases} \Delta\alpha_t = \frac{\lambda\bar{c}_t}{2\varphi_\alpha^t} \\ \Delta\beta_t = \frac{\lambda\overline{in}_t}{2\varphi_\beta^t} \\ \Delta\gamma_t = \frac{\lambda\overline{ex}_t}{2\varphi_\gamma^t} \end{cases} \tag{18}$$

$$\begin{cases} \Delta\alpha_t = \frac{\varphi_\gamma^t\bar{c}_t}{\varphi_\alpha^t\overline{ex}_t}\Delta\gamma_t \\ \Delta\beta_t = \frac{\varphi_\gamma^t\overline{in}_t}{\varphi_\beta^t\overline{ex}_t}\Delta\gamma_t \end{cases} \tag{19}$$

If $\varphi_\alpha^t = \varphi_\beta^t = \varphi_\gamma^t = 1$, then $\begin{cases} \Delta\alpha_t = \frac{\bar{c}_t}{\overline{ex}_t}\Delta\gamma_t \\ \Delta\beta_t = \frac{\overline{in}_t}{\overline{ex}_t}\Delta\gamma_t \end{cases}$, which denotes that the variation of domestic value-added share is influenced by the relative magnitude of the corresponding final demand. For example, if $\bar{c}_t$>$\overline{ex}_t$ and $\overline{in}_t$>$\overline{ex}_t$, then $\frac{\bar{c}_t}{\overline{ex}_t} > 1$ and$\frac{\overline{in}_t}{\overline{ex}_t} > 1$, thus, the variation of domestic value-added share of final consumption ($\Delta\alpha_t$) and capital formation ($\Delta\beta_t$) would be wider than that of gross export ($\Delta\gamma_t$). However, as the dimensionless indicators, the domestic value-added shares of different final demand and their variation should be independent with their magnitude. Thus, in order to avoid the influence from magnitude, we set $\frac{\varphi_\gamma^t\bar{c}_t}{\varphi_\alpha^t\overline{ex}_t} = 1$ and $\frac{\varphi_\gamma^t\overline{in}_t}{\varphi_\beta^t\overline{ex}_t} = 1$ at the first stage, i.e.,

$$\begin{cases} \varphi_\alpha^t = \frac{\bar{c}_t}{\overline{ex}_t}\varphi_\gamma^t \\ \varphi_\beta^t = \frac{\overline{in}_t}{\overline{ex}_t}\varphi_\gamma^t \end{cases} \tag{20}$$

Assuming the importance of variation at different year is equal, the stage-1 weights setting normalize $\varphi_\gamma^t = 1$ at each year, then $\varphi_\alpha^t = \frac{\bar{c}_t}{\overline{ex}_t}$ and $\varphi_\beta^t = \frac{\overline{in}_t}{\overline{ex}_t}$.

3.3 Weights Setting Stage-2: loosing the variation of DVASHGE

The significant "low value-added" attribute of processing production and its international relocation result in a greater variation of domestic value-added share of gross export than that of final consumption and capital formation. This is also proved by China's empirical results which is presented in figure 2. Thus, we need to increase the weights of domestic value-added share of final consumption (φ_α^t) and capital formation (φ_β^t) for narrowing their variation (relative to that of gross export) over time, namely given $\varphi > 1$, let $\varphi_\alpha^t = \frac{\bar{c}_t}{\overline{ex}_t}\varphi^2$ and $\varphi_\beta^t = \frac{\overline{in}_t}{\overline{ex}_t}\varphi^2$.

We use the simulation method to solve the reference value of φ. In detail, we calculate China's $\overline{\alpha_0}$, $\overline{\beta_0}$, and $\overline{\gamma_0}$ at year 2002 based on China's DPN input-output table, input China's final consumption, capital formation and gross export data from the time-series DPN input-output tables, and set $\varphi = 1 + 0.1 \times k$, $k = 0, 1, \dots, 40$. Then, using the method proposed in section 3.1, we solve the time-series domestic value-added share of final consumption, capital formation and gross export for each specific φ, and calculate the sum of the squared error (SSE) by comparing the solved results with the actual value calculated by DPN input-output model, as shown in figure 3. The φ with the least SSE is set as the reference value ($\varphi = 2.3$) and will be used in the empirical section. In the end, as shown in figure 4, the changing trend of China's DVASHGE solution is consistent with that of the actual value.

