Global Value Chains, Firms, and Wage Inequality: Evidence from China

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Abstract

How does participating or upgrading in the global value chains (GVCs) affect wage inequality between skilled and unskilled labor within firms? In this paper, we develop a trade model of heterogeneous firms with intermediate trade and various skill inputs, in which we apply the fair wage hypothesis to predict changes in the wage premium as a result of participating or upgrading in GVCs. The model predicts that increasing participation in GVCs, as measured by the share of foreign value-added content in exports (FVAR), improves a firm's profits and amplifies the wage inequality between skilled and unskilled labor. Moreover, moving to upstream sectors in GVCs, as measured by the exporting varieties' upstreamness (or average distance from final use), raises a firm's wage premium by increasing the productivity of skilled workers. Using detail Chinese firm-level data from 2000 to 2006, we develop a Miner-type empirical model to study the wage premium changes associated with FVAR and upstreamness. We find robust empirical evidence that China's FVAR is positively associated with skill wage premium within firms. We also observe that Chinese firms with higher upstreamness in GVCs tend to have larger wage inequality with more skilled workforces. (*JEL code: F12; F16; F66*)

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1 Introduction

The recent years have seen a dramatic rise of the global value chains (GVCs), in which each country specializes in several stages of production and cooperates to produce the final goods [OECD (2014)]. The international fragmentation in GVCs is also known as the second "unbundling" of production [Baldwin (2006)], which allow firms to use more imported intermediates for production. The extent of the firms' vertical specialization in GVCs is measured by the ratio of foreign value-added content in exports relative to total exports (FVAR)[1]. As suggested by the recent literature, most countries have a rising level FVAR after deepening their participation in GVCs [Vries et al. (2014), Koopman et al. (2014), Johnson and Noguera (2012a), Los et al. (2015)].

As one of the largest export markets with abundant labor resource, China plays an essential role in global production. Despite its deep engagement in GVCs, however, a trend of rising levels of FVAR is not observed in China. In fact, recent evidence suggested that the average FVAR of Chinese firms declined from 35% in 2000 to 30% in 2007, which is the opposite of most countries participating in GVCs[2] [Kee and Tang (2016)]. The decline of FVAR in China is partly due to the substitution of domestic materials for imported intermediates by Chinese processing firms[Kee and Tang (2016)].The substitution of domestic materials has changed the demands for domestic skills, which have important implications on domestic labor market [Vries et al. (2014)]. The impacts of globalization on employment and wage inequality have been extensively studied by many studies [Goldberg and Pavcnik (2007), Helpman (2016), Pavcnik (2017)], but few of them are focused on the impacts of GVC activities on wage inequality, especially at the firm level. In this paper, we quantify the participation and position of firms in GVCs and explore how participating and upgrading in GVCs affect the wage inequality of skills within Chinese manufacturing firms.

[1] The recently available international input and output tables enable us to decompose gross trade into multiple value-added terms by origins and destinations. The share of domestic value-added in gross exports is defined as DVAR, which estimates the domestic contribution to exports. The share of foreign value-added in exports is defined as FVAR, which measures the extent of international fragmentation across borders. At the aggregated level, $DVAR + FVAR = 1$

[2] Koopman et al. (2014) found the trend of declining FVAR in China using the international input and output tables. Upward et al. (2013) confirmed the decline of FVAR using the Chinese firm-level data.

To undertake this, we include both skilled and unskilled workers as inputs in a trade model of heterogeneous firms and then we seek to explain variations in firms' wage premiums in terms of changes in their GVC activities. These GVC activities, in particular, include using imported intermediates for the production of exports (measured by the share of foreign value-added in exports, FVAR), and moving up to more upstream sectors in GVCs (measured by the upstreamness of firms in GVCs). In this model, we follow the setup of Melitz (2003) and further apply the fair wage hypothesis of Amiti and Davis (2011) in order to tie the wage premium to firms' performance [Chen et al. (2017)]. The fair wage hypothesis assumes that workers determine their efforts by the difference between the real wage and the reference (fair) wage with respect to their efforts [Egger and Kreickemeier (2009)]. Workers in more profitable firms would expect higher fair wages [Egger et al. (2013)]. Thus, in equilibrium, profitable firms tend to give high wages to workers to elicit their efforts [Egger and Kreickemeier (2012), Egger et al. (2013)]. We further assume that skilled workers have more bargaining power than unskilled workers according to firms' performance[3]. Profitable firms tend to have a large wage premium of skills [Chen et al. (2017)]. In the model, firms make decisions on participating in GVCs by overcoming the sunk costs of entering import and export markets. Only firms with higher productivity or larger scales are able to participate in GVCs by importing foreign intermediates for the production of exports. Similar to Amiti and Davis (2011), GVC firms tend to be more profitable and pay higher wages to the skilled workers than firms which failed to enter the GVCs. Moreover, firms with a larger share of foreign value-added in exports (FVAR) tend to have higher profits and wider wage inequality between skilled and unskilled workers. Moving to upstream sectors in GVCs needs higher productivity of skilled workers, which improves firms' profits and widens the wage inequality of skills.

We examine the predictions of the model with Chinese firm-level data from 2000 to 2006. The firm-level GVC participation and position indexes are measured by the Chinese enterprise

[3]The assumption that skilled labor has a larger bargaining power on wages than unskilled workers follows Chen et al. (2017). The assumption is consistent with the predictions of bargaining model by Helpman et al. (2010) where firms with higher value added have more surplus to share among specific skill groups. Chen et al. (2017) also discussed the possibility that the skilled and unskilled labor have the same bargaining power in wages but it is skilled workers who gain more additional surpluses. In this paper, we assume that only skilled workers have the bargaining power in wages to simplify the model, but the predictions with the equal bargaining power of both skills should keep robust.

survey data combined with transactional-level customs data. This dataset enables us to estimate the firm-level data value-added trade, which is different from the approach of recent literature that used the international input-output tables (IIOTs) to decompose the value-added terms of gross exports [Johnson and Noguera (2012a), Koopman et al. (2012), Koopman et al. (2014)]. Despite the advantage of capturing global input-output structure across borders and sectors, the value-added approach using IIOTs estimates the value-added trade at the aggregated level, which assumed that all firms within a sector use the same ratio of imported intermediates for production [INOMATA (2017)]. In fact, firms are heterogeneous in GVCs. For example, processing exporters tend to use a higher proportion of imported intermediates than ordinary exporters. Thus, in some developing countries with prominent processing trade (e.g., China, Vietnam, Philippines, etc.), the oversampling of processing firms in the construction of IIOTs leads to aggregation biases in the estimation of DVAR and FVAR [Koopman et al. (2012), Kee and Tang (2016)].

As noted, this paper embraces firm heterogeneity in value-added trade. The firm-level GVC participation index is measured by the share of foreign value-added content in exports (FVAR), which captures the extent of firms' participation in GVCs through backward production linkages[4]. We measure the firms' position in GVCs by the upstreamness index, which represents the "distances" of firms' outputs to the final demands in the international input-output tables (IIOTs). The more stages the output takes to reach the final use, the more upstream it is located in a GVC and the higher is the index value. As noted, we find that firms in China show a decline trend in FVAR between 2000 and 2006, which is consistent to the firm-level analysis results from Kee and Tang (2016) and Upward et al. (2013) and conclusions of I-O approach by Koopman et al. (2014) and Johnson and Noguera (2012a). We also observe a rising value of the average upstreamness index value for Chinese manufacturing firms,indicating the upgrading of Chinese firms from downstream sectors to upstream sectors in GVCs [Antràs et al. (2012)].

[4] Koopman et al. (2014) defined the backward GVC participation index as the share of foreign value-added in exports. He also defined the forward GVC participation index as the share of domestic value added in exports of third countries. The firm-level FVAR is measured following the procedures of Kee and Tang (2016) and Upward et al. (2013).

Our interest is to study the impacts of GVC activities on skill wage inequality at the firm level. There have been many studies focusing on the wage inequality of skills at the country-level, within sectors, and across firms. However, there are very few studies on the wage inequality within firms, especially for China[5]. One major obstacle of investigating the wage inequality within Chinese firms is lack of direct measurement of skilled wage and unskilled wage. To overcome this problem, in this paper, we develop a Mincer-type econometric framework to construct the firm-level wage premium according to the average wage of two skill groups and their skill share using the data of Chinese manufacturing firms from 2000 to 2006[6]. This approach makes up the data limitation of Chinese firm-level wage by skills [Chen et al. (2017)]. We introduce measures of firm-level GVC participation and GVC position into the empirical specification as predictors of wage inequality.We find two key results. First, we find that the FVAR of Chinese manufacturing firms was associated positively with the higher wage premiums with the employment of more skilled workers within firms[7]. Second, we find that the upgrading of firms in GVCs, as measured by an increase in the upstreamness index, widens the wage inequality with more skilled workforces.

One primary challenge in this paper is the possible endogenous nexus between GVC participation and firms' wage inequality. As we know, not every firm participates in GVCs. Recent studies found that the GVC firms are more productive with larger scales and higher profits than the non-GVC firms [Baldwin et al. (2014)][8]. Similar to exports, firms with better economic performance are more likely to overcome the sunk costs of integration and self-select

[5] Verhoogen (2008) and Galiani and Sanguinetti (2003) found trade liberalization increased skill wage premium in Mexican and Argentinean firms, but limited studies explored the firm-level wage inequality of China due to data limitation. Li and Xu (2008) observed an increasing trend of wage inequality of skills within firms using a small survey sample. Chen et al. (2017) studied the firm-level wage inequality changes in response to input trade liberalization and found a rising skill wage inequality within Chinese manufacturing firms.

[6] In the Mincer-type wage equation, the average wage of a firm is the average wage of skilled labor and unskilled labor weighted by the skill share of labor. Following Chen et al. (2017), after the logarithm transformation, the average wage is determined by the firms' wage premium, their skill share and the wage of unskilled labor.Average firm-level wage is available in the Chinese Manufacturing Survey data during the sample period. However, the share of skilled labor in total employment (skill share) at the firm level is only available for 2004. We provide more details on how to construct the measured employment share of skills at the firm level following Chen et al. (2017) in section 3.

[7] The declining FVAR in China tended to reduce the wage inequality between skilled and unskilled workers with the lower share of skilled workforces.

[8] Similar evidence can also be found in studies about offshoring firms and non-offshoring firms [Antras and Helpman (2004), Geishecker and Görg (2008), Wagner (2011)].

into GVCs. The self-selection effect of firms in participating GVCs may lead to biased estimation [Antras and Helpman (2004)]. To address the challenge, a Heckman two-step selection model is adopted to control for the possible endogeneity. We use the fitted value of FVAR after controlling for the self-selection effect as the proxy for GVC participation. Moreover, we adopt the one-year lagged upstreamness as the instrument for GVC position to eliminate the reverse causality between upstreamness and wage premium. The empirical results remained robust after controlling for the endogeneity.

This paper is closely related to other studies on vertical specialization and value-added trade[9].To address firm heterogeneity in GVCs, recent studies merged the enterprise survey data with customs data to estimate firms' value-added content embodied in trade, which provided complementary estimation of DVAR and FVAR compared to the I-O table-based approach [Dean et al. (2011), Upward et al. (2013), Ahmad et al. (2013), Kee and Tang (2016)]. This paper combined the procedures of Kee and Tang (2016) and Upward et al. (2013) to estimate the share of foreign value-added content in exports (FVAR) as the proxy of GVC participation index [Koopman et al. (2014)]. In addition, this paper also relates to the studies on GVC length and organization [Fally (2012), Antràs et al. (2012), Wang et al. (2017), Johnson (2017)]. Following Antràs et al. (2012) and Ju and Yu (2015), we calculate the weighted average upstreamness of export varieties at the firm level as the proxy for firms' GVC positions.

This paper is related but relatively independent of the previous research about globalization and its impact on wage inequality[10]. Some recent literature focused on the new characteristics

[9]Hummels et al. (2001) estimated the share of imported inputs in the production for exports as the proxy for vertical specialization using the multi-national input and output tables. Several studies developed Hummels et al. (2001)'s approach to construct the international input-output tables (IIOTs), which revealed the structure of global supply chains across borders and sectors [Johnson and Noguera (2012b), Koopman et al. (2014), Timmer et al. (2015)]. Some studies decomposed the IIOTs into value-added terms by sources with extra double-counting terms, which enables us to trace the value-added trade from source to destination [Johnson and Noguera (2012a), Koopman et al. (2014),Wang et al. (2013), Johnson (2014)]. But the studies of value-added estimation based on input-output tables neglected firm heterogeneity in GVCs, which leads to aggregation bias [Kee and Tang (2016)].

[10]Goldberg and Pavcnik (2007) provided a detailed summary of the relevant literature on globalization and wage inequality, concluding trade liberalization increases skill wage premium at the country-level, within sectors, and within firms. But most of the studies use the gross trade data to estimate the labor market outcomes, which may overestimate the employment effect of trade [Jiang (2015)]. It is the domestic value-added trade that represents the real demands for domestic labor[Timmer et al. (2014)]. The discrepancy between domestic value-added trade and gross trade is enlarging with the rise of GVCs [Johnson and Noguera (2012b)].

of GVCs and studied their effects on the labor market. For example, Mion and Zhu (2013) highlighted the role of intermediate trade and concluded that offshoring to China in both intermediates and final goods increased the share of skilled workers in Belgian manufacturing firms. Kasahara et al. (2016) suggested that importing intermediates increased the demands for educated workers at the plant level. Other studies found that offshoring hurts labor performing routine tasks while benefiting to the workers performing tasks which are complementary to offshored jobs [Feenstra and Hanson (1996), Criscuolo and Garicano (2010), Goos et al. (2009)]. Nevertheless, these studies focused on specific aspects of GVCs (intermediate trade, offshoring, etc.), and none of them gave a full picture of firms' GVC activities and their linkages with wage inequality. This paper captures firms' intermediate trade, offshoring and other GVC activities by value-added trade, and explores firms' wage premiums changes associated with their GVC activities. To the best of our knowledge, this is the first paper that provides the theoretical and empirical framework on how participating and upgrading in GVCs affects the wage inequality among skills within firms.

The rest of paper proceeds as follows. In section 2, we develop the model of heterogeneous firms to address the changes of skill wage premiums via GVC participation or GVC upgrading. In section 3, we describe the dataset and present the measurement of GVC indicators. We also derive the empirical model from the theoretical specifications. In section 4, we show the empirical results with robustness tests. In section 5, we conclude and provide some policy implications.

2 Theoretical Framework

In the section, we construct a model of wage inequality, intermediate trade and GVC upstreamness under the framework of heterogeneous firms of trade following Amiti and Davis (2011) and Chen et al. (2017). In this model, there are n countries with identical factor endowment. Each country has M firms, which are ex-ante homogeneous but face two uncertainties in their production. One is their production cost determined by the productivity and labor costs. Another is the globalization modes of firms. Firms have to overcome the sunk cost to enter the domestic and international markets. Each firm produces one variety, which is ex-ante given and unaffected by firms' productivity and globalization mode. The setup of the model is as follows:

2.1 Demand

A representative consumer consumes a continuum variety of final goods ω with the CES preference to minimize total expenditure E. The demand arises from the following expenditure function:

$$MinE = \int p(\omega)x(\omega)d\omega \qquad s.t.[\int x(\omega)^{\frac{\sigma-1}{\sigma}}d\omega]^{\frac{\sigma}{\sigma-1}} = U \tag{1}$$

where $p(\omega)$ is the price of the variety ω. $x(\omega)$ is the demand for variety ω. σ is the elasticity of substitution between final goods with $\sigma > 1$. The consumer has a CES preference over the continuum varieties, thus the demand for the variety ω equals to $x(\omega) = [\frac{p(\omega)}{P}]^{-\sigma}Q$ ($Q \equiv U$). Similarly, the revenue from selling final product ω is $r(\omega) = p(\omega)x(\omega) = [\frac{p(\omega)}{P}]^{1-\sigma}R$, where R is the total revenue of the country satisfying $PQ = R$ and P is the aggregate price index in the form of $P = [\int p(\omega)^{1-\sigma}d\omega]^{\frac{1}{1-\sigma}}$.

