Economic Modelling 99 (2021) 105489

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Does global value chains participation improve skill premium? Mediating role of skill-biased technological change

Huijuan Li [a], Weihong Cai [b,*], Wenxiu Li [c]

[a] School of Management, Guangzhou University, Guangzhou, 510006, PR China
[b] School of Finance, Guangdong University of Foreign Studies, Guangzhou, 510006, PR China
[c] School of Economics & Trade, Guangdong University of Finance, Guangzhou, 510006, PR China

ARTICLE INFO

JEL classification:
D10
D21
D41
E13

Keywords:
Global value chains participation
Skill premium
Skill-biased technological change
Mediation effect
China

ABSTRACT

Since the rising skill premium in developing countries is paradoxical of what Heckscher-Ohlin-Samuelson have predicted, the global value chains (GVCs) participation seems to be a weak explanation for such rise in skill premium, while the skill-biased technological change (SBTC), which is induced by GVCs participation, becomes a dominant driver. Previous studies have treated GVCs participation and SBTC as two separate determinants of the skill premium and lacked an unified model to analyse their interactions. Therefore, we add SBTC into the trade model to strengthen the effect of GVCs participation on skill premium. Using an updated dataset of China's service industry from 1995 to 2014, we examine whether GVCs participation increases skill premium via SBTC channel. We find that SBTC accounts for 75–82% of the total effect across sectors, especially in high-tech intensive sectors. Our empirical results provide many policy implications including strengthening the SBTC mechanism to improve the skill premium.

1. Introduction

As the largest developing economy in the world, China has experienced rapid globalization and achieved unprecedented economic growth. China's rapid economic growth has been marked by growing skilled-unskilled wage inequality. As shown in Fig. 1, China's skilled-unskilled wage gap has increased by an average annual growth rate of 6.3% over the period of 1995–2014. A lot of studies indicate that the widening skilled-unskilled wage inequality observed in both developed and developing countries should be attributed to their participation in GVCs (Caselli, 2014; Chaudhuri et al., 2010; Egger et al., 2013; Li et al., 2016; Shen and Zheng, 2020). For example, Chongvilaivan and Thangavelu (2012) used a translog production function to predict that a 1% rise in GVCs participation leads to a rise in skill premium by nearly 2.5% in Thailand. Mehta and Hasan (2012) found that GVCs participation of services had accounted for 30–66% of the increase in skill premium from 1993 to 2004 in India. However, for the developing countries, which export mostly low-tech intensive products, the rising skill premium as an impact of GVCs participation can't be explained by the Heckscher-Ohlin-Samuelson (HOS) theorem (Stolper and Samuelson, 1941), which predicted trade globalization would lead to increasing skill premium in developed countries whereas decreasing in developing countries according to the principle of comparative advantage. Accordingly, a question then arises: would the impact of GVCs participation on skill premium in developing countries deviate from the principle of comparative advantage?

A convincing explanation for this question is that it is not GVCs participation itself but GVCs participation mediated by skill-biased technological change (SBTC), has resulted in such a rise in skill premium. The argument is that, the Heckscher-Ohlin-Samuelson models are based on extremely restrictive assumptions of the perfect competition and technology fixed in inter-industry trade, yet these assumptions are incompatible with our context of intra-industry trade featuring the monopolistic competition and heterogeneous products. With the rapid growth of intra-industry trade, differences in individual preferences and the increase in scale inherent generate differences in the firms' incentives to invest in R&D, thereby endogenizing the technology that is biased towards skilled labors. Consequently, if introducing endogenous SBTC into the prior trade model, the increased GVCs participation attracts more and more modern firms using high-tech imported intermediates in production. This enhances the rapid development of technological change, which favours skilled over unskilled labor, and hence causes that

* Corresponding author. Room 202, No. 25, Peizheng East Street, Peizheng Road, Yuexiu District, Guangzhou, 510080, Guangdong Province, China.
E-mail addresses: huijuanli@gzhu.edu.cn (H. Li), weihong@oamail.gdufs.edu.cn (W. Cai), lwxasu@126.com (W. Li).

https://doi.org/10.1016/j.econmod.2021.03.008
Received 13 April 2019; Received in revised form 14 February 2021; Accepted 8 March 2021
Available online 15 March 2021

the relative demand for skilled labor rises more quickly than the relative supply, thus driving up the relative wage of skilled labor. In other words, the decreasing skill premium driven by the Heckscher-Ohlin-Samuelson mechanism related to labor supply, is likely to be offset by the SBTC mechanism related to demand for labors, thereby leading to rising skill premium in developing countries, which is a reasonable explanation for the inconsistency between the Heckscher-Ohlin-Samuelson prediction and empirical evidence.