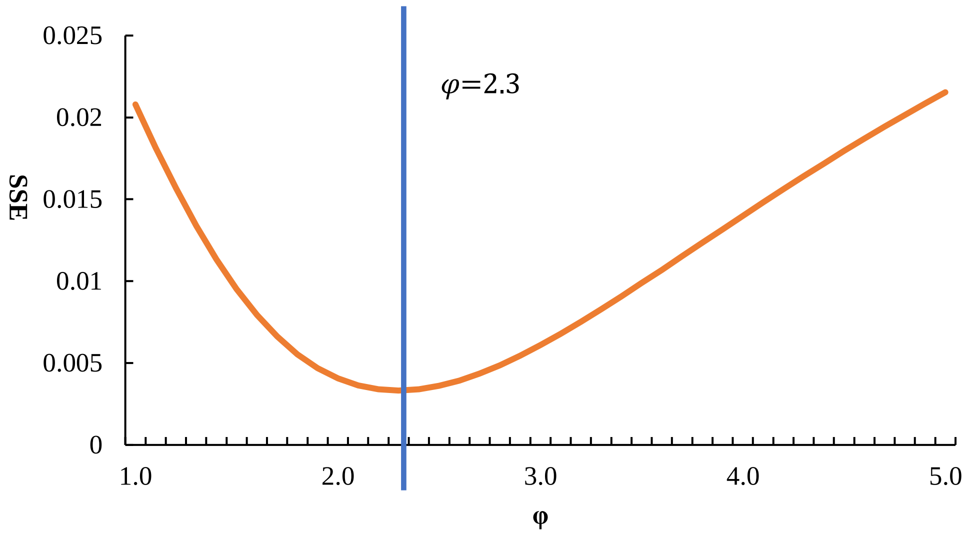
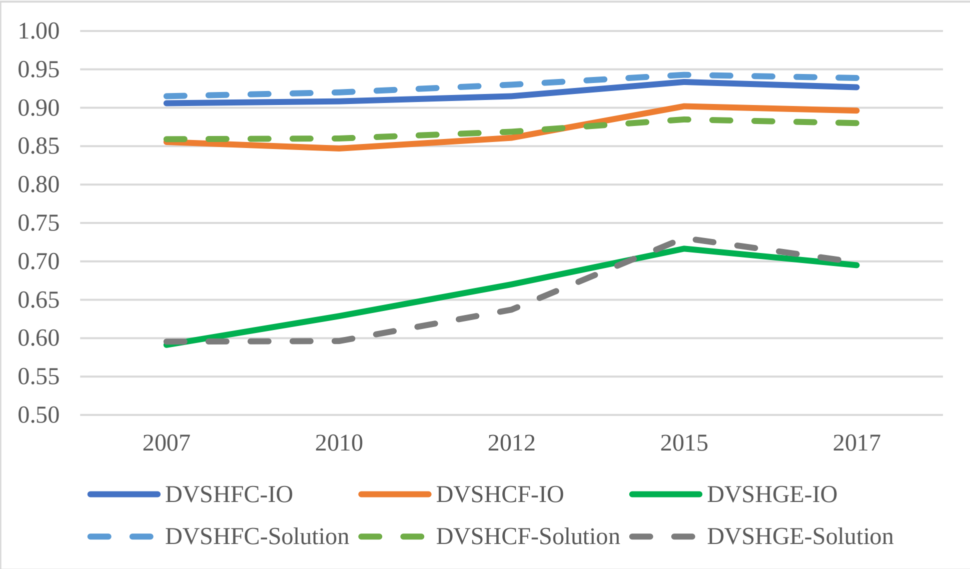


Figure 3: φ and sum of the squared error (SSE)



Note: DVASHFC, DVASHCF, and DVASHGE denotes the domestic value-added share of final consumption, capital formation, and gross export, respectively. The suffix "solution" denotes the results estimated by the constrained weighted least squares optimization, while the suffix "IO" denotes the actual value calculated based on China's DPN input-output tables.

Figure 4: China's solution of domestic value-added shares and the actual values

4. Empirical Analysis

4.1 Data sources

4.1.1 The selected economies

The paper picks 19 developing economies as the candidates of host economy of processing production and conducts the empirical analysis of their DVASHGE. They are: Thailand, Chile, Indonesia, Vietnam, Mexico, Bulgaria, the Philippines, Columbia, Cambodia, Romania, Malaysia, Bengal, Hungary, India, Pakistan, Turkey, Tunisia, Sri Lanka, Morocco.[5]

As the prior major host economy of processing production, China's processing export reaches a stationary phase since 2008, while its non-processing export continuously grows, as shown in figure 5. This denotes that the international relocation of processing production has been changed since 2008. As a consequence, we set the research time period as 2008-2020.[6]

[5] The selection is conducted based on the available evidence from past news reports and the data accessibility.

[6] The paper did not include the period 2021-2022 when the shocks generated by Covid-19 crisis and Russia-Ukraine war caused many outliers.