2.2 Production

We assume that each firm produces one variety of final goods ω. The value of variety ω origins from two sources: the domestic value-added content ($D(\omega)$) and the foreign value-added content ($F(\omega)$). The domestic value-added content ($D(\omega)$) is produced by the domestic inputs, while the foreign value-added content ($F(\omega)$) is embodied in the imported intermediates. The production of final goods ω follows a Cobb-Douglas function as follows:

$$x(\omega) = \varphi D(\omega)^{\alpha}F(\omega)^{1-\alpha} \tag{2}$$

where φ is the firm-specific productivity following the distribution of a probability density function as $g(\varphi)$. α is the share of domestic value-added content in output with $\alpha \in (0,1)$. The domestic value added $D(\omega)$ is further assumed to be produced with domestic skills following the CES production function as indicated below:

$$D_{\omega}(S,U) = [\Phi_u^{\frac{1}{\rho}} U(\omega)^{\frac{\rho-1}{\rho}} + \Phi_s(z)^{\frac{1}{\rho}} S(\omega)^{\frac{\rho-1}{\rho}}]^{\frac{\rho}{\rho-1}} \tag{3}$$

where $S(\omega)$ and $U(\omega)$ are the skilled and unskilled labor inputs in producing the domestic value-added content D_{ω}. ρ is the elasticity of substitution between skilled and unskilled labor ($\rho > 1$). Φ_u and Φ_s are productivity parameters of unskilled labor and skilled labor respectively, which are affected by variety ω's upstreamness in GVCs. We assume there is a larger productivity difference between skilled and unskilled labor in the upstream sectors of GVCs than that in the downstream industries. If we denote the sector-level upstreamness as z, $\frac{\Phi_s}{\Phi_u}$ is an increasing function of the firm's upstreamness z. Increasing z motivates firms to improve the productivity of skilled workers relative to unskilled labor. For simplicity, we assume the exporting variety is ex-ante given; thus, the sector-level upstreamness is exogenous and barely affected by firms' performance and wage premium.

ω_s and ω_u are denoted as the unit wage of skilled and unskilled labor. Under the constraint of cost minimization, the wage premium of skilled and unskilled workers in this firm is written as follows:

$$W_{\omega} = \frac{w_s}{w_u} = [\frac{\Phi_s}{\Phi_u}(z)]^{\frac{1}{\rho}} [\frac{S}{U}]^{-\frac{1}{\rho}} \tag{4}$$

Equation (4) suggests that the wage premium of skilled and unskilled labor is determined by the input ratio of skilled and unskilled workers and firms' upstreamness. Increasing the inputs of specific skill would reduce the relative wage of this skill over the other. Moving to upstream sectors improve firms' productivity of skilled labor, which further enlarges the wage inequality between skilled and unskilled workers.

The marginal cost of domestic value-added content is thus written as follows:

$$c_d^{\omega}(z, W_{\omega}) = [\Phi_u \omega_u^{1-\rho} + \Phi_s \omega_s^{1-\rho}]^{\frac{1}{1-\rho}} = \Phi_u^{\frac{1}{1-\rho}} \omega_u [1 + \frac{\Phi_s}{\Phi_u}(z)(\frac{\omega_s}{\omega_u})^{1-\rho}]^{\frac{1}{1-\rho}} \tag{5}$$

Equation (5) describes the determinants of domestic value-added content. For simplicity, we assume productivity parameter of unskilled labor is fixed. The marginal cost of domestic value added is determined by the skill wage premium (W_ω), the upstreamness of the firm (z), and the unskilled wage (ω_u). Improving the wage premium of skills increases the marginal cost of producing domestic value-added content. Upstream firms have a smaller marginal cost of domestic value-added content than the downstream firms. The marginal cost of domestic value added c_d^ω is an increasing function of wage inequality whereas a decreasing function of upstreamness.

Firms also use the imported intermediates for production. Let i represents the domestic market, firms import intermediates from the other $n-1$ countries. The foreign value-added content of ω is written as a CES function of imported intermediates as follows:

$$F(\omega) = [\sum_j \beta_j^{\frac{1-\gamma}{\gamma}} f_{ij}^{\omega \frac{\gamma-1}{\gamma}}]^{\frac{\gamma}{\gamma-1}} \tag{6}$$

where β_j measures the preference of consumers for intermediates from country j. γ is the elasticity of substitution among intermediates from all the countries ($\gamma > 1$). f_{ij}^ω is the value of intermediates imported from country j. Country i has to bear the iceberg cost of importing intermediates from country j as $\tau_{ij}^m > 1$. Let $p_{ij}^\omega = p_j * \tau_{ij}^m$ equal to the importing price of firm ω from country j. We assume that the price of domestic intermediates equals to 1 for simplicity, and the import price satisfies $p_j \tau_{ij}^m \leq 1$ [11]. The price of foreign intermediate composite equals to $P^f = [\sum_j (\beta_j p_j \tau_{ij}^m)^{1-\gamma}]^{\frac{1}{1-\gamma}}$ satisfying $P^f \leq 1$ under the constraint of $\gamma > 1$ and $p_j \tau_{ij}^m \leq 1$.

As a result, the marginal cost of producing the variety ω becomes:

$$c_\omega(\varphi, W_\omega, z, \tau) = \frac{\kappa c_d^\alpha P_f^{1-\alpha}}{\varphi} \tag{7}$$

where $\kappa = \alpha^{-\alpha}(1-\alpha)^{\alpha-1}$. As the price of variety ω equals to $p_\omega = \frac{c_\omega}{\mu}$ with $\mu = 1 - \frac{1}{\sigma}$,

[11] Only when the imported intermediates have lower costs than domestic inputs, the firm chooses to import intermediates.

the revenue of producing variety ω could be written as:

$$r(\omega) = p_\omega x(\omega) = [\frac{\kappa c_d^\alpha P_f^{1-\alpha}}{\mu\varphi}]^{1-\sigma} R P^{\sigma-1} \tag{8}$$

Following Amiti and Davis (2011), we define $\Gamma_{m\omega} = [P_f^{1-\alpha}]^{1-\sigma} = [\sum_j (\beta_j p_j \tau_{ij}^m)^{1-\gamma}]^{\frac{(1-\alpha)(1-\sigma)}{1-\gamma}}$ as the "import globalization" factor, which contains the factors affecting import price. As $\gamma > 1, \sigma > 1$ and $\beta_j p_j \tau_{ij}^m < 1$, we have $\Gamma_{m\omega} > 1$. Using imported intermediates improves firms' revenue. Similar to import, we assume that firms need to pay sunk cost f_x and the iceberg cost $\tau_{x\omega}$ for exports. The revenue of firms that export to n identical countries could be written as $(1+n\tau_{x\omega}^{1-\sigma})r(\omega)$, where $n\tau_{x\omega}^{1-\sigma}$ represents the aggregated iceberg costs of exporting to n foreign markets . We denote $\Gamma_{x\omega} = (1+n\tau_{x\omega}^{1-\delta})$ as the "export globalization factor" with $\Gamma_{x\omega} > 1$, indicating exporters tend to have higher revenues than domestic firms. We further define GVC firms as exporters which use the imported intermediates for the production of exports, while defining the other firms as non-GVC firms. The profits of firms depend not only on their marginal costs but also on their globalization modes, which could be written as follows:

$$\pi(\omega) = \begin{cases} 0 & \text{exited firms} & (9) \\ \frac{RP^{\sigma-1}}{\sigma}[\frac{\kappa c_d^\alpha}{\mu\varphi}]^{1-\sigma} - f_e & \text{domestic firms only} & (10) \\ \Gamma_{m\omega}\frac{RP^{\sigma-1}}{\sigma}[\frac{\kappa c_d^\alpha}{\mu\varphi}]^{1-\sigma} - f_e - nf_m & \text{domestic firms with imported intermediates} & (11) \\ \Gamma_{x\omega}\frac{RP^{\sigma-1}}{\sigma}[\frac{\kappa c_d^\alpha}{\mu\varphi}]^{1-\sigma} - f_e - nf_x & \text{exporters using domestic inputs only} & (12) \\ \Gamma_{m\omega}\Gamma_{x\omega}\frac{RP^{\sigma-1}}{\sigma}[\frac{\kappa c_d^\alpha}{\mu\varphi}]^{1-\sigma} - f_e - n(f_m+f_x) & \text{exporters using imported intermediates} & (13) \end{cases}$$

where f_e is the fixed cost of entering domestic markets while f_m and f_x are the sunk costs of importing and exporting respectively. As shown in Equation (13), despite the extra fixed costs of importing or exporting, the GVC firms could gain extra revenue either by importing intermediates with low costs ($\Gamma_{m\omega} > 1$) or by exporting to multiple foreign markets ($\Gamma_{x\omega} > 1$) [12]. Moreover, given the variety's upstreamness in GVCs, firms' profits increase with the growth

[12] Following Amiti and Davis (2011), we assume $f_x > \frac{f_e}{n}\Gamma_{x\omega}$ and $f_m > (\frac{f_e}{n}\Gamma_{m\omega})$.The first condition ensures the zero-profit firms would not export. The second condition makes sure that zero-profit firms would not import

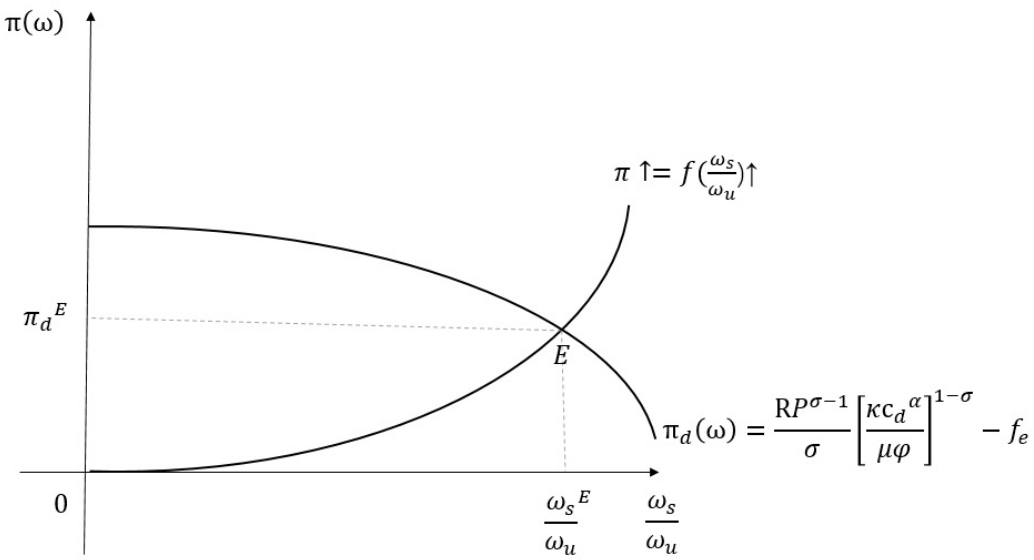
of productivity while lessening with the wage premium. Ceteris Paribus, in autarky economy, the negative relationship between wage premium and firm's profit is depicted by the declining curve in Figure (1).

2.3 Fair Wage Hypothesis and Skill Wage Inequality

There are two sources of heterogeneity in the model: productivity and the relative inputs of skills. Productivity follows a specific distribution with the density function of $g(\varphi)$ [Melitz (2003)]. To tie the firm's wage premium with the firm's performance, we follow Amiti and Davis (2011) to introduce the fair wage constraint into the model. The fair-wage constraint is based on the premise that workers have the motivation to adjust their efforts according to their fairness preference. The fairness depends on the difference between the real wage that workers receive and the reference wage that they expect to get as fair for their efforts [Akerlof (1982), Egger et al. (2013)]. Workers who fail to get the reference wage tend to reduce their efforts to ensure fairness. For firms with better performance, workers would expect a higher reference wage according to the firm's profit and their efforts [Akerlof and Yellen (1990)]. The more profitable firms tend to set up a higher fair wage to elicit the efforts of workers [Danthine and Kurmann (2004)]. Following Amiti and Davis (2011), we assume that there is no cost to employ workers and the fair wage of zero-profit firms is the numeraire. We further assume that different skills have different bargaining power in their fair wage [13]. Following Chen et al. (2017), we suppose the skilled workers would adjust their efforts according to their firms' performance. Thus, the skilled wage is an increasing function of firms' profits. However, the unskilled workers barely have bargaining power in their wages, and thus unskilled wage is unrelated to firms' performance. As a result, the firm-level wage premium of skills is positively correlated with firms' profits, as shown by the rising curve in Figure (1).

intermediates.

[13]The assumption that skilled labor has a larger bargaining power on wages than unskilled workers follows Chen et al. (2017). The assumption is consistent with the predictions of the bargaining model by Helpman et al. (2010) where firms with higher value-added have more surplus to share among specific skill groups. Chen et al. (2017) also discussed the possibility that the skilled and unskilled labor have the same bargaining power in wages but it is skilled workers who gain more additional surpluses. In this paper, we assume that only skilled workers have the bargaining power in wages to simplify the model, but the predictions with the equal bargaining power of both skills should keep robust.



Note: Without loss of generality, the macro variables (i.e., R and P) are assumed to be exogenous. The sector-level upstreamness z is en-ante given. Firms' productivity follow a given distribution with intensity $g(\varphi)$. All else given, we get a unique equilibrium between the firm's profit and it wage premium.

Figure 1: Firms' Wage Inequality and Profits Determination in the Autarky Economy

Figure (1) depicts the determination of firms' wage inequality and their profits in autarky. As shown in Equation (10), profits of firms decrease with the marginal cost of domestic value-added content, which further positively correlates to wage premium. Thus increasing skill wage premium would reduce domestic profits of firms. According to the fair wage hypothesis, profitable firms tend to commit higher fair wage to skilled workers to elicit their efforts, which enlarges the wage inequality between skilled and unskilled workers. All else equal, there would be a unique equilibrium between firms' profits and the wage premium of skills under the constraint of fair wage hypothesis [Amiti and Davis (2011)]. As shown in equation (11)-(13), after opening up to trade, firms choose their globalization modes by which the GVC firms tend to have higher profits than non-GVC firms. In the following section, we analyze firms' decision in participating GVCs and its impacts on the wage inequality of skills.