Three lines of models accounting for the above issue can be identified within the trade literature. The first line is the international trade model, which concerns trade globalization and skill premium under the assumption that perfect competition and homothetic preference. In this case, technological change is exogenously given and plays no role in the relationship between trade globalization and skill premium since everyone prefers to consume the same skill intensive products. By contrast, the between-sector labor supply shift is regarded as the channel through which trade globalization affects the skill premium. For example, the Stolper-Samuelson theorem extended the Heckscher-Ohlin model by predicting a positive (negative) relationship between trade globalization and skill premium in developed (developing) countries from the perspective of labor supply. Specifically, for developing countries, which had a comparative advantage in low-tech intensive sectors with abundant unskilled labor supply, openness to trade led to increasing the use of unskilled labor in low-tech export sectors whereas reducing the use of skilled labor in the high-tech import sectors since high-tech intensive products could be imported at a low price, thus decreasing the relative return to skilled labor. However exactly the opposite has been found in developing countries. The main reason of such contradiction is that, in the Heckscher-Ohlin-Samuelson models, international trade affects skill premium only as far as it generates between-sector changes in the relative factor prices according to the between-sector labor supply shifts. Under fixed endowments with skilled and unskilled labors across sectors, the relative supply of skilled labor cannot react to the increased demand for skilled labor that comes along with trade globalization, thus the increased demand for skills leads to the recent widening skilled-unskilled wage gap within sectors. Therefore, the early international trade model, which have focused the attention on the supply-driving hypothesis and neglected the increased skill demand arising from technological change, seem to be a weak explanation for the rising in skill premium, especially in developing countries. This paper helps to fill this void.

Subsequently, an alternative model, which concerns technology diffusion of the intra-industry trade, was developed in the mid-80s (Helpman and Krugman, 1985). The technology diffusion model argued that the trade flow of intermediate goods is a vehicle for technological-knowledge diffusion from developed to developing countries (Acemoglu et al., 2015; Afonso et al., 2016; Goldberg et al., 2009). Feenstra and Hanson (1996) pointed out that 'international industrial transfer' or 'shadow migration' outsourced relative skilled intensive products to developing countries, which may result in the rapid growing up of high-tech sectors and hence the improvement in technological change. The technology diffusion model is then found to be silent about the changes in skill premium, yet it provides an important clue for our study, that is, technological change, which is accompanied by globalization, is likely to have an impact on the skill premium.