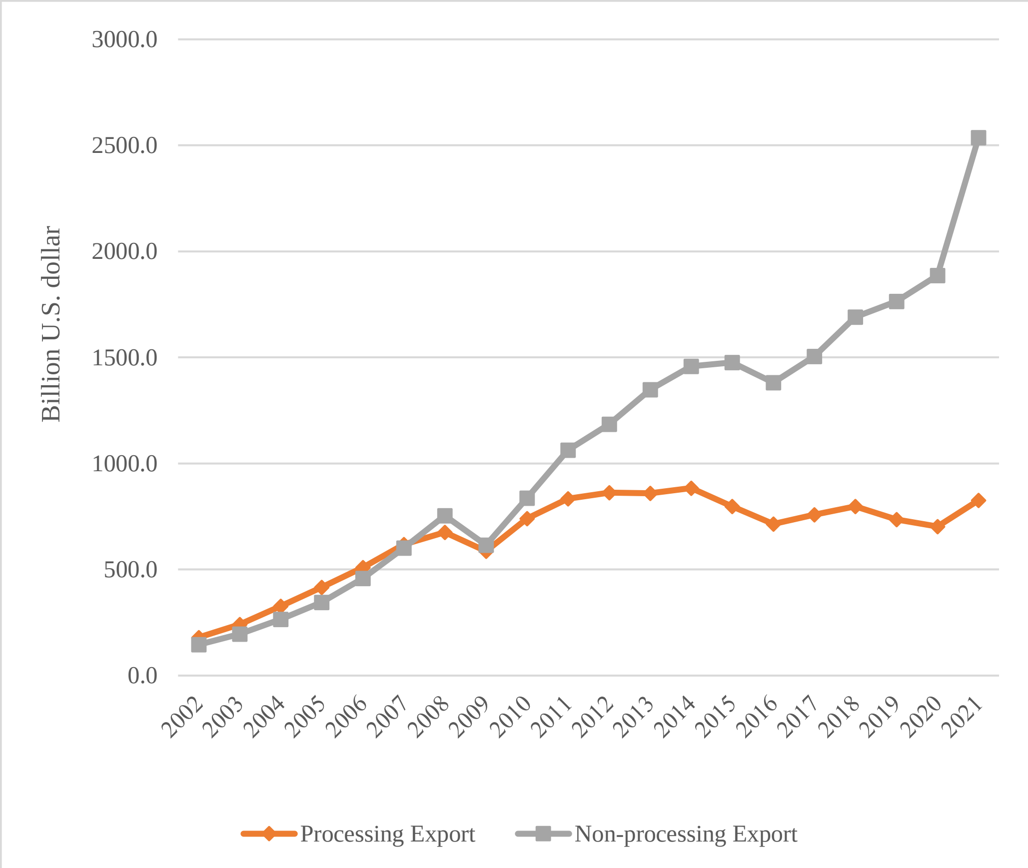


Figure 5: China's processing export and non-processing export during 2002-2021

4.1.2 Data sources and data processing

The empirical application of the model necessitates two types of inputs for each economy, i.e., 1) its final consumption, capital formation, and gross export of domestic goods/services, as well as its GDP; 2) the reference value of the domestic value-added shares of those final demand at the start year.

(1) The final consumption, capital formation, and gross export of domestic goods/services and GDP

These data are obtained according to the following steps.

Step 1: acquire the final consumption (c_t^*), capital formation (in_t^*), gross export ($\overline{ex}_t$), gross import ($\overline{im}_t$), and GDP (GDP_t) of each economy at each year from the World Bank Indicator database (WDI).[7]

Step 2: exclude the imported consumption and imported capital goods. Based on the HS6 import data from UNComtrade database and the classification by Broad Economic Categories 4 (BEC 4), the paper calculated the proportion of consumption goods in gross import (p_t^c) and proportion of capital goods in gross import (p_t^{in}) at each year for each economy. Then, the imported consumption and

[7] https://databank.worldbank.org/source/world-development-indicators

imported capital goods are excluded as $\bar{c}_t = c_t^* - p_{ct} \cdot \overline{im}_t$, $\overline{in}_t = in_t^* - p_{ft} \cdot \overline{im}_t$ (suppose the imported goods will not be exported again).

(2) The reference value of the domestic value-added shares of different final demand at the start year

This data is calculated from the non-competitive input-output table for each economy, according to equation (1) - (5). In section 5.2, we also discussed how to give this parameter when the non-competitive input-output table is not available, and the potential impact if this parameter is biased. The data source of the non-competitive input-output table for each economy is shown in table 3.

Table 3: The input-output data resources of the economies

Country/region	The input-output data resources
Thailand, Indonesia, Vietnam, the Philippines, Cambodia, Malaysia, Chile, Mexico, Columbia, Bulgaria, Romania, Hungary, Turkey, Tunisia, Morocco, India, Pakistan	2018 edition of OECD-ICIO
Bengal, Sri Lanka	Asian Development Bank Database

4.2 Empirical Results

The paper has estimated the DVASHGE solutions for all candidates. The numerical results are presented in the table 4. In this section, we will first present the result of a typical host economy of the processing production in recent years, i.e., Vietnam. And then, we will use the clustering techniques to identify which economies exhibit the similarly decreasing DVASHGE as Vietnam.