2.4 Firms' Decisions to Participate in GVCs

For potential market entrants, their expected profit from the market is written as $V(c_\omega) = max\{0, \sum_0^\infty (1-\delta)^t \pi(c_\omega)\} = max\{0, \frac{1}{\delta}\pi(c_\omega)\}$ where δ is the exogenous probability of firms' exit [Melitz (2003)]. Only firms with positive expected profits ($V(c_\omega) \geq 0$) choose to enter the market. The profit of the marginal firm ω^* satisfies $\pi(c_\omega^*) = 0$ with cut-off productivity φ^*. Inspired by Amiti and Davis (2011), we assume that each firm has to pay the fixed cost f_e to produce the final product ω. The production follows a random draw $\lambda_\omega = (\varphi, z_\omega, \tau)$ which depends on productivity, the upstreamness of the variety, and the marginal trade cost of imported intermediates. The joint probability density function of λ_ω is $g(\lambda_\omega)$, and its marginal probability density function could be written as $g_\Phi(\varphi) = \int_z \int_\tau g(\lambda) d\tau dz$. The probability of firms entering the market successfully becomes:

$$v(\varphi) = \begin{cases} \dfrac{g_\Phi(\varphi)}{1 - G_\Phi(\varphi^*)} & \text{if } \varphi > \varphi^* \quad (14) \\ 0 & \text{otherwise} \quad (15) \end{cases}$$

where $G(\varphi)$ is the cumulative distribution function of $g_\Phi(\varphi)$ and φ^* is the cut-off productivity of the marginal firm that enters the domestic market successfully. For successful entrants of domestic market, their average costs are $\tilde{c_\omega}(\varphi, W_\omega) = [\int_{\varphi^*}^{\infty} c_\omega(\varphi, W_\omega)^{\sigma-1} v(\varphi) d\varphi]^{\frac{1}{\sigma-1}}$ where W_ω denotes the wage premium within firms. And the average profit of the domestic market would be $\bar{\pi}(c_\omega) = \frac{1}{\delta} r(\tilde{c_\omega}) - f_e = \frac{1}{\delta} \int_{\varphi^*}^{\infty} r(c_\omega)^{\sigma-1} v(\varphi) d\varphi - f_e$. The free entry condition (FE) ensures the expected value of firms equals to zero where the expected revenue equals to the sunk cost f_e with $\int V(c_\omega)^{\sigma-1} g(\varphi) d\varphi = f_e$. The free-entry condition (FE) satisfies:

$$\bar{\pi}(c_\omega) = \frac{\delta f_e}{1 - G_\Phi(\varphi^*)} \tag{16}$$

Equation (16) reveals the relationship between the average market profit and the cut-off productivity. Higher cut-off productivity indicates a lower cut-off marginal cost c_ω^* with the smaller possibility for firms to enter the market. In this case, firms would expect to get higher profits to overcome the fixed costs. As a result, the average market profit decreases with the cut-off marginal cost c_ω^*.

The marginal firms get zero profits (ZCP) in equilibrium [Melitz (2003)], which is written as $\pi(c_\omega^*) = \frac{1}{\delta} r(c_\omega^*) - f_e = 0$. c_ω^* represents the cut-off marginal cost. The average market profit conditional on c_ω^* would be:

$$\bar{\pi}(c_\omega) = \{[\frac{\tilde{c_\omega}}{c_\omega^*}]^{1-\sigma} - 1\} f_e \tag{17}$$

Equation (17) indicates that the average profit depends on the cut-off marginal cost c_ω^*, which is further determined by cut-off productivity φ and wage premium W_ω^*. Lower cut-off cost c_ω^* expels the inefficient firms out of the market and decreases the average profit of the market due to the tougher competition. The zero-profit condition (ZCP) suggests the positive correlation between the average industrial profit and marginal cost c_ω^*.

Given the macro variables as exogenous, the marginal cost c_ω^* would be uniquely determined by the free-entry and zero-profit conditions as shown in Figure (2).Only those firms with the marginal cost $c_\omega < c_\omega^*$ could enter the domestic market successfully. For the marginal firms with the cut-off productivity, their profits in the market equal to zero. The wage premium of the marginal firms satisfies $W_\omega^* = \frac{\Phi_s}{\Phi_u}(z)^{\frac{1}{\rho-1}}\{\eta[\frac{\mu\varphi^*}{\kappa}]^{\frac{1-\rho}{\alpha}} - 1\}^{\frac{1}{1-\rho}}$ given $\eta = \Phi_u \omega_u^{\rho-1}[\frac{\sigma f_e}{RP^{1-\sigma}}]^{\frac{1-\rho}{\alpha(1-\sigma)}}$ as exogenous. Higher cut-off productivity leads to a larger wage inequality between skilled and unskilled workers in the marginal firms. Moreover, given a higher z, the wage premium of firms would be improved by increasing the productivity shifter of skilled labor.

Similar to Melitz (2003), firms choose to import or export after opening up, which lowers the cut-off marginal cost of domestic firms and forces inefficient firms to exit the market. For example, for importers, the marginal firms of imports have the zero profit and marginal cost c_ω^m* to enter the foreign market. These firms have to bear extra sunk cost of importing (f_m), and their expected profits is written as $\frac{r_d(c_\omega^{m*})\tau_{ij}^{m\,1-\sigma}}{\sigma} - f_m - f_e = 0$. Thereby the marginal cost of importing could be written as $c_\omega^{m*} = \frac{1}{\tau_{ij}^m}(\frac{f_e}{f_m+f_e})^{\frac{1}{\sigma-1}} c_\omega^*$ where c_ω^* is the marginal cost in autarky economy. As we know $\tau_{ij}^m > 1$ and $\sigma > 1$, the cut-off cost for importing firms(c_ω^{m*}) is smaller than the that of domestic firms(c_ω^*), which rules the high-cost domestic firms out of the importing market.

Moreover, the probability of entering the foreign market is written as $prob_m = \frac{1-G_\Phi(\varphi_m^*)}{1-G_\Phi(\varphi^*)}$ where φ_m^* is the cut-off productivity for marginal importing firms. For importing firms, their average cost of importing equals to $\tilde{c_m} = [\int_{\varphi_m^*}^{\infty} c(\varphi, W_\omega)^{\sigma-1} prob_m \cdot v(\varphi) d\varphi]^{\frac{1}{\sigma-1}}$. And their average profit of importing intermediates from one country becomes $\bar{\pi}_{mj}(\tilde{c_m}) = f_m[(\frac{\tilde{c_m}}{c_w^{m*}})^{1-\sigma} - 1]$.

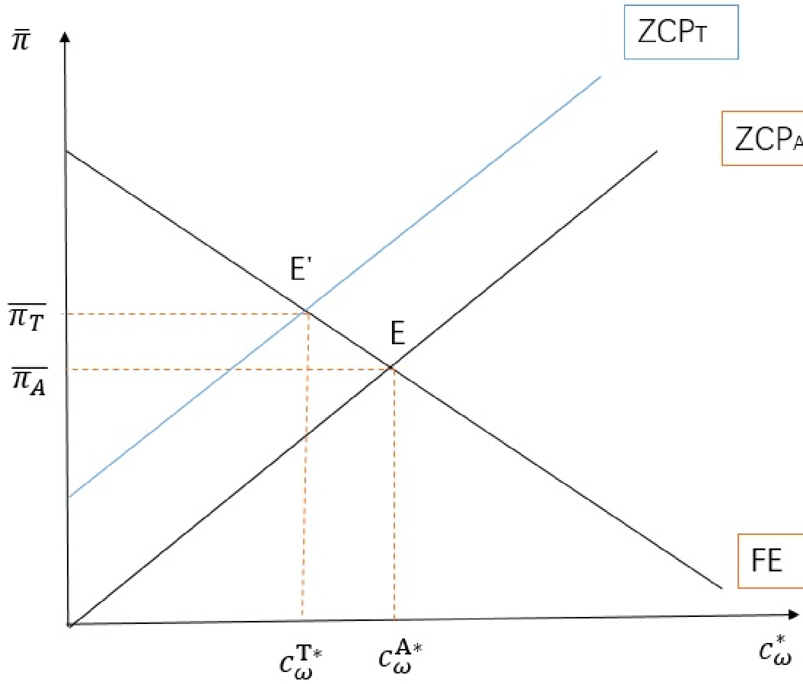


Figure 2: Industrial Equilibrium in Autarky and Trade

If firms import from N countries at the same time, the average profits from importing would equal to $\bar{\pi}_m(\tilde{c_m}) = \sum_j^N prob_m \cdot f_m[(\frac{\tilde{c_m}}{c_w^{m*}})^{1-\sigma} - 1]$. And their average profit from domestic market and importing markets becomes:

$$\bar{\pi}(c_\omega) = f_e[(\frac{\tilde{c}_\omega}{c_\omega^*})^{1-\sigma} - 1] + \sum_j^N prob_m \cdot f_m[(\frac{\tilde{c_m}}{c_w^{m*}})^{1-\sigma} - 1] \tag{18}$$

Equation (18) indicates the average profit for firms using imported intermediates are higher than that of the closed economy. Firms could lower their average cost and gain extra profits by importing intermediate inputs. According to Melitz (2003), the same pattern exists for firms of exporting. As shown in Figure (2), there is a unique equilibrium with the free-entry and zero-profit conditions in autarky, which determines the cut-off marginal costs of entering the market and the average industrial profit. Trade liberalization moves the zero-profit curve upwards while keeping the free-entry condition unchanged, which lowers the marginal cost of entering the market. The high-cost firms are ruled out of the market, which further improves the average profit of the industry.

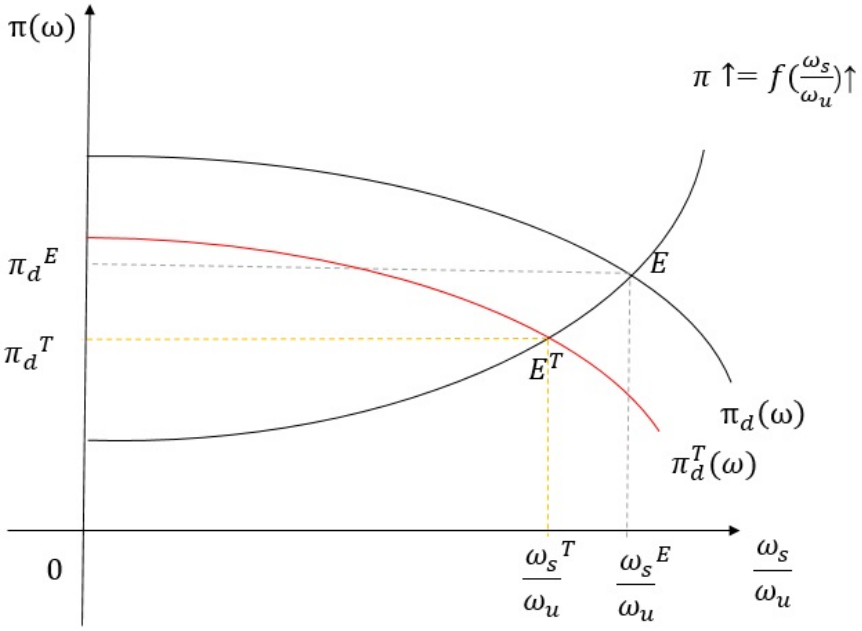


Figure 3: Domestic Firms' Wage Premium Changes in Open Economy

For the domestic firms, their profits are reduced by opening up from $\pi_d(\omega) = f_e[(\frac{c_\omega}{c_\omega^*})^{1-\sigma} - 1]$ in autarky to $\pi_d^T(\omega) = f_e[(\frac{c_\omega}{c_\omega^{T*}})^{1-\sigma} - 1]$ in open economy as $c_\omega^{T*} < c_\omega^*$. The fierce competition after opening up reduces domestic firms' profit from $\pi_d(\omega)$ to $\pi_d^T(\omega)$ in Figure (3). According to the fair wage hypothesis, firms with low profits would cut the skilled workers' fair wage to reduce their costs. The change narrows the wage inequality between skilled and unskilled workers within the firms. The same trend exists in the marginal importers or exports, which enter the foreign markets with zero profits. The profits from foreign markets could not make up the loss in the domestic market, and as a result, the marginal importers or exporters would like to reduce their wage premium to maintain the profits in the open economy as shown in Figure (3).

Firms would choose to import intermediates for the production of exports if their marginal costs satisfy the following condition:

$$c_\omega^{T*} < c_\omega^* < c_\omega^{T*}(\Gamma_{m\omega}\Gamma_{x\omega})^{\frac{1}{\sigma-1}} \tag{19}$$

where c_ω^{T*} is the cut-off marginal cost of trade. c_ω^* is the cut-off marginal cost in autarky. $\Gamma_{m\omega}$ is the import globalization factor and $\Gamma_{m\omega} > 1$. $\Gamma_{m\omega}$ is determined by the CIF price of imported

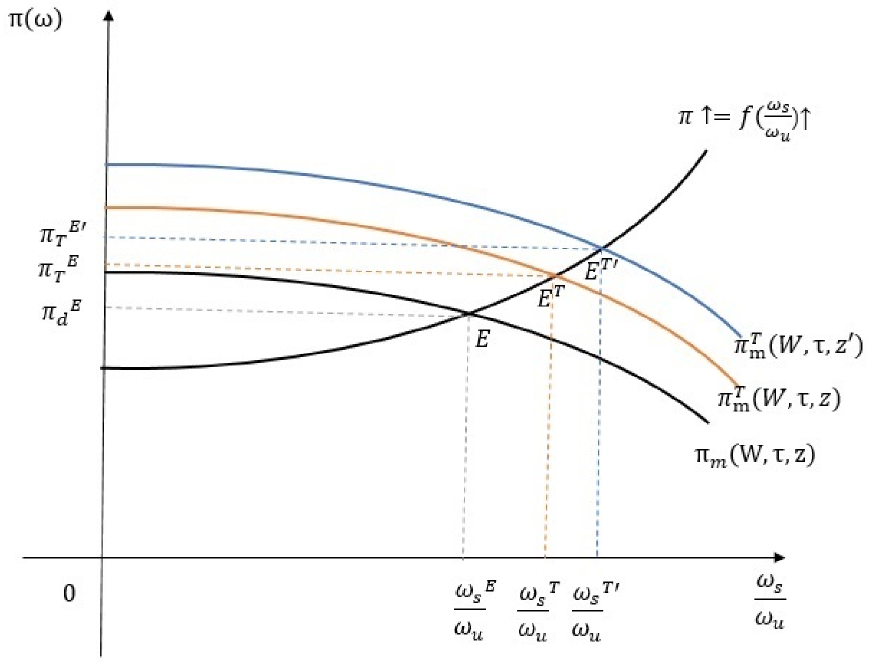


Figure 4: The Wage Premium Changes by Importing Intermediates and GVC Upgrading

intermediates ($p_{ij}\tau_{ij}^m$) and the number of importing countries ($N,\ j \in N$). $\Gamma_{x\omega}$ is the export globalization factor with $\Gamma_{x\omega} > 1$. The GVC firms gain extra profits by importing intermediates and export to foreign markets, which is shown in Figure (4). Under the fair wage constraint, the rising profits enable GVC firms to pay higher wages to the skilled workers, which increases the skill wage premium from equilibrium point E to E^T.

Moreover, as shown in equation (13), the profits of GVC firms are negatively correlated to the marginal cost of domestic value added (c_d) where $c_d = \Phi_u^{\frac{1}{1-\rho}}\omega_u[1+\frac{\Phi_s}{\Phi_u}(z)(\frac{\omega_s}{\omega_u})^{1-\rho}]^{\frac{1}{1-\rho}}$. Given the macro-variables R and P, the unskilled productivity parameter (Φ_u) and the sector-level upstreamness z as exogenous, the GVC firms have a unique equilibrium at E^T after opening up, where they have higher profits as well as skill wage premiums than those in autarky. Suppose moving to the upstream sectors generates no extra fixed cost, a larger upstreamness index z' would lead to an increase in the productivity shifter $\Phi_s(z)$ and reduce the marginal cost of domestic value-added c_d. The lower marginal cost of domestic value-added increases GVC firms' equilibrium profit from $\pi_m^T(W,\tau,z)$ to $\pi_m^T(W,\tau,z')$, suggesting upgrading in GVCs requires firms to be more profitable. The higher upstreamness z' also improves the productivity of skilled labor, which widens the equilibrium wage premium from $\frac{w_s}{w_u}^T$ to $\frac{w_s}{w_u}^{T'}$ in Figure (4).