Since the 1980s, the applications of information and communication technology (ICT) have provided firms with strong new incentives to extensively use skilled labor in production to improve the product quality for large market size (Acemoglu, 2002). On the other hand, with the world economy becoming more integrated and significant heterogeneous, people prefer to consume differentiated high-tech intensive products due to preference heterogeneity. Meanwhile, the lower birth rate and higher goods prices have boosted the wage of unskilled labor. With the deepening globalization, considering the increased import competition, production cost and non-homothetic preferences, firms are more willing to produce differentiated products with the newly available foreign technology to guarantee their profits. As a result, a sustainable increase of skill-biased technological change benefited from a rapid development of GVCs integration, will create a big rise in the demand for skilled labors, and hence their relative wages. In this case, we would expect to observe a positive relationship between GVCs participation and skill premium from the perspective of labor demand side. Subsequently, the demand-driving hypothesis is supported by the directed technical change model (Acemoglu, 1998), which suggested the skill-biased technological change, shaped by the price effect and market size effect, favoured skilled over unskilled labor by increasing its relative productivity, thereby improving its relative demand and hence wage. Autor et al. (2008) claimed that SBTC was a main driver of skill premium. Notably, the directed technical change model treats SBTC as the only cause of skill premium, without taking into account the trade globalization. However, from the above three lines of models, we can infer the effect of GVCs participation (i.e., the recent phase of trade globalization) on skill premium is indirect, operating through SBTC channel. The intuition behind it is that, the SBTC, which is induced by GVCs participation according to the technology diffusion literature, will lead to a rise in skill premium according to the directed technical change literature, so the SBTC is likely to play a mediating role in the relationship between GVCs participation and skill premium. If this is the case, it helps to provide an alternative underlying mechanism of GVCs participation on skill premium, that is, neither GVCs participation nor SBTC alone but GVCs participation mediated by SBTC is responsible for a relative large increase in skill premium. More specifically, not only does the GVCs participation cause a direct increase in relative wage of skilled labors, it also increases the relative wage indirectly via reinforcement of SBTC channel. For developing countries, the observed rise in the skill premium is because the SBTC mechanism is relatively strong compared to the Heckscher-Ohlin-Samuelson mechanism (Burstein and Vogel, 2017). As shown by Zeira (2007), trade globalization isn't the only cause of the widened skilled-unskilled wage gap. The role of trade globalization has been rather small, whilst adding SBTC to the trade model would increase the effect on the skilled-unskilled wage gap. The similar view is related to Marouan et al. (2016), who claimed that a decrease in the wage premium of skilled labor could only be avoided if there was an increase in the relative technological efficiency. However, there is a lack of empirical analysis on the causal mechanisms among GVCs participation, SBTC and skill premium, so this paper will try to explore this relationship.

Based on the original framework proposed by Acemoglu (2002), we present a simple model with endogenous SBTC, allowing for choosing imported or domestic intermediates. The model features a final product and four factors (skilled labor, unskilled labor, imported intermediate input, and domestic intermediate input). It is shown in the extension that when two intermediates are substitutes, increased GVCs participation makes the firms more efficient by using imported intermediate products and skilled labors in high-tech sectors production, thus amplifying the skill-biased technology mechanism, finally increasing the wage of skilled labors. However, in the opposite case, when two intermediates are complementary, all the intermediate products and labors are absorbed by low-tech sectors, thereby reducing skill-biased technology and hence the wage of skilled labors. We then use this model to guide our empirical analysis using data collected in China's service industry from 1995 to 2014. Drastic trade liberalization in China makes the country a good case for valid empirical investigation of such an issue. The results show that GVCs participation of China's service industry increases skill premium via SBTC channel. Moreover, we find SBTC explains the dominant share of the total effect, and high-tech sectors are likely to have higher mediating effect of SBTC. Our results remain robust to different variable measurements and samples. In particular, our results are related closely to that of Chowdhury (2010), who used a two-country occupational choice model to show that the skilled-unskilled wage gap increased in developing countries purely due to trade globalization whereas the increase in the same in developed countries was because of technology progress. Our conclusion is also very similar to that of Mallick and Sousa

(2017), who showed that technology had favoured skilled labors since the 1980s based on US manufacturing data, thus the difference of productivity led to a rise in the relative demand for skilled labors and hence their relative wage when skilled and unskilled labors were imperfect substitutes. Moreover, Vannoorenberghe (2011) developed an one-sector monopolistic competition framework with heterogeneous firms to address the US trade globalization exerted a bias towards skill demand and hence raises the skill wage premium. These research highlighted SBTC had contributed to the widening wage inequality in developed countries. However, they ignored the mediating role of SBTC in the link between trade globalization and wage inequality, especially in developing countries, which have been largely neglected in the existing literature since developing countries are always characterized by inefficiency and integrated into the low end of GVCs. In fact, the developing countries would benefit from intermediate goods trade through deriving externalities in the form of learning-by-export effect or technology spillover, which will further improve their productivity and competitiveness in the international market (Chen et al., 2018; Mallick and Yang, 2013). Subsequently, Burstein and Vogel (2017) presented a multicountry quantitative trade model to integrate skill-biased productivity mechanism with Heckscher-Ohlin mechanism as the two forces through which trade globalization affected skill premium, and they emphasized the skill-biased productivity mechanism was stronger than the Heckscher-Ohlin mechanism. This conclusion is very similar to ours, but Burstein and Vogel view trade globalization as a decrease in the cost of trade whereas in our study it is regarded as an increase in the imported intermediates relative to domestic intermediates. Goel (2017) presented a novel model to test for the manufacturing industries in the United States, and indicated the imports of intermediate inputs had both direct effect on the wage inequality and the indirect effect via the skill-biased technology. Although Burstein, Vogel and Goel have noticed the mediating role of the SBTC in trade and wage inequality, but their models lack empirical studies to test to what extent the mediating role of SBTC plays in the link, which will be the focus of our study.