Table 4: The numerical results of the DVASHGE solutions for all economies

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Thailand	0.577	0.656	0.618	0.582	0.596	0.606	0.614	0.641	0.666	0.666	0.662	0.695	0.722
Chile	0.753	0.860	0.851	0.815	0.829	0.845	0.842	0.892	0.925	0.926	0.903	0.904	0.926
Indonesia	0.776	0.819	0.835	0.806	0.778	0.777	0.753	0.781	0.812	0.812	0.801	0.845	0.851
Vietnam	0.566	0.632	0.587	0.576	0.596	0.579	0.563	0.550	0.533	0.513	0.497	0.499	0.501
Mexico	0.626	0.652	0.634	0.620	0.603	0.602	0.632	0.615	0.604	0.616	0.614	0.636	0.639
Bulgaria	0.586	0.730	0.676	0.630	0.594	0.601	0.607	0.641	0.675	0.644	0.642	0.656	0.712
the Philippines	0.644	0.685	0.668	0.697	0.665	0.672	0.668	0.664	0.646	0.617	0.570	0.601	0.650
Columbia	0.847	0.886	0.887	0.862	0.852	0.851	0.832	0.807	0.807	0.818	0.809	0.795	0.803
Cambodia	0.552	0.648	0.592	0.569	0.563	0.560	0.550	0.559	0.553	0.583	0.601	0.624	0.595
Romania	0.711	0.763	0.683	0.647	0.649	0.678	0.680	0.687	0.692	0.678	0.662	0.675	0.705
Malaysia	0.578	0.609	0.596	0.595	0.599	0.595	0.603	0.622	0.638	0.620	0.621	0.634	0.653
Bengal	0.651	0.654	0.673	0.600	0.574	0.579	0.574	0.587	0.627	0.634	0.566	0.581	0.625
Hungary	0.571	0.606	0.562	0.544	0.549	0.557	0.550	0.564	0.579	0.573	0.578	0.583	0.597
India	0.715	0.713	0.698	0.641	0.658	0.684	0.694	0.776	0.826	0.809	0.751	0.770	0.804
Pakistan	0.748	0.826	0.821	0.796	0.755	0.745	0.781	0.837	0.871	0.825	0.754	0.750	0.825
Turkey	0.739	0.785	0.755	0.705	0.724	0.718	0.726	0.759	0.765	0.697	0.688	0.705	0.673
Tunisia	0.523	0.612	0.572	0.525	0.518	0.497	0.491	0.515	0.516	0.475	0.429	0.443	0.475
Sri Lanka	0.570	0.712	0.750	0.644	0.658	0.688	0.688	0.731	0.715	0.699	0.678	0.683	0.720
Morocco	0.562	0.671	0.626	0.540	0.522	0.545	0.555	0.622	0.608	0.599	0.578	0.594	0.634

4.2.1 The typical case analysis - Vietnam

In recent years, especially after the outbreak of US-China trade war, Vietnam has become the most frequently mentioned destination as the production tend to relocate out from China. Its low labor cost, tax preferences for industrial parks, close proximity to China's complete industrial supply chain, and high customs clearance efficiency of China-Vietnam trade make Vietnam an ideal destination for processing production. Meanwhile, the economic development pattern of Vietnam is also in line with the characteristic of processing trade that heavily relies on the international supply chain. As shown in figure 6 (Panel A), after the global financial crisis in 2008, both Vietnam's gross export and import have increased rapidly, with the growth rate obviously higher than that of final consumption and capital formation, as well as the GDP. The empirical results of our model also confirmed that Vietnam's DVASHGE has continuously declined from about 0.60 during 2009-2012 to 0.50 during 2018-2020, as shown in figure 6 (Panel B). As a conclusion, Vietnam is the typical host economy of the processing production in recent years.