According to the Cobb-Douglas production function,the share of domestic value-added in total inputs equals to α (DVAR), which is assumed to be exogenous with $\alpha \in (0,1)$. Thus the share of foreign value-added content in output is $1-\alpha$. The partial derivative for the log profit of GVC firms over α equals to $\frac{\partial ln\pi}{\partial\alpha} = -\frac{1-\sigma}{1-\gamma} lnP^f + (1-\sigma)[-ln\alpha - ln(1-\alpha+lnc_d)] < 0$. As a result, firms with higher shares of foreign value-added content (smaller α) tend to have larger profits and wage inequality. This result is consistent with the intuition that using more imported intermediate inputs reduces the marginal costs of exporters and increases the profitability of firms. The wage of skilled workers is positively correlated to firm performance, therefore increasing FVAR increases the profits of firms, which in turn raises firms' wage premium between skilled and unskilled labor. The predictions of wage premium changes in reaction to the GVC participation, GVC upgrading, and rising FVAR are summarized as follows:

Proposition *Compared to the domestic and non-GVC firms, the GVC firms are more profitable and associated with larger wage inequality between skilled and unskilled workers. All else equal, firms with a higher share of foreign value added in the production tend to have larger wage inequality of skills. Moreover, moving to upstream sectors in the global value chains enlarges firms' wage inequality.*

3 Data and Measures

In this section, three critical indicators are measured at the firm level: the share of foreign value-added content in exports, the upstreamness, and the wage inequality of skills. We extend the procedures of Kee and Tang (2016) and Upward et al. (2013) to measure the share of foreign value-added in exports (FVAR) using Chinese manufacturing firm-level data. We follow Antràs et al. (2012) to measure the upstreamness of exporting varieties and calculate firms' position in GVCs by aggregating the upstreamness of exporting varieties to the firm level. Finally, we adopt Chen et al. (2017)'s approach to develop a Mincer-type econometric model that estimates the firm-level wage premium with the average wage and skill share.

3.1 Data description

We use two micro-datasets of China to construct the firm-level GVC indicators: (a) the Chinese manufacturing enterprise survey data from China's National Bureau of Statistics (NBS), (b) the Chinese transaction-level trade data from China's General Administration of Customs (GAC). The NBS dataset is an annual survey covering two types of manufacturing firms: the state-owned (SOE) enterprises and the non-SOEs with annual sales over RMB 5 million (around the US $770,000). The NBS enterprises in the sample account for almost 95% of China's manufacturing outputs. The NBS dataset provides detailed information about firms with more than 130 financial indicators. The data in our study covers from 2000 to 2006, during which China entered the WTO and rapidly integrated into the global economy.

As a survey dataset, the NBS data inevitably contains some statistical discrepancies such as abnormal values, missing variables and misreporting. Despite the high consistency, the NBS database fails to identify firms across years without the uniform identification code. Thus, we first encoded enterprises by their name and address to form a unique identification code for each firm across time [Brandt et al. (2014)]. Following Cai and Liu (2009), we eliminated the misreporting information. First, we omitted the duplicates and abnormal values from the sample and then removed the observations with missing critical values, e.g., profits, inputs, employment, fixed assets, etc. Second, we deleted the small-scale firms with less than eight employees to rule out the extreme values. Third, we removed companies that break the "Generally Accepted Accounting Principles (GAAP)?[14]. Around 1,560,004 observations of 79,810 firms were omitted from the NBS database after data filter, accounting for 5.1% of the sample.

Another limitation of the NBS data is the lack of detailed information about skills within firms, except for the year 2004. In the NBS dataset, firms' employment and average wage are available annually, but the detailed information of skills, categorized by education and occupation, is only available for the 2004 survey data. Inspired by Chen et al. (2017), we construct the firm-level employment of skills by assuming skills have the identical growth rate

[14]For example, total asset exceeds cash or capital; net value of fixed assets is smaller than the total asset; capital is less than 0 or exports are higher than the sales.

in the same province. We get the province-level growth rate of skills from the China Statistical Yearbook [15]. Meanwhile, the 2004 NBS data enabled the calculation of the real employment of skilled and unskilled workers within firms by education[16]. Under the assumption of identical skill growth rate within provinces, we derived the firm-level employment of skills using the 2004 firm-level skill employment data and the province-level skill growth rate in the other years. This approach makes up the data limitation with consideration of firm heterogeneity. We further measure the wage of unskilled workers using the provincial data. The unskilled workers are assumed to have no bargaining power in their salaries. Thus, the unskilled workers accept the minimum wage, which is assumed to be the 25 percentiles of the province-level average salary[17]. The average wage of provinces is collected from the Chinese Trade Unions Statistics Yearbook.

To calculate the share of imported intermediates exports, we match the NBS dataset with the Chinese Customs dataset. China's GAC dataset provides detail trade information at the transaction level. In each transaction, three types of information are covered: (a) trading firm's characteristics such as name, address, postcode and telephone number; (b) the shipment information such as trade volume, quantity, destinations or origins; and (c) the trading regime information such as ordinary trade, processing trade, and the others. We matched the NBS database with the GAC data following the procedures of Feenstra et al. (2014)[18]. We consider firms with the same name, telephone number (the last seven digits) and postcode across time as the same firm. The matched firms account for around 20% of the NBS samples and 35% of firms in the GAC databases. We summarize the matched data in Table (1).

[15]The China Statistical Yearbook provides the employment data by province and education. There are seven categories of education including illiteracy, primary education level, secondary school education level, high school education level, college, undergraduate, postgraduate and over. We categorize the employees with the college degree and above as the skilled workers while considering the others as the unskilled workers.

[16]We also provide an alternative categorization of skills by occupation in the section of robustness checks, and the results keep unchanged.

[17]The minimum wage regulations of China started since 2004, which partly overlaps with our sample period. We follow Chen et al. (2017) to use the 25 percentile of the provincial average wage as the proxy for the unskilled wage. We also provide an alternative measurement in the section of robustness checks by using the rural wage as the alternative proxy for the unskilled wage.

[18]The NBS and GAC databases both have identification code of firms, but they belong to different systems and unable to match directly.

Table 1: Matched Data Description

Year	Observations	Firms	ratio in NBS	ratio in GAC
2000	1,168,745	21,584	15.02%	26.90%
2001	1,302,202	31,248	19.75%	35.75%
2002	1,473,416	34,041	19.91%	35.03%
2003	1,682,256	37,436	19.87%	33.09%
2004	2,257,771	56,650	21.47%	42.00%
2005	2,204,878	53,804	20.45%	38.44%
2006	2,370,679	82,479	28.24%	41.76%

Note: The table reports the matched result of NBS and GAC databases. The ratio refers to the number of matched firms over the total number of firms in the two databases.

Firms participate in the GVCs by using imported intermediate inputs for the production of exports. According to trade regimes, GVC firms are further categorized into three types: (a) the ordinary exporters, (b) the processing exporters and (c) the mixed exporters performing processing trade and ordinary trade at the same time[19]. China exempts the tariff of imported intermediates for processing exports to boost export growth. The tariff-free policies require processing exporters to use all imported intermediate inputs for the production of exports. The ordinary exporters do not receive the tariff exemption on imported intermediates; thus, they could use the imported intermediate inputs for domestic production and sales. The categorization of Chinese exporters by trade regimes is summarized in Table (2). We observe around 60% of China's exporters engage in processing trade in the sample period. It suggests that the estimation of FVAR using international input-output tables (IIOTs) could be biased without considering the heterogeneity of processing firms in using foreign intermediates [Kee and Tang (2016)].

We use the World Input and Output tables (WIOD) to measure the upstreamness of exporting varieties. The WIOD dataset traces the input and output linkages of production across 43 countries and 35 sectors from 2000 to 2014. We follow Antràs et al. (2012)'s procedures to measure the upstreamness of varieties using the WIOD dataset. The upstreamness of each

[19]In processing trade, firms import the raw materials and intermediates for processing, and export the finished products, in the form of final goods or intermediates, to the other countries. Processing exports are massive in China, accounting for more than 45% of the total exports in 2010 [Feenstra et al. (2014)]. Processing exporters use more imported intermediates in production than ordinary exporters[Koopman et al. (2012).]

Table 2: Exporting Firms by Trade Regimes

Year	Ordinary exporters	Processing exporters	Mixed Exporters	Total	Share of NBS	Share of GAC
2000	6,105	2,991	7,542	16,638	11.58%	20.74%
2001	10,455	3,419	9,123	22,997	14.54%	26.31%
2002	12,729	3,172	10,170	26,071	15.25%	26.83%
2003	15,919	3,188	11,138	30,245	16.05%	26.73%
2004	25,208	4,787	15,140	45,135	17.11%	33.46%
2005	26,738	4,855	15,253	46,846	17.81%	22.46%
2006	32,645	5,334	15,754	53,733	18.40%	27.21%

Note: We define firms that use imported intermediates for exports as GVC firms. According to trade regimes, the GVC firms could be categorized into firms in ordinary trade, firms in processing trade and firms in both ordinary and processing trade (Mixed exporters).

variety is estimated by its weighted average ”distance” to the final demand. The matched dataset of NBS and GAC enables us to identify the exporting varieties of each firm and calculate the firm-level average upstreamness weighted by the export share of each variety in the total exports of the firm[Ju and Yu (2015)].

3.2 GVC measurement

3.2.1 Firm-level GVC participation

In this paper, we define the backward GVC participation index of firms as the share of foreign value-added content in exports (FVAR) [Koopman et al. (2014)]. FVAR comes from two sources of firms: (a) the imported intermediates, (b) the foreign value-added embodied in the domestic materials [Kee and Tang (2016)]. Chinese processing exporters have to use all their imported intermediates for the production of exports. However, the ordinary exporters could use part of imported intermediates for domestic sales [20]. We estimate the share of foreign value added in exports (FVAR) for processing firms as follows:

$$FVAR_i^p = \frac{Import_i^p}{Export_i^p} + \frac{\sigma_i^F}{Export_i^p} \tag{20}$$

where $Import_i^p$ is the imported intermediates of the processing exporter i. σ_i^F denotes the foreign value-added content embodied in domestic materials that are used for exporting pro-

[20]The excessive importers and exporters are ruled out from the sample following Kee and Tang (2016). The excessive importers are the firms which import more intermediates than they need and sell the imported intermediates to the other firms, leading to an overestimation of FVAR. The excessive exporters are the firms that import intermediates from other domestic firms rather than foreign countries, and thus underestimates the FVAR.

duction [21]. In this paper, we use Kee and Tang (2016)'s estimation of σ_i^F to calculate the share of foreign value added in domestic materials for exporting production ($\frac{\sigma_i^F}{Export_i^p}$).

The measurement of FVAR for non-processing exporters is more complicated than that of processing exporters. Apart from importing intermediates, the non-processing exporters also import capital and final products for consumption[22]. We use the United Nations Broad Economic Categories (BEC) to distinguish the imported intermediates from capital and equipment imports and estimate total value of imported intermediates. Let $Import_i^{o\_int}$ denote the total value of imported intermediates of firm i, where "o" refers to ordinary exporters while "int" stands for the imported intermediate. The imported intermediates of ordinary exporters are used for either exports or domestic sales. However, it is challenging to calculate the ratio of imported intermediate inputs in exports over the total imported intermediates. We further assume the share of imported intermediate inputs in exports is proportional to the share of exports in total sales, which ensures the same ratio of imported intermediate inputs in both domestic sales and exports. Under the proportion assumption, the FVAR of ordinary exporters and mixed exporters is written as follows:

$$FVAR_i^o = \frac{import_i^{o\_int}}{Export_i^o + dom\_sales} + \frac{\sigma_i^F}{Export_i^o} \tag{21}$$

$$FVAR_i^m = \frac{Import_i^p}{Export_i} + \frac{\frac{import_i^{o\_int}}{export_i^o + dom\_sales} * export_i^o}{Export_i} + \frac{\sigma_i^F}{Export_i} \tag{22}$$

The mixed exporters conduct processing exports and ordinary exports at the same time. As shown in Equation (22), the superscripts p and o denote processing trade and ordinary trade. "int" refers to the import of intermediates. "dom_sales" represents the domestic sales of firms.

[21] From the GVC perspective, the imported intermediates also contain domestic value added σ_i^D , which should be subtracted from the value of imported intermediates. Koopman et al. (2014) estimated the share of domestic value added in imported intermediates (σ_i^D) and found σ_i^D only accounts for 0.7% of the ordinary exports and almost 0% of the processing exports. Kee and Tang (2016) neglected σ_i^D in calculating the share of domestic value added in Chinese processing exports. We follow Kee and Tang (2016) to assume that $\sigma_i^D = 0$ for processing exporters.

[22] The imported capital and equipment of processing firms are listed separately in the category of "Equipment for Processing Trade" in GAC database. Thus $Import_i^p$ only measures the value of imported intermediates of processing exporters. But we have to distinguish the imported intermediates from imported capital and equipment in the ordinary trade.

$Export_i$ is the gross exports of mixed exporters, while $export_i^o$ stands for the part of ordinary exports. Mixed exporters have to use all the imported intermediates of processing trade in exports. Thus the foreign value-added share of the processing export is shown in the first item of Equation (22). The share of imported intermediates by ordinary imports in exports is shown in the second item of Equation (22). The share of foreign value added embodied in the domestic materials for exports lies in the third item.

We further calculate the aggregated industry- and country-level FVAR index with the firm-level FVAR data [23] [Kee and Tang (2016)]:

$$FVAR_j = \sum_{i\in\Omega_j} \frac{EXP_i}{\sum_{i\in\Omega_j} EXP_i} FVAR_i \tag{23}$$

$$FVAR = \sum_j \sum_{i\in\Omega_j} \frac{EXP_i}{\sum_j \sum_{i\in\Omega_j} EXP_i} FVAR_i \tag{24}$$

The aggregated country- and sectoral level FVAR are the weighted average of firm-level FVAR with firms? exporting share as weights [Kee and Tang (2016)]. We estimate China's aggregated FVAR index by trade regimes during 2000-2006 as given in Figure (5). We observe a higher FVAR in processing exports than in ordinary exports, which is consistent with the findings of Koopman et al. (2012) and Kee and Tang (2016). We also find that the average FVAR of Chinese manufacturing firms decreased from 0.42 in 2000 to 0.30 in 2006 respectively. The declining FVAR is primarily due to the processing exporters, whose FVAR dropped from 0.51 to 0.45 in the sample period. The FVAR of ordinary exports also reduced from 0.16 in 2000 to 0.13 in 2006.

We also calculate the weighted average FVAR by different types of firms in Figure (6). The processing exporters used the highest share of foreign value-added with around 50% FVAR in processing exports. The ordinary exporters only use about 10% of foreign content in exports.

[23] The approach applies to firms in one sector with direct trading. For firms in multiple industries, extra constraints should be applied to rule out excessive processing importers[Kee and Tang (2016)].