This paper is distinguished from the existing literature by the following three aspects. First, as far as the above literature is concerned, GVCs participation and SBTC are treated as two separate determinants of the skilled-unskilled wage gap, making it hard to judge the contribution of each. It would be desirable to have a unified framework that can jointly explain the causal relationship. We argue that the rise in the skilled-unskilled wage gap is not driven by GVCs participation or SBTC alone, but is driven by GVCs participation indirectly via SBTC. Consequently, we incorporate the mediated role of SBTC into the trade model to unveil a novel channel through which GVCs participation affects skill premium. Our model investigates this interrelationship within a comprehensive research framework for the first time, which can be seen as a development and extension of the neoclassical international trade literature. Furthermore, we calibrate the model for China's service industry to assess this underlying mechanism by the generalized forecast error variance decomposition(GFEVD) and the principle of mediation effect, which is one of the first to undertake such an empirical test and will provide a significant supplement to the analysis of this relation. By comparing GFEVD results of full panel vector autoregression(PVAR) model (including mediating variable) and that of benchmark PVAR model (excluding mediating variable), we acknowledge that the effect of GVCs participation on skill premium is mediated by SBTC. This is a new try.

Secondly, this paper enriches the literature that empirically analyzes the service industry which is more technology-intensive and sensitive to GVCs participation (Anwar et al., 2013). The existing studies have explored the relationship between trade globalization and wage inequality in manufacturing sectors (Goldberg and Pavcnik, 2005; Orazio et al., 2004). However, there is still a lack of systematic, in-depth investigation and persuasive empirical research on this relationship in service sectors. For a long time, due to non-storability and simultaneity of production and consumption in the service sectors, most existing studies have assumed that services are not traded. However, with the development of technology and the decrease of transportation cost, the services can be traded by means of cross-border delivery, overseas consumption, commercial existence and natural person flow (Stringfellow et al., 2008). In the context of global economy, China has experienced a massive expansion in trade of services. The service export value has risen from \$11.19 billion in 1993 to \$22.21 billion in 2014, with an average annual growth rate of 15.3%. Therefore, the studies based on China's service industry will provide some insights into how GVCs participation affects skill premium.

Thirdly, this paper uses the index of vertical specialization to measure the degree of GVCs participation. The traditional measures of the degree of GVCs participation are usually based on final goods trade, such as the Grubel-Lloyd (GL) index, which is represented by the proportion of net imports in total imports and exports, and focuses on the import of final goods (See Section 4.4 for details). With the deepening of globalization, the production process is divided into several different production links, which are distributed in different countries, so there will be more and more inter-country intermediate goods trade. Accordingly, if a new measure was to be introduced, it should be significantly different with traditional indicators that only consider gross export value of final goods trade. The index of vertical specialization, proposed by Hummels et al. (2001), is represented by the proportion of imported intermediate inputs in total exports, multiplied by imported consumption coefficient matrix, and it can separate foreign and domestic value-added components in the gross export values based on World Input-Output Database (WIOD) to avoid double-accounting (Basu and Guariglia, 2007), so the index of vertical specialization is considered as a suitable measure for the degree of GVCs participation.