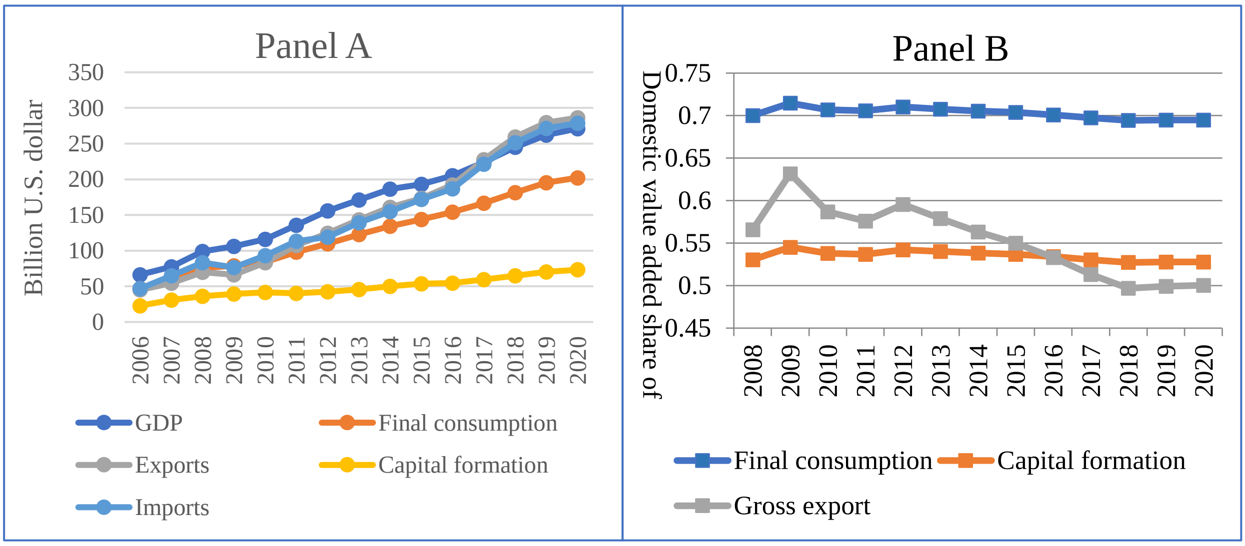


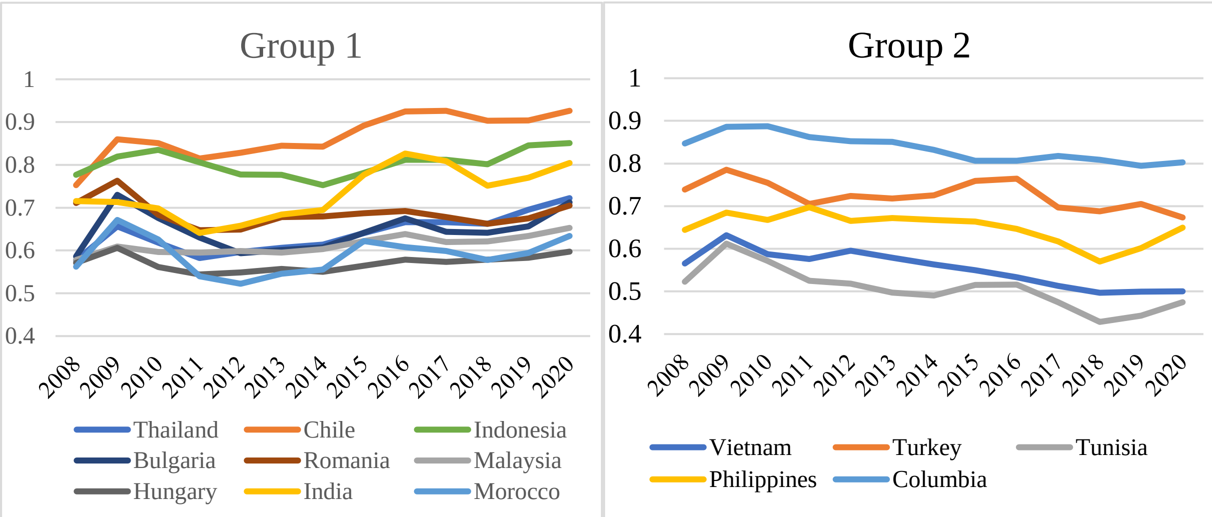
Figure 6: Vietnam's macro-economic data and its DVASHGE solution

4.2.2 The clustering analysis – the host economies of processing production

Clustering analysis is an unsupervised method used to group similar individuals into one or more clusters, discovering the inherent structure within the data points and classifying them (Barreto et al., 2007; Xu et al.,2009). In this section, we use the Density-Based Spatial Clustering of Applications with Noise (DBSCAN; Ester et al., 1996; Khan et al., 2014) method[8] to cluster the economies having the

[8] The basic idea of DBSCAN algorithm is to classify data points as core points, border points, or noise points. Core points

similar continuously decreasing DVASHGE as Vietnam. We set the minimum distance across group member as 0.25 (then their correlation in DVASHGE should be more than 0.75) and the minimum member of each group as 2 (at least two economies constitute a group)[9], then the 19 candidates are clustered into two group, as shown in figure 7. Vietnam, the Philippines, Turkey, Tunisia and Columbia are clustered together (the group 2). Their DVASHGE has been declining during 2008-2020.



Note: the economies not in any group are treated as the noise. The variation of their DVASHGE is not similar with others.