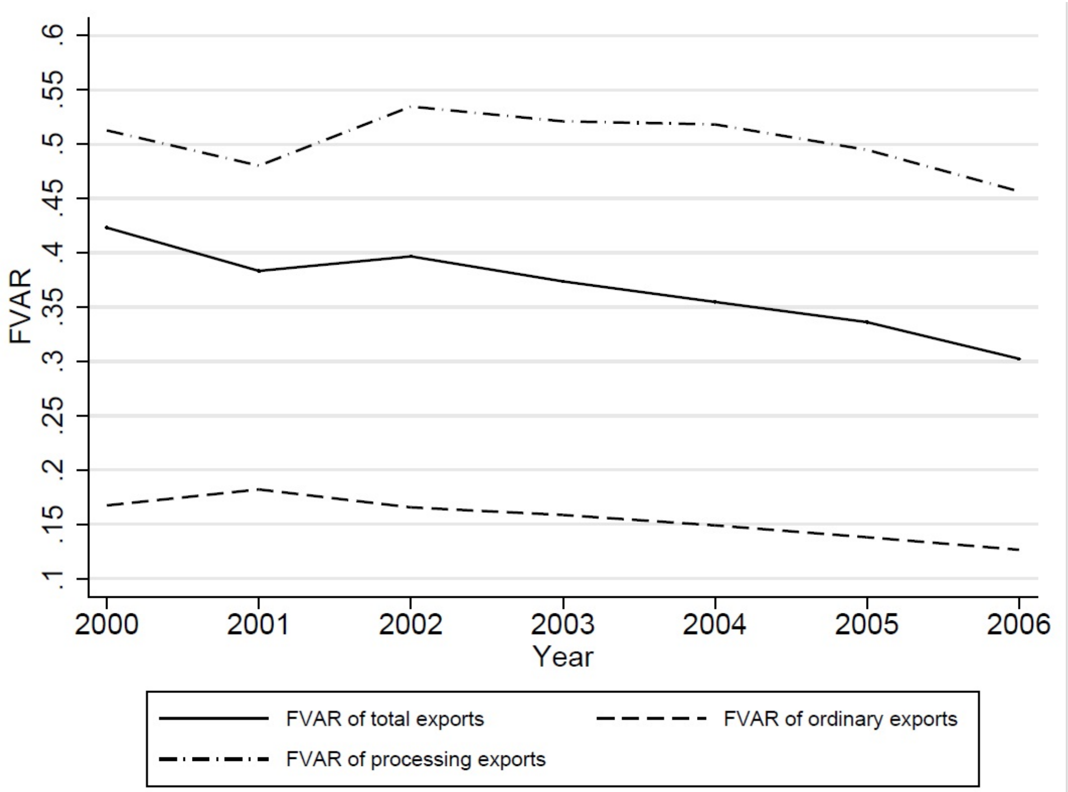


Figure 5: Country-level FVAR in Chinese Exports

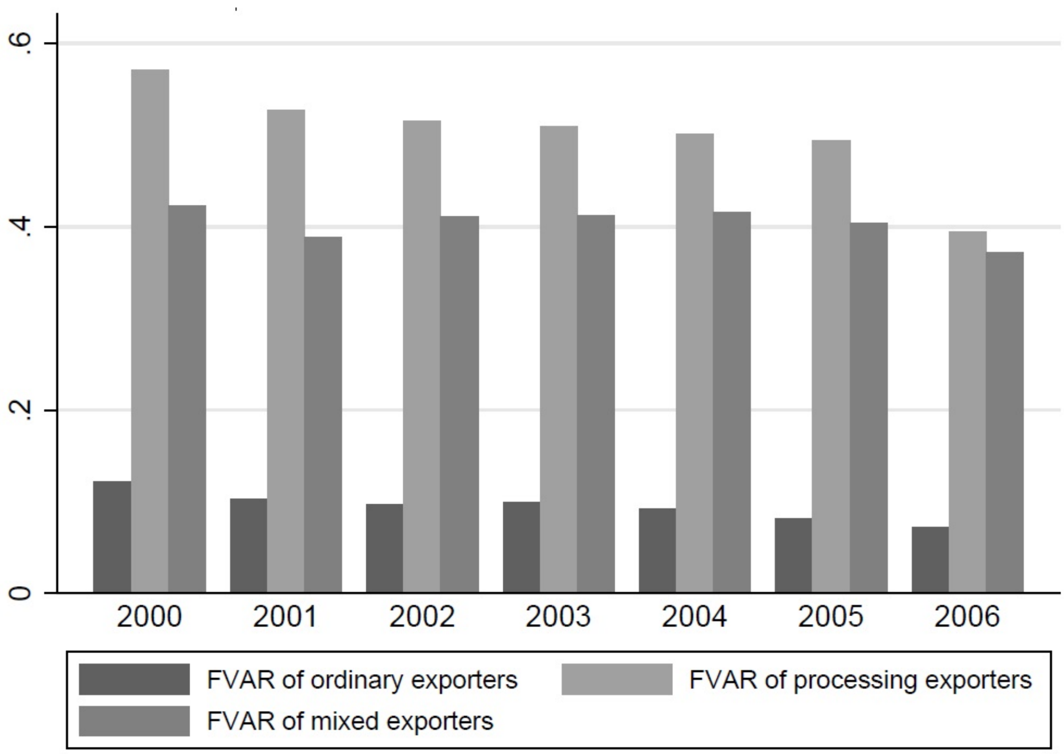


Figure 6: Average FVAR by the types of firms, 2000-2006

The mixed exporters use almost 40% of foreign value added in exports. The processing exporters reduced their FVAR from 0.57 in 2000 to 0.39 in 2006, while the ordinary exporters' FVAR was declining from 0.12 to 0.07 between 2000 and 2006. The mixed firms also had a descending trend of FVAR from 0.43 to 0.37 during the sample period. The results indicate that all the manufacturing firms in China tend to use less imported intermediates for exports and participate less in the backward production linkages of GVCs.

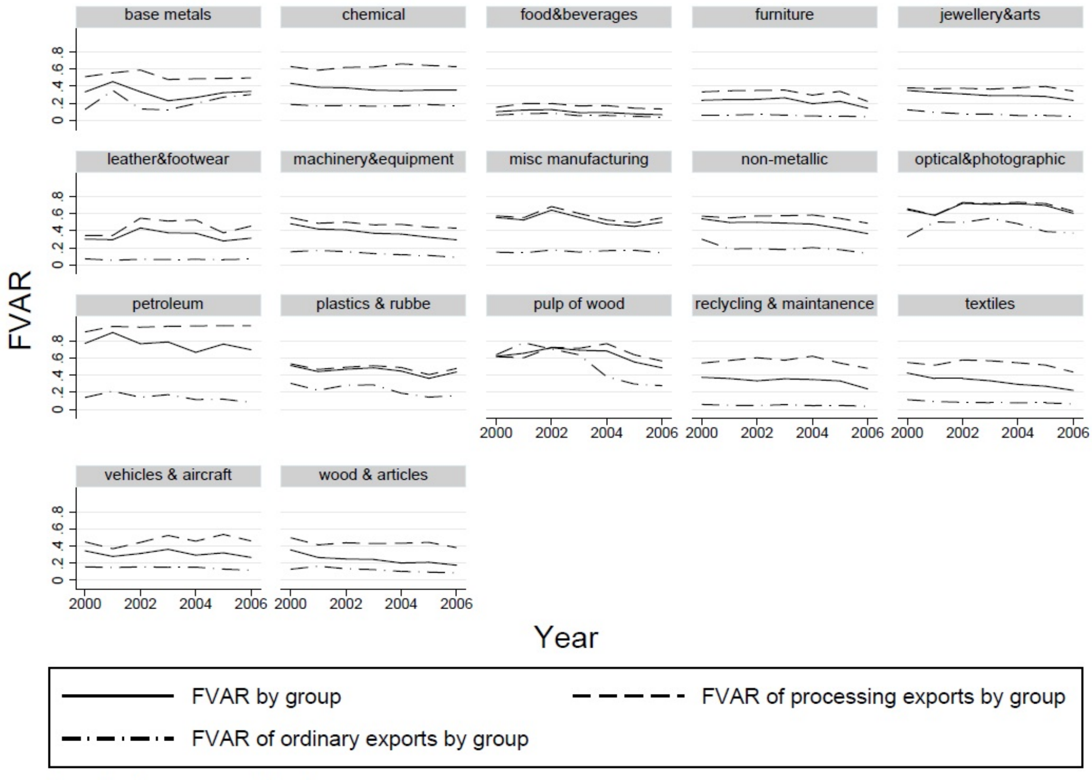


Figure 7: FVAR trend by industry during 2000-2006

We further plot the FVAR trend by different manufacturing industries in Figure (7). Except for the industry of base metal, all the manufacturing sectors in China had a declining trend of FVAR during the sample period. We find that the industries with prominent processing trade, such as textile, machinery and non-metallic processing, experienced the most significant declines in FVAR by 21%, 17%, and 15% respectively during 2000-2006. It suggests that the Chinese manufacturing exporters tended to substitute domestic materials for the imported intermediates. It may because the domestic materials in China are available at lower prices and with more varieties in the process of trade liberalization[Kee and Tang (2016)].

3.2.2 Firm-level GVC position

Mapping firm's position in GVCs is crucial to study firms' GVC activities and their impacts on the labor market. Antràs et al. (2012) proposed the methodology to measure the position of sectors in GVCs, which was named as the "upstreamness" of industries in GVCs. The sector-level upstreamness is the weighted average distance from this industry to the final demands through GVCs. The distance is measured by the number of steps from the industry to the final goods in the international input-output tables. As we know, the manufacturing firms export several varieties at the same time and we derive the upstreamness of each exporting variety in GVCs in our sample.

For any variety j, its output (Y_j) could be either used as intermediates of other sectors (I_j) or consumed as final goods directly (F_j). As we know, $Y_j = I_j + F_j$. Assume there are N industries in GVCs, the total output of j is written as $Y_j = \sum_{k=1}^{N} d_{jk}Y_k + F_j$, where d_{jk} refers to the amount of j's output as intermediates to produce 1 unit of industry k's final goods. In the international input-output tables, the variety j's output could be iterated with infinite terms as follows:

$$Y_j = F_j + \sum_{k=1}^{N} d_{jk}F_k + \sum_{k=1}^{N}\sum_{m=1}^{N} d_{jm}d_{mk}F_k + \sum_{k=1}^{N}\sum_{m=1}^{N}\sum_{n=1}^{N} d_{jn}d_{nm}d_{mk}F_k + \ldots \tag{25}$$

Equation (25) shows the outputs of industry j could be absorbed either directly or indirectly in the final demand. The second right term of Equation (25) indicates that the output of industry j is directly used in the production of final goods k, by which the distance between industry j and the final demand is one step. The third right term of Equation(25) suggests that industry j's output is firstly used as intermediates of industry m and then absorbed the final goods k, then the distance between industry j and final demand is two steps. Similarly, the distance of industry j to the final demand in the fourth right term is three steps, suggesting industry j's output comes into the final use through two industries. We can get the distance of all the intermediates from industry j to the final goods k and measure its average distance to the final goods using its input coefficients as weights in Equation (26):

$$U_j = 1 \times \frac{F_j}{Y_j} + 2 \times \frac{\sum_{k=1}^{N} d_{jk} F_k}{Y_j} + 3 \times \frac{\sum_{k=1}^{N} \sum_{m=1}^{N} d_{jm} d_{mk} F_k}{Y_j} + 4 \times \frac{\sum_{k=1}^{N} \sum_{m=1}^{N} \sum_{n=1}^{N} d_{jn} d_{nm} d_{mj} F_k}{Y_j} + .. \tag{26}$$

where U_j denotes the upstreamness of industry j relative to the final demand in the international input-output tables. d_{jk} stands for the $(j,k)^{th}$ element in the $N \times N$ input matrix of the international input-output tables. It represents how many output of variety j should be used to produce 1 unit of final goods k. Y_j is the total output of variety j.

The larger the distance between variety j and the final demand is, the more upstream position the variety j lies in GVCs. A firm could export multiple varieties at the same time. Thus we estimate the firm-level GVC position by taking the weighted average of upstreamness across industries using the share of each variety's exports in total exports of the firm as the weight. The measurement is shown in Equation (27).

$$F\_Upstreamness_i = \sum_{j}^{N} U_j \frac{exp_{ij}}{exp_i} \tag{27}$$

where U_j is the industry-level upstreamness of variety j. exp_{ij} is firm i's gross exports of variety j. exp_i is firm i's total exports of all the varieties. We identify the exporting varieties and their exporting values from the GAC dataset.

Figure (8) shows the average upstreamness index of Chinese manufacturing firms by industries and trade regimes. The upstreamness index varied from 1.9 (leather and footwear) to 4.4 (petroleum) during 2000-2006. The energy and raw material industries (petroleum, base metals, pulp, and wood) locate at the upstream of GVCs. The high-tech manufacturing industries, such as machinery, optical and photographic equipment, vehicles and aircraft, have higher positions in GVCs than the unskilled-labor intensive sectors such as textile, furniture, leather, and footwear. All the manufacturing industries in China have a rising trend of upstreamness, indicating the upgrading of Chinese manufacturing firms to upstream sectors of GVCs. There is no significant difference between the position of processing exporters and that of ordinary

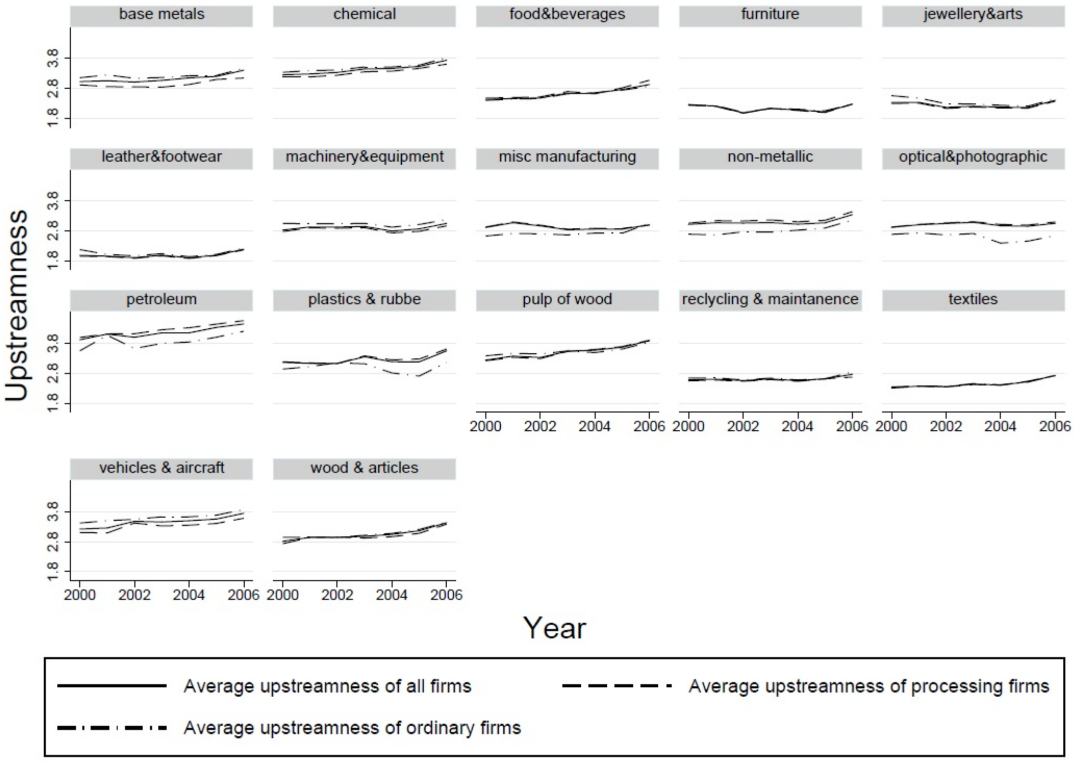


Figure 8: Upstreamness Trend by Industry and Trade Regime,2000-2006

exporters for most industries.