In order to isolate the mechanism of GVCs participation on skill premium via SBTC in a simple and transparent way, we abstract from many other mechanisms, such as labor market mechanism, which are mainly used to discuss the assortative matching effect, suggesting skilled labors will be more valuable to exporters, which are more productive, and have higher profits or rents for them to employ labors with higher abilities. Consequently, better labors will be matched to better exporters, and this assortative matching will increase wage inequality within industries. However, the assortative matching effect is most likely to happen in high-tech intensive sectors (Avalos and Savvides, 2006; Parteka and Wolszczak-Derlacz, 2015; Borrs and Knauth, 2021). For developing countries, which have more low-tech intensive sectors, lower profits or rents, and less unionised labour markets, the scope of the labor market hypothesis in explaining the observed rise in the skill premium seems rather limited. Surprisingly, Avalos and Savvides (2006) found the relative labor supply was the most important factor in explaining the wage inequality whereas technological change had a smaller weight. Their conclusions are contrary to ours. There are two reasons for it. First, the researchers use different indices to measure the trade globalization and technological change. The alternative measures may generate different insights. Second, they restrict their analysis to manufacturing industries in inter-industry trade pattern whereas our study focus on service industries in intra-industry trade pattern, which represent the new trends of industry and trade. In fact, the SBTC is regarded as the cause of the shift in labor market since routine tasks are replacing by machines thereby causing polarization of labor market. Moreover, empirical results of this paper support the dominant mediating effect of SBTC. Therefore, we only consider the mechanism of GVCs participation on skill premium via SBTC, holding all other exogenous variables fixed, and incorporating the relative supply of skilled labor as control variable.

The rest of the paper is structured as follows. Section 2 presents a simple theoretical model. Section 3 contains the methodology, variables and data description. Section 4 discusses the empirical results. Section 5 is our conclusions.

2. Theoretical analysis

2.1. Production

Following Acemoglu (2002), we set up a simple model by introducing trade of intermediate products. Consumers determine the demand for final products in terms of the maximization of utility. The final products are assumed to be produced by intermediate products of high-tech and low-tech intensive sectors. The intermediate products of high-tech intensive sectors are produced by skilled labors and imported intermediate inputs. The intermediate products of low-tech intensive sectors are produced by unskilled labors and domestic intermediate inputs. There are a continuum of firms. Each firm produces one unique variety of intermediate input, suggesting each variety is supplied only by the lowest-cost firm, which uses the state-of-the-art quality rung to produce. It is assumed that, if the firm produces a new design of intermediates, it obtains monopoly rights for one period and all these rights are secured regarding innovation improvements. As a result, the firm, which produces one variety of intermediate product, won't share its market, and (fully) appropriate the monopoly rent from selling intermediates to guarantee its profits. Therefore, each firm may become a technology monopolist. Moreover, the joining of opportunism and inefficiency with transaction-specific investments is the leading factor in explaining decisions to monopoly market structures of intermediate inputs. Meanwhile, imported intermediates are assumed to be more technology-intensive than domestic intermediates because of scale economy and international competition. The increased GVCs participation in this model refers to the increase in the quantity of varieties of the high-tech imported intermediates relative to the low-tech domestic intermediates.

The production function of final product is specified as follows:

$$Y = \left[\lambda (Y_H)^{\frac{\sigma-1}{\sigma}} + \left(1-\lambda\right)(Y_L)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where Y denotes aggregate output of final products. Y_H and Y_L denote output of high-tech and low-tech intensive intermediate products, respectively. λ is a distribution parameter which determines how important high-tech intensive intermediate product is in aggregate production. Thus Eq. (1) implies aggregate output of final products Y, is produced by two intermediate products, Y_H and Y_L. σ is the substitution elasticity of the high-tech and low-tech intermediate products.