Figure 7: The clustering results (data range:2008-2020; minimum distance: 0.25; minimum member: 2)

The global major emergencies usually make waves in DVASHGE (Degain et al., 2019). As shown in figure 7, the DVASHGE fluctuated during the shock of global financial crisis (2008-2010) and experienced a common rise after the Covid-19 crisis. Thus, we extract the DVASHGE for each economy during 2010-2019 and conduct the clustering analysis with the same settings. As shown in figure 8, Vietnam, the Philippines, Tunisia and Columbia are still clustered together (the group 2), while Turkey is excluded as the noise. In addition, the economies with increasing DVASHGE are clustered into the group 1, and the economies with fluctuated DVASHGE are clustered into the group 3. These results are

are those with enough data points within a radius ε, while border points are not core points but are within a radius ε of some core point. Noise points are neither core points nor border points. DBSCAN algorithm starts with any data point, looks for all density-reachable data points within a radius ε, and groups them into a cluster. If a point is neither a core point nor a border point, it is labeled as a noise point. By recursively searching for density-reachable points, DBSCAN algorithm can divide the dataset into several clusters and detect noise points. In this paper, we defined the distance of two economies as "1-the correlation coefficient of their time series DVASHGE". Thus, the economy pair with higher correlation in DVASHGE will be seen as closer.

[9] The minimum distance across group member and the minimum member of each group are two parameters required in DBSCAN

robust even if the minimum distance across group member is decreased to 0.2 (their correlation in DVASHGE should be more than 0.8), the group members are almost the same (only Indonesia and Cambodia will be excluded from group 3 in this case).

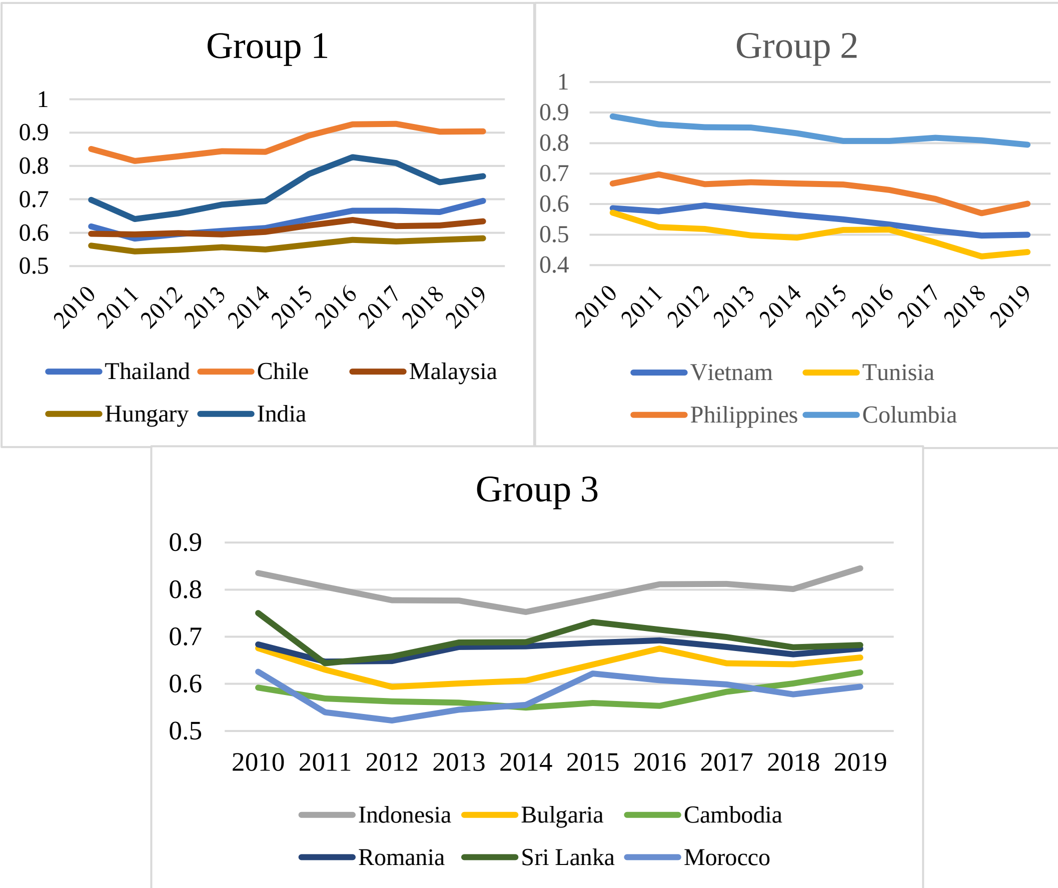


Figure 8: The clustering results (data range:2010-2019; minimum distance: 0.25; minimum member: 2)

5. Robustness Check

The robustness analysis of the model requires the comparison between the solution of DVASHGE and that measured based on the input-output tables capturing the heterogeneity of processing export. However, to the best of our knowledge, only China's DPN input-output tables and the OECD inter-country input-output tables (OECD-ICIO) differentiate the processing production in China and Mexico. Thus, in this section, we will conduct the robustness check according to the solutions for these two countries. Since the proposed constrained weighted least squares optimization model requires two types of input, i.e., 1) the macro-economic data (final consumption, capital formation, gross export, gross import, and GDP) and 2) the reference value of the domestic value-added shares across different final demands, the robustness analysis is also conducted from these two aspects.