3.3 Skill Share and Wage Inequality

In this paper, we categorize firms' employees into the skilled and unskilled labor by education. There are five categories of education in the NBS dataset: postgraduate or above, undergraduate, college, high school, and secondary school or below. According to the International Standard Classification of Education (ISCED 2011), employees with a college degree or above are categorized as skilled labor, while those with high school education or below are classified as unskilled workers. As discussed in the data part, the details of employment by skills are only available in 2004. We assume all the firms within province have the same growth rate of skills. Using the province-level skill growth rate and 2004 firm-level data, we estimate firms' employment of skills for the other years during 2000-2006.

We denote the measured skill share as θ_{ijlt} where i is the firm, j is the industry, l is the province and t is time. The wage of skilled and unskilled workers of the firm are written as

w^s_{ijlt} and w^u_{jlt}. As discussed, w^s_{ijlt} relies on firm i's profits, but w^u_{jlt} is assumed to be determined by the provincial-level minimum wage. Following Chen et al. (2017), the average wage of firm i is $\bar{w_{ijlt}} = \theta^s_{ijlt} w^s_{ijlt} + (1-\theta^s_{ijlt}) w^u_{jlt}$, which equals to $\frac{\bar{w_{ijlt}}}{w^u_{jlt}} = \theta_{ijlt}(\frac{w^s_{ijlt}}{w^u_{jlt}} - 1) + 1$. Assuming $s_{ijlt} = \frac{w^s_{ijlt}}{w^u_{jlt}} - 1$ as a monotonic function of wage premium $\frac{w^s_{ijlt}}{w^u_{jlt}}$, the logarithmic of average wage in firm i is written as follows:

$$lnw\bar{_{ijlt}} = lnw^u_{jlt} + ln(1 + \theta_{ijlt} s_{ijlt}) \approx lnw^u_{jlt} + \theta_{ijlt} s_{ijlt} \tag{28}$$

The average wage of the firm equals to the aggregated wage of skills weighted by skill share. It can be further written as a function of skilled share θ_{ijlt}, wage premium $\frac{w^s_{ijlt}}{w^u_{jlt}}$ and unskilled wage. When $\theta_{ijlt} s_{ijlt}$ is small enough, $ln(1 + \theta_{ijlt} s_{ijlt}) \approx \theta_{ijlt} s_{ijlt}$. We get the approximate Mincer-type income function at the firm level.

According to the theoretical model, the wage inequality of skills is affected by firms' characteristics and their GVC activities. For simplicity, we suppose the function of wage premium s_{ijlt} is a linear form of firm characteristics and GVC indicators as follows:

$$s_{ijlt} = \sum_{g=0}^{G} \gamma_g x^g_{ijlt} + \varepsilon_{ijlt} \tag{29}$$

where x^g_{ijlt} is the vector of indicators that affect the skill wage inequality. It includes firms' participation index (FVAR) and position index (upstreamness) of GVCs and other firm-level characteristics. Substituting equation (29) into equation (28), we get a Mincer-type empirical specification as follows:

$$lnw\bar{_{ijlt}} = \gamma_0 + \gamma_u lnw^u_{jlt} + \gamma_1 \theta_{ijlt} FVAR_{ijlt} + \gamma_2 \theta_{ijlt} F\_Upstreamness_{ijlt} + \gamma \theta_{ijlt} \boldsymbol{X}_{ijlt} + \sigma_i + \sigma_{jl} + \sigma_t + \epsilon_{ijlt} \tag{30}$$

where $\epsilon_{ijlt} = \varepsilon_{ijlt} \theta_{ijlt}$. lnw^u_{jlt} is the unskilled wage at the provincial level. The interactions between firm-level GVC indicators and skill share (θ_{ijlt}) investigate whether firms' GVC activities affect the skill wage inequality via changing skill shares. $FVAR_{ijlt}$ measures firms' backward participation in the global value chains and $F\_Upstreamness_{ijlt}$ captures firms' position in the global value chains. As predicted in the theory, using more foreign content in exports (FVAR) enlarges firms' wage inequality between skilled and unskilled labor. Thus we expect γ_1 to be positive and statistically significant. We also predict that moving to upstream sectors widens firms' wage inequality of skills. Thus γ_2 is also expected to be significantly positive. $\boldsymbol{X}_{ijlt}$ is a vector of control variables interacted with skill share (θ_{ijlt}) including firm size, age, capital-labor ratio, dummy for state-owned enterprises, foreign ownership and processing trade. Firm size is measured by the ratio of the firm's sales over the industrial sales to control for the within-industry heterogeneity. The model also controls the time-specific, firm-specific and sector-province specific fixed effects. We describe the main variables in the regression in Table (3).

Table 3: Variable description

	2004			2000-2006		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
log Firm Average wage	45,698	7.814	1.236	245,121	7.900	1.271
log Unskilled Wage	45,735	8.502	0.256	245,381	8.467	0.350
skill share	45,735	0.143	0.176	209,405	0.131	0.168
FVAR	24,561	0.449	0.382	133,547	0.442	0.377
Firm-level Upstreamness	41,177	2.782	0.664	220,742	2.871	0.666
log Firm size	45,735	-5.496	1.282	245,381	-5.310	1.339
Firm age	45,729	7.887	8.467	245,201	8.870	16.887
log TFP by OP	45,117	1.769	0.146	244,393	1.774	0.152
log TFP by LP	45,589	1.886	0.198	244,296	1.907	0.186
log capital labor ratio	45,690	3.662	1.425	244,769	3.721	1.419
SOE dummy	45,735	0.029	0.167	245,381	0.040	0.197
processing firm dummy	45,735	0.105	0.306	245,381	0.113	0.317
foreign ownership dummy	45,735	0.474	0.499	245,381	0.481	0.500
log value added per worker	35,229	-3.476	1.432	244,950	3.873	1.154
log profit per worker	22,217	0.250	0.132	193,348	-3.495	1.414
fitted FVAR by Heckman	21,812	0.256	0.131	152,793	0.254	0.131

Note: The first three columns describe the variables of the 2004 cross-section data where skill share is available. The last three columns summarize the panel data between 2000 and 2006 with measured skill share.

4 Estimation

4.1 Baseline Estimation

In the baseline estimation, we use both 2004 cross-section data and 2000-2006 panel data to explore the nexus between GVC activities and the wage inequality of skills within firms. The advantage of 2004 data is the availability of firm-level skill share. Despite the measured skill share, the panel data between 2000 and 2006 provides a better understanding of the skill premium variation within firms in response to the GVC activities. The baseline estimation results are shown in Tables (4) and (5) respectively.

Table (4) reports the estimation of the cross-sectional regression. Column (1) examines the determinants of firm-level wage inequality with a simple ordinary least square (OLS) regression. Column (2) regresses the determinants interacted with skill share following the empirical specification of Equation (28) without controlling for the fixed effects. As predicted, the interaction between FVAR and skill share is significantly positive, suggesting firms with higher FVAR are associated with larger wage inequality between skilled and unskilled workers. The interaction between upstreamness and skill share, however, is not significant in column (2). We also observe that the interactions of firms' size and capital-labor ratio are significantly positive. It means the large-scale firms and capital-intensive firms tend to use more skilled labor in the production, which in turn raises the firm's skill premium. We control for the industry-, province- and province-sector specific fixed effects in the last three columns. Column (3) reports the OLS regression of wage determinants with fixed effects. Column (4) reports the estimation of Mincer-type wage model with controlling for the fixed effects. The coefficient of FVAR interacted with the skill share is still positive and significant, suggesting increasing FVAR enlarges the wage inequality of skills at the firm level. The interaction coefficient between upstreamness and skill share turns to be significant after controlling for the fixed effects. It means that firms in the upstream sectors tend to have larger skill wage premiums and skill shares than those in the downstream industries. The estimation results of firms' size and capital intensity keep robust in the column (4) after controlling for the fixed effects.

Table 4: Baseline Estimation Using 2004 Cross-sectional Data

	(1)	(2)	(3)	(4)	(5)
		$\times$ Skill share		$\times$ Skill share	$\times$Skill share$\times$processing
ln unskilled wage	0.300***	0.310***	0.843**	0.864**	0.881**
	(0.030)	(0.030)	(0.386)	(0.380)	(0.380)
Skill share (θ_{ijlt})	-0.299***	-1.076***	-0.497***	-1.667***	-1.675***
	(0.048)	(0.316)	(0.059)	(0.385)	(0.384)
FVAR	0.304***	0.185***	0.225***	0.098***	0.116***
	(0.021)	(0.028)	(0.022)	(0.029)	(0.030)
f_upstreamness	-0.152***	-0.153***	-0.052***	-0.079***	-0.082***
	(0.012)	(0.016)	(0.017)	(0.021)	(0.021)
lnsize	-0.015**	-0.041***	0.013	-0.027**	-0.027**
	(0.006)	(0.008)	(0.009)	(0.011)	(0.011)
lnK/L	0.069***	0.017**	0.089***	0.028***	0.029***
	(0.006)	(0.008)	(0.007)	(0.008)	(0.008)
age	0.041***	0.041***	0.039***	0.039***	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Foreign ownership	-0.015	0.043**	-0.037**	-0.023	-0.026
	(0.017)	(0.022)	(0.018)	(0.022)	(0.022)
Processing firm	-0.267***	-0.247***	-0.406***	-0.379***	-0.380***
	(0.022)	(0.028)	(0.025)	(0.030)	(0.030)
SOE	0.567***	0.574***	0.390***	0.429***	0.430***
	(0.051)	(0.078)	(0.063)	(0.092)	(0.092)
θ_{ijlt}*FVAR		0.615***		0.600***	0.606***
		(0.111)		(0.127)	(0.127)
θ_{ijlt}*upstreamness		0.105		0.197**	0.200**
		(0.067)		(0.081)	(0.081)
θ_{ijlt}*lnsize		0.250***		0.280***	0.279***
		(0.036)		(0.044)	(0.044)
θ_{ijlt}*lnK/L		0.384***		0.419***	0.417***
		(0.030)		(0.036)	(0.036)
θ_{ijlt} foreign		-0.409***		-0.145	-0.142
		(0.093)		(0.111)	(0.111)
θ_{ijlt}*processing		-0.359*		-0.375	
		(0.212)		(0.242)	
θ_{ijlt}*SOE		-0.133		-0.199	-0.206
		(0.264)		(0.348)	(0.348)
θ_{ijlt}*FVAR* processing					-2.046***
					(0.590)
θ_{ijlt}* upstreamness*processing					0.345**
					(0.151)
Constant	5.241***	5.234***	-0.411	-0.434	-0.585
	(0.260)	(0.262)	(3.140)	(3.090)	(3.091)
Province-sector FE	NO	NO	YES	YES	YES
Observations	24521	24521	24521	24521	24521
r2	0.114	0.126	0.199	0.212	0.213

Note: Standard errors clustered at the firm level are listed in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. We control the province-, sector- and province-sector specific fixed effects in the last three columns to eliminate the effects of unobservable variables.

We also consider the difference between processing exporters and ordinary exporters in GVCs. As analyzed above, processing exporters decrease more in FVAR than ordinary exporters as they substitute domestic for imported intermediates [Kee and Tang (2016)], which indirectly substitute domestic skills for foreign workforces. To examine the impact, we include a triple interaction among FVAR, skill share, and the dummy for processing firms in the column (5). The coefficient of the triple interaction is significantly negative with the net effect equals to $0.116 + (0.606 - 2.046) \times 0.143 = -0.09 < 0$ given the average skill share in 2004 as 0.143. It suggests the declining FVAR in processing firms has raised the wage inequality of skills, which seems to be contrary to the effect of the overall FVAR on skill premium. One possible explanation is that the imported intermediates of processing trade tend to be skill-biased inputs[Feenstra and Hanson (1996), Ho et al. (2005)]. The substitution of imported intermediate inputs with domestic materials has shifted the demands for foreign skilled workers embodied in imported intermediates to the domestic labor market. As a result, the net effect of FVAR on wage premium is smaller for processing exporters than ordinary firms, which partially offset the net effect of FVAR on skill premium via changing firms' profits according to the fair wage hypothesis. Another possible reason for the coefficient is the existence of unobserved variables correlated with the GVC participation and processing dummy that may lead to biased estimation of the baseline model. We will correct the endogenous problem in the next section. For the ordinary firms, the net effect of FVAR on wages equals to $0.116 + 0.606 \times 0.143 = 0.203 > 0$, which suggests the declining FVAR lower firms' skill wage premium. We also observe a positive coefficient of the triple interaction among upstreamness, skill share, and processing dummy, suggesting the processing firms in the upstream sectors have higher wage premium of skills than those in the downstream sectors. The result is similar to the ordinary firms with a significantly positive coefficient of upstreamness interacted with the skill share.

The regression results using the panel data of 2000-2006 are shown in Table (5). The first two columns demonstrate the estimation of wage determinants without controlling for the fixed effects. As shown in Column (2), the coefficient of FVAR interacted with the measured skill share keeps positive and significant, suggesting rising FVAR leads to higher wage premium within firms. The interaction between skilled-share and upstreamness is insignificant without

Table 5: Baseline Estimation Using 2000-2006 Panel Data

	(1)	(2)	(3)	(4)	(5)
		× Skill share		Skill share	×Skill share×processing
ln unskilled wage	0.878***	0.870***	-0.014	1.013***	1.013***
	(0.016)	(0.019)	(0.024)	(0.016)	(0.016)
skilled share (θ_{ijlt})	0.193***	-1.034***	0.233***	-1.683***	-1.679***
	(0.040)	(0.217)	(0.089)	(0.315)	(0.315)
FVAR	0.017*	-0.011	-0.015	-0.067***	-0.062***
	(0.010)	(0.013)	(0.011)	(0.015)	(0.015)
upstreamness	0.026***	0.018*	-0.062***	0.022	0.022
	(0.008)	(0.011)	(0.013)	(0.015)	(0.015)
ln size	-0.038***	-0.040***	-0.016***	-0.039***	-0.039***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)
ln K/L	-0.027***	-0.051***	-0.099***	-0.094***	-0.094***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
age	0.004*	0.000	0.000	0.001	0.001
	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)
foreign	-0.000	-0.007	0.033***	0.004	0.004
	(0.009)	(0.012)	(0.011)	(0.015)	(0.015)
processing	-0.111***	-0.089***	-0.065***	-0.056***	-0.060***
	(0.009)	(0.012)	(0.010)	(0.013)	(0.012)
SOE	0.268***	0.369***	0.067***	0.119***	0.119***
	(0.021)	(0.028)	(0.018)	(0.027)	(0.027)
θ_{ijlt}*fvar		0.188***		0.114*	0.121*
		(0.058)		(0.065)	(0.065)
θ_{ijlt}*upstreamness		0.050		0.144**	0.143**
		(0.051)		(0.066)	(0.066)
θ_{ijlt}*lnsize		0.034		-0.134***	-0.133***
		(0.024)		(0.028)	(0.028)
θ_{ijlt}*lnK/L		0.194***		0.040	0.040
		(0.027)		(0.036)	(0.036)
θ_{ijlt}age		0.033**		0.001	0.001
		(0.014)		(0.006)	(0.006)
θ_{ijlt}*foreign		0.054		0.270***	0.269***
		(0.065)		(0.084)	(0.084)
θ_{ijlt}*processing		-0.330***		-0.321***	
		(0.105)		(0.117)	
θ_{ijlt}*SOE		-0.469***		-0.344***	-0.344***
		(0.103)		(0.104)	(0.104)
θ_{ijlt}*fvar*processing					-0.622***
					(0.222)
θ_{ijlt}*upstreamness*processing					0.046
					(0.057)
Constant	0.407***	0.615***	10.380***	0.377	1.876***
	(0.122)	(0.144)	(0.271)	(0.307)	(0.226)
Year FE	NO	NO	YES	YES	YES
Firm FE	NO	NO	YES	YES	YES
Province-sector FE	NO	NO	YES	YES	YES
Observations	114697	114697	114697	114697	114697
R^2	0.208	0.204	0.261	0.230	0.230

Note: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. All the regressions use the robust estimator of variance. Column(1) reports the determinants of firms' wage using OLS without fixed effects.Column(2) add the interactions with skill share. Column(3) control the firm-, time- and province-sectoral fixed effects. Column (4) reports the results with interactions and fixed effects. Column (5) examines the net effect of GVC activities on firm wages for processing firms.

controlling for the fixed effects. Large-scale and capital-intensive firms tend to be more skill-intensive in their production and have higher wage premium of skills. We control the year-specific, province-sector specific and firm-specific fixed effects in the last three columns. The interactive coefficient of FVAR is robust in column (4), suggesting the decline of China' overall FVAR narrows firms' wage inequality between skilled and unskilled labor over the sample period. The coefficient of upstreamness interaction is positive and significant, indicating moving to upstream sectors along GVCs increases the wage premium of skills. Column (5) considers the heterogeneity of processing firms in the global value chains over the sample period. The coefficient of triple interaction among FVAR, skill share, and processing firms is significantly negative. It suggests Chinese processing firms have an overturned effect of FVAR on skill wage premium as they switch their demand for skilled labor from imported intermediate inputs to domestic materials. However, the result may be biased due to endogeneity in the model. There is also no significant difference between processing firms and non-processing firms in terms of GVC upgrading on wage premium because the triple interaction among upstreamness, processing dummy and skill share is statistically insignificant.