5.1 The macro-economic data from different sources

The macro-economic data of each specific economy can be obtained from the national statistics institutions (in the corresponding economy), the international database (e.g. WDI), and the world input-output tables (e.g., OECD-ICIO). Since the value of the same indicator varies in different data sources, it is important to consider whether such variations could impact the changing trend of the DVASHGE solutions.

For China, when using the macro-economic data from China's DPN input-output tables, the changing trend of China's DVASHGE solution is consistent with that of the actual value measured based on China's DPN input-output tables, as shown in figure 4. Moreover, after substituting the macro-economic data by that from the WDI or China's National Bureau of Statistics (NBS), the changes of China's DVASHGE solution is still robust, as shown in table 5, Panel A. The correlations between China's DVASHGE solutions based on different data sources are not less than 0.70, and the correlations between the actual value of China's DVASHGE and the solutions are not less than 0.55.

For Mexico, we use the Marco-economic data from OECD-ICIO and WDI to conduct the robustness analysis, as shown in Penal B. The correlations across solutions with different data sources and the actual value also confirm the robustness when using the macro-economic data from different sources.

Table 5: The correlations across solutions with different data sources and the actual value

		WDI	NBS	DPN	Actual Value
Pnael A - China	WDI	1.00	0.87	0.70	0.57
	NBS	0.87	1.00	0.85	0.63
	DPN	0.70	0.85	1.00	0.94
	Actual Value	0.57	0.63	0.94	1.00
		WDI	OECD-ICIO	Actual Value	
Pnael B - Mexico	WDI	1.00	0.54	0.29	
	OECD-ICIO	0.54	1.00	0.91	
	Actual Value	0.29	0.91	1.00	

Note: WDI: World Bank Indicator database; NBS: China's National Bureau of Statistics; DPN: China's DPN input-output tables; OECD-ICIO: OECD inter-country input-output tables; Actual Value: the DVASHGE measured from China's DPN input-output tables (Panel A) and OECD-ICIO tables (Panel B).

5.2 The biased reference value of the domestic value-added shares

The reference values of the domestic value-added shares of different final demands are calculated from the input-output tables. However, as mentioned in the introduction section, on the one hand, many developing economies neither possess official input-output data nor are included in the WIOTs. Thus, for those economies, we have to input the reference value of their domestic value-added shares according to the economies with similar characteristics, which will lead to the bias. On the other hand, the input-output tables around the world rarely distinguish the production of processing trade, which can result in significant overestimation of the DVASHGE and biased reference values. So, it is important to consider whether these biased reference values can also bias the changing trend of the DVASHGE solutions.

We designed a random experiment to test the robustness with biased reference values. In detail, record the true reference values as $\widehat{\alpha_0}$, $\widehat{\beta_0}$, and $\widehat{\gamma_0}$ corresponding to the domestic value-added share of gross final consumption, gross capital formation, and gross export, respectively. Assume the bias is ε, then the biased reference values are randomly given from interval ($\widehat{\alpha_0}$-ε, min($\widehat{\alpha_0}$+ε, 1)), ($\widehat{\beta_0}$-ε, min($\widehat{\beta_0}$+ε, 1)), and ($\widehat{\gamma_0}$-ε, min($\widehat{\gamma_0}$+ε, 1)),[10] respectively (assume they follow an uniform distribution). Input the biased reference values to solve the solution, calculate the correlation between the DVASHGE solution and the actual value, and repeat the random experiment. Then the robustness can be concluded according to the empirical cumulative distribution function (ECDF) of the correlation between the DVASHGE solutions and the actual value.

Figure 9 presents the empirical cumulative distribution function (ECDF) of the correlation between the DVASHGE solutions and the actual value after the 10000 rounds random experiment. The panel A corresponds to the ECDF for China,[11] where the correlation equals 0.85 (ε =0.1) and 0.85 (ε =0.2) when the cumulative probability reaches 5% respectively. This indicates that, even if the reference values are biased, the correlation between China's DVASHGE solutions and the actual value is higher than 0.85 in most cases (95%), proving the robustness. The results of Mexico (Panel B) also lead to the same conclusion[12].

[10] min($\widehat{\alpha_0}$+ε, 1) denote the lower value between $\widehat{\alpha_0}$+ε and 1. This is because the domestic value-added share cannot exceed 1.

[11] The true reference values and the macro-economic data is (calculated) from China's DPN input-output tables.

[12] The true reference values and the macro-economic data is (calculated) from OECD-ICIO input-output tables.

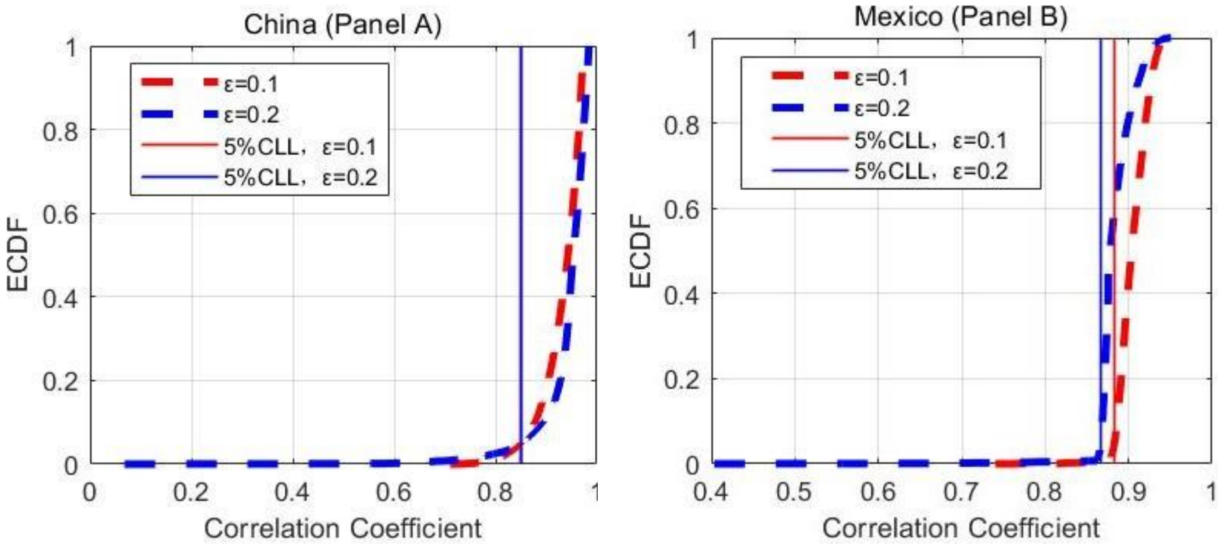


Figure 9: The ECDF of the correlation between the DVASHGE solutions and the actual value

6. Conclusion and Discussion

As the bellwether of global production relocation, capturing the international relocation of processing trade in the recent past would shed light on the current complicated production location reconfiguration. However, directly identifying the host economies of processing production is challenging because of the lack of data (countries across the world rarely distinguish the processing trade from ordinary trade). To overcome this challenge, the paper proves that the continuously decreasing DVASHGE is a sufficient condition for identifying the host economies of processing production and put forward the idea of identifying the host economies according to their DVASHGE. On the other hand, measuring the DVASHGE based on the national or world input-output tables is not suitable for the paper due to the significant time lag of input-output data, the lack of data in low-income economies, and the lack of global processing trade statistics which will bias the results. Thus, the paper proposed a constrained weighted least squares optimization for unfolding the changes of DVASHGE in each specific economy.

In the empirical section, the paper selected 19 developing economies as the candidates for the host economy of processing production and conducted the empirical analysis of their DVASHGE. The empirical findings indicate that, since the global financial crisis in 2008, Vietnam's DVASHGE has been continuously declining from about 0.60 during 2009-2012 to 0.50 during 2018-2020, confirming that Vietnam is the typical host economy of the processing production in recent years. Moreover, among the 19 candidates, Vietnam and the Philippines in Southeast Asia, Colombia in South America, and

Tunisia in North Africa are the host economies of processing production; while Turkey in the Middle East also exhibits some numeric features for receiving such relocation, to some extent. Those economies also correspond to the extensions of three major regional production networks, i.e., the Asian production network centered on China, the American production network centered on the USA, and the European production network centered on Germany.

In the robustness check section, the paper has proved that the changes of the DVASHGE solutions remain robust and similar to that of the actual value, even if the macro-economic data is from different sources or the reference value is biased. However, it is important to note that the numerical results of the DVASHGE solutions presented in this paper are estimators and cannot replace the TiVA indicators measured based on input-output tables. In other words, the paper does not intend to substitute the input-output-based measurements with the proposed model. Instead, we believe that these two methods are essential complements since our DVASHGE solutions can provide an important reference for the GVC studies centered on input-output-based TiVA indicators.

In conclusion, this paper serves as an important starting point by introducing an approach to identify the host economies of processing production. Moreover, what characteristics makes them the host economies? What are the policy implications in the supply chain management and the GVC governance? These questions will be explored in our further researches.

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Figure captions

Figure 1: The continuously decreasing DVASHGE and the host economies of processing production

Figure 2: China's domestic value-added share of different final demand and the processing production intensity

Figure 3: φ and sum of the squared error (SSE)

Figure 4: China's solution of domestic value-added shares and the actual values

Figure 5: China's processing export and non-processing export during 2002-2021

Figure 6: Vietnam's macro-economic data and its DVASHGE solution

Figure 7: The clustering results (data range:2008-2020; minimum distance: 0.25; minimum member: 2)

Figure 8: The clustering results (data range:2010-2019; minimum distance: 0.25; minimum member: 2)

Figure 9: The ECDF of the correlation between the DVASHGE solutions and the actual value