The baseline results highlight several interesting implications for the impacts GVC activities on the wage premium at the firm level. Firstly, increasing FVAR induces skill-biased production and widens the wage inequality of skills within firms. This result is consistent with the prediction of the theory. Imported intermediates reduce firms' marginal costs and thus leads to higher profits. According to the fair wage hypothesis, more profitable firms tend to pay higher wages to their skilled workers to elicit their efforts, leading to a higher wage inequality of skills of these firms. For Chinese manufacturing firms, on average, the declining FVAR reduces firm-level wage premium and narrows the wage inequality between skilled and unskilled workers. However, this effect is different for processing firms, which decrease their FVAR by replacing imported intermediate inputs with cheaper domestic inputs and induce new demands for the skilled workforce. Besides, moving up to upstream sectors along the GVCs raises the wage premium of skills at the firm level. This result supports the intuition that upgrading positions in the global value chains encourage firms to employ more skilled workers, which widens the wage inequality of skills of these firms.

4.2 Endogeneity

One critical problem of the baseline estimation is endogeneity. Similar to exporting, participating in GVCs incurs sunk costs, e.g., the fixed costs of equipment, new plant, communication, and logistics network. The sunk costs make it impossible for every firm to participate in GVCs. Only firms with higher productivity, larger size, or higher profits are more likely to overcome the sunk costs and engage in GVCs [Baldwin et al. (2014)]. The self-selection of firms into the GVCs may lead to an endogeneity problem in estimating the effect of GVC participation on firm wage. Moreover, the upstreamness of firms in the global value chains may also have a reciprocal relationship with their wage inequality where skill-intensive firms are more likely to upgrade in the global value chains. These unobserved factors could be partly absorbed by the year- and sector-province specific fixed effects. However, if the unobserved variables are time variant, the estimation of the baseline model would be biased without controlling for the endogeneity in the estimation.

We first control for the self-selection effect in GVCs. The decision to participate in GVCs is endogenous to firm within industries due to self-selection effect. Moreover, the extent of engagement in GVCs($FVAR$) is also endogenous due to reciprocal causality if skill-intensive firms participate more in GVCs. The coefficient of $FVAR_{ijlt}$ in the baseline model varies across firms, and its heterogeneity is correlated with covariates within industries. One way to solve the endogenous problem is to replace the endogenous variable $FVAR$ with the Heckman corrected value of FVAR and re-estimate the baseline model with the fitted FVAR [24]. The estimation is implemented by bootstrap to correct standard errors [Wooldridge (2008)].

We use the Heckman two-step selection model to predict the fitted value of FVAR after controlling for the self-selection effect. The GVC firms use imported intermediates for the production of exports. Thus, we define the exporters that have no imports or only import capital and consumption goods as non-GVC firms. The probability of participating in GVCs

[24] Several studies have used the approach to deal with the endogeneity of self-selection effect such as Feenstra et al. (2014) which studied the impacts of credit constraint on exports and Yu (2015) which explored the endogenous processing trade's impacts on productivity

$(E_{ij,t})$ is written as:

$$Prob(Enter_{ijlt} = 1) = \Phi(\alpha_i + \alpha_t + \gamma \boldsymbol{Z}_{ijlt}) \tag{31}$$

where $\boldsymbol{Z}_{ijlt}$ is the vector of exogenous variables affecting the decision of entering the GVCs. We use the one-period lagged $\boldsymbol{X}_{ijl,t}$ (e.g., size, SOE, foreign ownership, capital/labor ratio and unskilled wage) as regressors of $\boldsymbol{Z}_{ijlt}$. ADB (2017) found that older companies are more likely to join in GVCs as they tend to have better infrastructure and performance to overcome the sunk costs of GVCs. We choose the lagged one-period of firm's age as the excluded variable that affects firms' entering decision but has no impact on the extent of participation in GVCs.

The estimation results are shown in Table (6). The 1^{st} step of Heckman two-step selection model shows firms with higher productivity[25] are more likely to participate in GVCs. The capital-intensive firms, state-owned firms, and foreign firms also have a higher possibility of entering the GVCs. Older firms are more likely to enter the GVCs than the young firms. The large-scale firms are less likely to participate in GVCs than small companies, but they tend to have higher FVAR once they entered. The inverse Mills ratio is significant at the significance level of 0.05, rejecting the null hypothesis that there is no endogenous problem in the estimation.

The Heckman two-step selection model predicts the fitted value of FVAR conditional on the unobserved self-selection effect. The outcome equation of FVAR after controlling for the self-selection effect is written as follows:

$$FVAR_{ijlt} = E(FVAR_{ijlt}|Z_{ijlt}) + \varepsilon_{ijlt}, with E(\varepsilon_{ijlt}|Z_{ijlt}) = 0 \tag{32}$$

We reestimate the baseline model with the predicted FVAR following the empirical specification as below:

$$\begin{aligned} ln\bar{w_{ijlt}} = \gamma_0 + \gamma_u lnw^u_{jlt} + \gamma_1 \theta_{ijlt} E(FVAR_{ijlt}|Z_{ijlt}) + \gamma_2 \theta_{ijlt} F\_Upstreamness_{ijlt} \\ + \gamma \boldsymbol{X}_{ijlt} + \sigma_i + \sigma_{jl} + \sigma_t + \varepsilon_{ijlt}\theta_{ijlt} \end{aligned} \tag{33}$$

[25]We use the approach ofOlley and Pakes (1992) to estimate the productivity of firms. We also adopt the methodology of Petrin and Levinsohn (2012) to measure the alternative productivity in the robustness check

Table 6: Heckman Two Step Estimation Results

	1^{st} Step	2^{nd} Step
	$Pr(Enter)$	FVAR
lagged size	-0.009**	0.004***
	(0.004)	(0.001)
lagged K/L	0.090***	0.030***
	(0.003)	(0.001)
lagged SOE	0.147***	-0.022***
	(0.018)	(0.008)
lagged unskilled wage	0.144***	-0.015
	(0.054)	(0.020)
lagged foreign	0.690***	-0.020**
	(0.008)	(0.008)
lagged age	0.001***	
	(0.000)	
lagged TFP by OP	0.515***	
	(0.026)	
Constant	-2.797***	0.554***
	(0.479)	(0.181)
Inverse Mills Ratio		-0.375***
		(0.022)
Year Fixed Effect	Yes	Yes
Sector-Province Fixed Effect	Yes	Yes
Observations	152793	152793

Note: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Column(1) reports the first stage of Heckman two-step regression.$Pr(Enter)$ refers the possibility of engaging in GVCs. Column (2) shows the $2nd$ step of Heckman regression. Both columns control for the time fixed effects and sector-province specific fixed effects.

where $E(FVAR_{ijlt}|\boldsymbol{Z}_{ijlt})$ is the fitted value of FVAR, which absorbs the unobserved self-selection effects. $F\_Upstreamness_{ijlt}$ represents the firms' position in GVCs. It's challenging to find a perfect instrument for the upstreamness. Inspired by Amiti and Davis (2011) and Chen et al. (2017), we use the one-year lag of upstreamness as the instrument of GVC position. The lagged upstreamness is less likely to be affected by the current wage, which eliminates the reverse causality between upstreamness and wage inequality. We report the 2SLS estimation results with fitted FVAR and instrument for upstreamness in Table (7).

Column (1) of Table (7) reports the coefficients of wage determinants with the FVAR fitted value and the instrument of upstreamness. Column (2) demonstrated the regression results jwith the interactions of skill share. The coefficient of fitted FVAR interacted with skill share is significant and positive, which is consistent with the baseline results. The interaction between upstreamness and skill share also keeps significantly positive, suggesting moving up to upstream sectors raises firms' wage premiums with more skilled workforces. The 2SLS estimation results of the other control variables also keep robust to the baseline estimation, which confirms large-scale and capital-intensive firms have wider wage inequality than the other firms. We also consider the heterogeneity of processing firms in determining wage premiums in column (3). The triple interaction among the wage premium, fitted FVAR and processing dummy turns to be insignificant, suggesting the opposite result of processing dummy in the baseline model may be due to endogeneity.

We also test the validity of instruments as shown at the bottom of the table (7). The Kleibergen-Paap rk LM statistic reports the null hypothesis that the excluded instrument is relevant to the endogenous regressors is rejected at the 1% significance level. The Cragg-Donald Wald F statistic and Kleibergen-Paap Wald F statistic also reject the null hypothesis of the weak instrument at the 1% significance level, suggesting the instrument is strong and valid. As the model is just identified, we do not report the over-identification test in the table.

Table 7: 2SLS Estimation with Fitted FVAR, 2000-2006

	(1)	(2)	(3)
		$\times$ Skill share	$\times$ Skill share $\times$processing
ln unskilled wage	-0.096*	-0.106*	-0.106*
	(0.058)	(0.057)	(0.057)
Skill share	-0.135***	-1.586***	-1.584***
	(0.032)	(0.216)	(0.216)
$E(fvar\|Pr(enter))$	2.140***	1.804***	1.809***
	(0.064)	(0.072)	(0.072)
upstreamness	-0.050***	-0.063***	-0.063***
	(0.008)	(0.009)	(0.009)
ln size	0.035***	-0.006	-0.006
	(0.004)	(0.005)	(0.005)
ln K/L	0.029***	-0.017***	-0.017***
	(0.003)	(0.004)	(0.004)
age	0.013***	0.005	0.005
	(0.004)	(0.003)	(0.003)
Foreign ownership	-0.349***	-0.261***	-0.262***
	(0.022)	(0.020)	(0.020)
Processing firm	-0.245***	-0.239***	-0.236***
	(0.013)	(0.015)	(0.015)
SOE	0.650***	0.702***	0.702***
	(0.055)	(0.056)	(0.056)
Skill share$\times$ E(fvar*—Pr(select))		1.972***	1.984***
		(0.394)	(0.394)
Skill share$\times$ upstreamness		0.087**	0.086**
		(0.044)	(0.044)
Skill share$\times$ lnsize		0.304***	0.304***
		(0.022)	(0.022)
skill share $\times$ lnK/L		0.380***	0.380***
		(0.023)	(0.023)
skill share$\times$ age		0.096***	0.096***
		(0.010)	(0.010)
skill share$\times$ foreign		-0.571***	-0.569***
		(0.107)	(0.107)
skill share$\times$ processing		-0.141	
		(0.122)	
skill share $\times$ SOE		-0.898***	-0.898***
		(0.187)	(0.187)
skill share $\times$ upstreamness$\times$ processing			0.057
			(0.091)
skill share$\times$ $E(fvar\|Pr(enter))\times$ processing			-1.060
			(0.805)
Constant	8.253***	8.492***	8.486***
	(0.539)	(0.530)	(0.530)
Kleibergen-Paap rk LM statistic		2.2e+04***	1.2e+04***
Cragg-Donald Wald F statistic		6.0e+05***	1,9e+05***
Kleibergen-Paap Wald F statistic		2.5e+05***	2.9e+05***
Year Fixed Effect	Yes	Yes	Yes
Sector-Province Fixed Effect	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Observations	125734	125734	125734
R2	0.177	0.197	0.197

Note: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$.

4.3 Robust Estimates

4.3.1 Mechanism

In this section, we provide more detailed evidence on how GVC participation or GVC upgrading improves the skill wage premium within firms. As shown in theory, importing intermediate inputs lowers the marginal costs of firms and increases their profits, which enlarges the wage inequality between skilled and unskilled labor. Upgrading in GVCs requires higher productivity of the skilled labor. In order to elicit the efforts of skilled workers, the upgrading firms have to commit a higher wage for the skilled workforces, which increases the wage premium of skills. The fair wage model has tied firms' wage premium with their GVC activities by adjusting profits and productivity. In this section, we examine the mechanism of the model with fair wage hypothesis empirically.

Inspired by Chen et al. (2017), we use the value-added per worker as a proxy for labor productivity and include its interaction with the FVAR and upstreamness in the empirical model. The labor productivity interactive coefficients are expected to be significantly positive, indicating rising FVAR or upgrading in GVCs improve firms' wage premium of skills via increasing productivity. Moreover, we measure the firm's average profit by calculating the profit per worker at the firm level. We also interact the average profit with FVAR and upstreamness. According to the fair wage hypothesis, profitable firms are more likely to pay high wages to the skilled workers. Thus the coefficients of interactions between GVC indicators and average profit are also expected to be positive as using more foreign value-added and upgrading in GVCs increase the skill premium via raising profits. We re-estimate Equation (28) with the new interactions using the 2004 data and 2000-2006 panel data respectively. The results are shown in Table (8).

Column (1) reports the OLS regression using the 2004 cross-sectional data with variables interacted with the labor productivity. The coefficient of interaction between FVAR and labor productivity is significantly positive, suggesting rising FVAR leads to a higher wage premium of skills via increasing the labor productivity. Similarly, the coefficient of upstreamness interacted with log value-added per worker is also significantly positive. It means that upstream firms are more productive than the downstream firms with larger wage premiums. Column (2) explores the impact of GVC activities on wage inequality via adjusting firms' profits. The significantly positive coefficient of FVAR interacted with the log of average profit suggests firms with higher FVAR tend to be more profitable and have larger wage inequality between skilled and unskilled workers. Moreover, we also observe upstream firms have wider wage inequality than the downstream firms with higher average profits. Columns (3) and (4) use the panel data of 2000-2006 to explore the mechanism of GVCs affecting the firm-level skill premium. We still use the fitted value of FVAR from the Heckman two-step estimation to control for the self-selection effect and use the one-year lagged upstreamness as the instrument. Again, the 2SLS estimation results are consistent with the OLS estimates using 2004 data. The coefficients of FVAR and upstreamness interacted with labor productivity are statistically significant and positive. Moreover, the interactions between GVC indicators and average profit, in column (4), are statistically significant and positive. Both results confirm the fact that rising firms' FVAR or upstreamness of GVCs boosts their skill wage premiums via improving profits and hence labor productivity of firms.

4.3.2 Further Robust Estimates

In this section, we include some additional robustness checks in the estimation using both cross-sectional and panel data. Skills are categorized by education in our previous estimation. In this part, we re-estimate the empirical model with the skill share categorized by occupation. The NBS dataset reports seven occupations of employees: Senior engineers, intermediate engineers, primary engineers, senior technicians, technicians, specialized workers and ordinary workers. According to the International Standard Classification of Occupations (ISCO), we define the engineers and technicians as skilled labor. The average skill share of Chinese manufacturing firms by occupation turns to be 0.134 in 2004, which is slightly lower than the skill share categorized by education. The estimation results with alternative skill share are shown in column (1) of Table (9). The coefficient of interaction between FVAR and the alternative skill share by occupation is positive and statistically significant. It indicates firms with higher

Table 8: Robustness Checks with Labor Productivity and Profit

	2004	2004	2000-2006	2000-2006
	×ln value-added per worker	× ln profit per worker	×ln value-added per worker	×ln profit per worker
	(1)	(2)	(3)	(4)
ln unskilled wage	-0.792	-1.487**	-0.118**	-0.120*
	(0.743)	(0.724)	(0.055)	(0.065)
FVAR	-0.202***	0.103***	-0.841***	1.378***
	(0.069)	(0.037)	(0.162)	(0.095)
Upstreamness	-0.253***	-0.087***	-0.148***	-0.079***
	(0.043)	(0.025)	(0.023)	(0.011)
ln value-added per worker	0.033		-0.024	
	(0.051)		(0.027)	
ln profit per worker		0.053		-0.014
		(0.037)		(0.020)
skill share	-0.644***	-0.570***	-0.209***	-0.218***
	(0.060)	(0.071)	(0.030)	(0.033)
ln size	-0.121***	-0.025**	-0.143***	0.003
	(0.021)	(0.013)	(0.011)	(0.006)
age	0.001	0.034***	-0.018***	0.008*
	(0.004)	(0.002)	(0.004)	(0.005)
foreign ownership	0.025	0.043	0.243***	-0.144***
	(0.058)	(0.027)	(0.048)	(0.030)
processing	-0.017	-0.316***	-0.088**	-0.176***
	(0.061)	(0.033)	(0.038)	(0.016)
SOE	0.131	0.495***	0.659***	0.920***
	(0.207)	(0.100)	(0.116)	(0.082)
interaction with fvar	0.112***	0.069***	0.745***	0.011***
	(0.018)	(0.013)	(0.039)	(0.001)
interaction with upstreamness	0.052***	0.027***	0.024***	0.010***
	(0.011)	(0.008)	(0.006)	(0.004)
interaction with lnsize	0.034***	0.017***	0.044***	0.017***
	(0.005)	(0.004)	(0.003)	(0.002)
interaction with age	0.010***	0.004***	0.011***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
interaction with foreign	-0.012	-0.040***	-0.144***	-0.111***
	(0.015)	(0.011)	(0.012)	(0.009)
interaction with processing	-0.118***	-0.089***	-0.049***	-0.044***
	(0.018)	(0.015)	(0.011)	(0.007)
interaction with SOE	0.078	0.007	-0.016	-0.091***
	(0.054)	(0.036)	(0.027)	(0.022)
Constant	24498	20.417***	8.545***	8.613***
	0.210	(6.193)	(0.525)	(0.609)
Kleibergen-Paap rk LM statistic			2.2e+04***	1.8e+04***
Cragg-Donald Wald F statistic			3.0e+05***	2.4e+05***
Kleibergen-Paap Wald F statistic			1.2e+05***	9.5e+04***
Year FE	NO	NO	YES	YES
Firm FE	NO	NO	YES	YES
Province-sector FE	YES	YES	YES	YES
Observations	24498	18485	125779	103159
R^2	0.210	0.219	0.202	0.205

Note: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Column (1)-(2) are OLS regression with robust standard errors clustered at firm-level. Column(3)-(4) report the 2SLS regression results with the Heckman corrected FVAR and one-year lagged upstreamness as instrument. The interacted terms are shown at the top of each column.

FVAR tend to be skilled-intensive and have large skill premium. The coefficient of upstreamness interacted with the alternative skill share is also significantly positive, confirming the fact that upstream firms tend to use more skilled workers and have larger skill wage inequality than downstream firms.

In the Column (2), we estimate the empirical model with alternative variables. As we know, the unskilled wage is measured by the 25^{th} percentile of the average wage by provinces [Chen et al. (2017)]. In this part, we use the rural wage of provinces as an alternative indicator of unskilled wage [26]. We also replace firms' capita-labor intensity with their productivity measured by the Olley and Pakes (1992)'s approach. The new regression results are shown in the second column of the table (9). We observe the coefficients keep robust with alternative indicators. Considering the heterogeneity of processing firms in FVAR, we rule out the processing firms from the sample in column (3) and keep processing firms only in the estimation of column (4). The estimation without processing firms is consistent with the baseline results in column (3) that FVAR is positively associated with skill wage premium and upgrading in GVCs improves skill wage premium with more skill workforces. However, the estimation with processing firms in column (4) shows no significant impacts of GVC activities on skill wage premium in 2004.

We also include the alternative indicators of unskilled wage and the capital-labor ratio in the regression of panel data between 2000 and 2006. The results are shown in the column (1) of Table (10). The panel data is still regressed with 2SLS using the Heckman corrected FVAR and the lagged one-period upstreamness as instruments. The results confirm that rising FVAR increases skill share and enlarges wage inequality between skilled and unskilled labor. It also conforms to our previous finding that upgrading in GVCs expands the skill wage inequality with more skilled workforces. Similarly, we drop the processing firms from the sample and re-estimate the empirical model in the column (2). The coefficients keep significant and robust with ordinary companies. We also regress the model using only processing firms in the sample and report the results in column (3). The results show that the coefficient of FVAR interacted

[26] The wage of rural areas of each province is collected from the China Rural Household Survey Yearbook, which provides annual survey data of Chinese rural population

Table 9: Further Robustness Using 2004 Data

	(1)	(2)	(3)	(4)
	×skill share by occupation	×skill share by occupation with alternative indicators	drop processing	processing only
ln unskilled wage	-0.333	-0.192	0.938**	2.746***
	(0.888)	(0.134)	(0.384)	(0.594)
skill share	-1.027***	-4.455***	-2.002***	-0.869
	(0.342)	(0.669)	(0.394)	(1.907)
FVAR	0.166***	0.155***	0.186***	-0.338***
	(0.026)	(0.025)	(0.032)	(0.075)
upstreamness	-0.092***	-0.125***	-0.071***	-0.122**
	(0.019)	(0.018)	(0.024)	(0.048)
ln size	-0.008	-0.043***	-0.030**	-0.010
	(0.010)	(0.009)	(0.012)	(0.028)
ln K/L	0.038***		0.054***	-0.059***
	(0.007)		(0.009)	(0.018)
ln TFP by OP		2.509***		
		(0.066)		
age	0.044***	0.040***	0.030***	0.028***
	(0.002)	(0.001)	(0.002)	(0.005)
foreign	0.045**	0.121***	-0.083***	0.227***
	(0.020)	(0.020)	(0.024)	(0.061)
processing	-0.378***	-0.277***		
	(0.027)	(0.025)		
SOE	0.262***	0.322***		
	(0.092)	(0.083)	0.475***	0.479
skill share ×FVAR	0.278**	0.190*	(0.097)	(0.352)
	(0.115)	(0.108)	0.443***	1.169
skill share ×upstreamness	0.261***	0.376***	(0.131)	(0.720)
	(0.071)	(0.065)	0.203**	0.108
skill share ×lnsize	0.088**	0.085**	(0.085)	(0.363)
	(0.036)	(0.035)	0.269***	0.355
skill share ×age	-0.021***	-0.016***	(0.045)	(0.216)
	(0.004)	(0.004)	0.373***	0.169
skill share ×lnK/L	0.289***		(0.038)	(0.131)
	(0.035)		0.052***	0.067
skill share ×foreign	-0.542***	-0.618***	(0.009)	(0.044)
	(0.097)	(0.092)	0.001	-0.219
skill share ×processing	-0.041	0.107	(0.114)	(0.501)
	(0.169)	(0.154)		
skill share ×SOE	0.256	0.338	-0.477	-3.535*
	(0.248)	(0.224)	(0.381)	(1.910)
skill share ×lntfpop		2.293***		
		(0.334)		
Constant	10.103	4.303***	-1.126	-14.768***
	(7.784)	(0.924)	(3.122)	(5.142)
Province-sector FE	YES	YES	YES	YES
Observations	24338	24001	20484	3854
R^2	0.205	0.292	0.234	0.172

Note: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table 10: Further Robustness Checks Using 2000-2006 Panel Data

	(1) alternative indicators	(2) drop processing	(3) processing only	(4) Pre-WTO period
ln unskilled wage	0.485***	-0.046	0.697**	-0.019
	(0.089)	(0.059)	(0.339)	(0.116)
skill share	-4.850***	-1.549***	-1.682*	-2.104***
	(0.380)	(0.219)	(0.989)	(0.589)
FVAR	0.990***	1.939***	1.240***	2.013***
	(0.063)	(0.079)	(0.191)	(0.170)
upstreamness	-0.104***	-0.065***	-0.069***	-0.145***
	(0.009)	(0.010)	(0.027)	(0.023)
lnsize	-0.040***	-0.008	0.014	-0.015
	(0.004)	(0.005)	(0.014)	(0.011)
age	0.005	0.004	0.016***	0.001
	(0.003)	(0.003)	(0.003)	(0.002)
foreign ownership	-0.043**	-0.302***	0.077	-0.357***
	(0.020)	(0.022)	(0.047)	(0.043)
processing	-0.130***			-0.267***
	(0.015)			(0.030)
SOE	0.817***	0.700***	0.170	0.702***
	(0.055)	(0.056)	(0.145)	(0.064)
lnK/L		-0.005	0.014	-0.031***
		(0.005)	(0.014)	(0.010)
ln TFP by OP	2.327***			
	(0.186)			
skill share ×FVAR	3.461***	1.681***	3.822**	1.633
	(0.327)	(0.406)	(1.714)	(1.214)
skill share ×upstreamness	0.351***	0.301***	0.154	0.318***
	(0.021)	(0.023)	(0.209)	(0.064)
skill share ×lnsize	0.351***	0.301***	0.187*	0.394***
	(0.021)	(0.023)	(0.104)	(0.112)
skill share ×lnK/L		0.364***	0.293***	0.480***
		(0.024)	(0.104)	(0.073)
skill share ×age	0.092***	0.099***	0.071***	0.120***
	(0.011)	(0.010)	(0.024)	(0.011)
skill share ×foreign	-1.022***	-0.488***	-1.206***	-0.934***
	(0.097)	(0.110)	(0.444)	(0.311)
skill share ×processing	-0.167			-0.297
	(0.121)			(0.275)
skill share ×SOE	-0.964***	-0.900***	2.204**	-1.383***
	(0.178)	(0.186)	(1.022)	(0.366)
skill share ×lnTFP by OP	2.327***			
	(0.186)			
Constant	-0.601	7.928***	2.418	7.441***
	(0.735)	(0.541)	(2.670)	(1.047)
Kleibergen-Paap rk LM statistic	1.3e+04***	1.2e+04***	1815.5***	3567.529***
Cragg-Donald Wald F statistic	2.8e+05***	2.4e+05***	3.3e+04***	5.9e+05***
Kleibergen-Paap Wald F statistic	4.9e+04***	4.1e+04***	1.1e+04***	1.9e+04***
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Province-sector FE	YES	YES	YES	YES
Observations	125554	111119	12411	23352
R^2	0.278	0.210	0.165	0.240

Note: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$.

with skill share of processing firms is significantly positive, suggesting rising FVAR is also associated with higher wage inequality of skills within processing firms. However, we fail to observe a significant impact of GVC upgrading on firm-level wage premium for the processing firms.

Our sample period contains a special event that China entered the WTO on 11 December 2001. Entering WTO has boosted the process of China's trade liberalization and deepened the integration of China into the global economy. China's tariff on manufacturing products was lowered from 35% to 17% in the first five years. Moreover, the foreign producers, which were forbidden to ship directly to Chinese firms, are allowed to export without the trade dealers since 2002. To ensure our results not driven by these factors, we add a placebo test that limits the estimation in the pre-WTO period (2000-2001) in the column (4). The estimation of the sub-sample shows that the coefficients are similar to the baseline results, suggesting entering WTO has no significant effect on our results.

5 Conclusion

Despite the massive literature on trade and wage inequality, there are few studies on the impacts of global value chains(GVCs), featured by vertical specialization and intermediate trade, on wage inequality within firms. In this paper, we provide a theoretical and empirical study on how participating and upgrading in GVCs affect the wage inequality between the skilled and unskilled labor within firms. Inspired by Amiti and Davis (2011) and Chen et al. (2017), we develop an open economy model of heterogeneous firms with intermediate input trade and different types of skill inputs to investigate the wage premium changes associated with firms' GVC activities. Firms participate in the GVCs via importing intermediates for the production of exports. Firms upgrade in the GVCs by moving from downstream sectors to more upstream sectors. In this paper, skilled workers are assumed to have higher bargaining power over wages than unskilled workers according to firms' performance. Profitable firms tend to pay higher wages to skilled labor. The model predicted that importing intermediates increase firms' profits and raises firms' wage inequality between skilled and unskilled workers. All else equal, firms which participate more in the GVCs tend to have higher profits with higher skill wage inequality of skills. Moreover, moving to upstream sectors also enlarges the firm's wage inequality via improving the productivity of skilled workers.

Using detailed China's firm- and transaction- level data during 2000-2006, we measure firms' GVC participation index as the share of foreign value added in exports (FVAR) [Koopman et al. (2014)]. We further estimate firms' upstreamness as the proxy of GVC position. We observe a declining share of foreign value-added content in exports (FVAR) for Chinese manufacturing firms, which is consistent with the estimation of Kee and Tang (2016). We also find a rising trend of upstreamness for Chinese manufacturing firms, suggesting the upgrading of GVC firms in the GVCs. As the firm-level data of skills is only available in 2004, we follow Chen et al. (2017) to develop a Mincer-type econometric approach to estimate the wage premium of firms. The empirical results strongly support the model predictions, which are robust to different robustness checks. We found that rising FVAR leads to an increase in the skill wage premium of firms with more skilled workforces. Similarly, moving to more upstream sectors in GVCs widens firms wage inequality of skills with higher skill share.

To the best our knowledge, this paper is the first one studying the impacts of GVC activities on the wage inequality within firms. Our results have critical policy implications for developing countries. Using imported intermediates improves firms' profits, but it also enlarges the wage inequality between skilled and unskilled workers at the same time. For most developing countries with rising FVAR, this result imposes a dilemma of deepening the integration into GVCs and reducing the wage gaps of skills. Moreover, upgrading in GVCs imposes new requirements for skilled workforces, which require emerging countries to align their human capital development with the GVC upgrading demands. Developing countries should tailor their training program of skills to meet the new demands of participating and upgrading in GVCs.

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