The production functions for each intermediate product are given by:

$$Y_H = \frac{1}{1-\varepsilon} A_H H^{\varepsilon} \int_0^{I_H} x_H(j)^{1-\varepsilon} dj \tag{2}$$

$$Y_L = \frac{1}{1-\varepsilon} A_L L^{\varepsilon} \int_0^{I_L} x_L(j)^{1-\varepsilon} dj \tag{3}$$

where a continuum of the j-th imported intermediate inputs in the high-tech intensive sector is indexed by $j \in (0, I_H)$, and that in the low-tech intensive sector is indexed by $j \in (0, I_L)$. Hence we assume the range of imported intermediates relative to domestic intermediates, $\frac{I_H}{I_L}$, will determine the degree of GVCs participation, which suggests the more imported intermediates, the higher degree of GVCs participation (Hummels et al., 2001; Shen and Zheng, 2020). H and L denote skilled and unskilled labors, respectively.ε is the output elasticity of labor and $\varepsilon \in (0,1)$. A_H and A_L denote two separate technology terms of skilled and unskilled labors, respectively. There are two types of technological change: 'extensive' and 'intensive' technological change. The type of technological change, which affects the relative productivity of both types of labors while given productivity of intermediates unchanged (i.e., a rise in a $\frac{A_H}{A_L}$), is referred to as extensive skill-biased technological change (extensive SBTC). The other type of technological change, which affects the productivity of one type of labors without necessarily affecting the productivity of the other (i.e., a rise in A_H or A_L), has been referred to as intensive skill-biased technological change (intensive SBTC). The skill-biased technological change in this paper is extensive SBTC (i.e., an increase in A_H relative to A_L) (Avalos and Savvides, 2006). $x_H(j)$ and $x_L(j)$ denote the j-th intermediate inputs of high-tech and low-tech intensive sectors, respectively.

2.2. Producer equilibrium

P_H and P_L denote the prices of high-tech and low-tech intensive products, respectively. The prices of the products are assumed to be the numeraire 1. Minimizing the cost function, $P_H Y_H + P_L Y_L$, subjecting to Eq. (1) will yield the optimal prices of high-tech and low-tech intensive products:

$$P_H = \lambda \left(\frac{Y}{Y_H}\right)^{\frac{1}{\sigma}},\ P_L = (1-\lambda)\left(\frac{Y}{Y_L}\right)^{\frac{1}{\sigma}} \tag{4}$$

$$\left[\lambda^{\sigma} P_H^{1-\sigma} + (1-\lambda)^{\sigma} P_L^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = 1 \tag{5}$$

Assuming that the firms will want to get the maximum profits:

$$\max P_H Y_H - W_H H - \int_0^{I_H} \chi_H(j) x_H(j) dj \tag{6}$$

$$\max P_L Y_L - W_L L - \int_0^{I_L} \chi_L(j) x_L(j) dj \tag{7}$$

where χ_H and χ_L denote the prices of imported and domestic intermediate inputs, respectively.

The first-order conditions for Eqs. (6) and (7) give the following intermediate input demand:

$$x_H(j) = \left(\frac{P_H}{\chi_H}\right)^{\frac{1}{\varepsilon}} H,\ x_L(j) = \left(\frac{P_L}{\chi_L}\right)^{\frac{1}{\varepsilon}} L \tag{8}$$

Next, the first-order conditions to H and L give the equilibrium wage rate for skilled and unskilled labors as:

$$\begin{aligned} W_H &= \tfrac{\varepsilon}{1-\varepsilon} P_H H^{\varepsilon-1} \textstyle\int_0^{I_H} \left[x_H(j)\right]^{1-\varepsilon} dj, \\ W_L &= \tfrac{\varepsilon}{1-\varepsilon} P_L L^{\varepsilon-1} \textstyle\int_0^{I_L} \left[x_L(j)\right]^{1-\varepsilon} dj \end{aligned} \tag{9}$$

Assuming the marginal cost of each intermediate input firm is ψ. Therefore, the profit of the firm supplying domestic intermediate input j can be written as $\pi_L(j) = [\chi_L(j) - \psi] x_L(j)$. The demand curve for intermediate input is iso-elastic (Acemoglu, 2002), so the profit-maximizing price will be a constant markup over marginal cost: $\chi_L(j) = \frac{\psi}{1-\varepsilon}$. To simplify the algebra, we normalize the marginal cost to $\psi \equiv 1-\varepsilon$, thus $\chi_L(j) = \chi_H(j) = 1$.

From Eq. (8), profits of the firms supplying intermediates are as follows:

$$\pi_H = \varepsilon P_H^{\frac{1}{\varepsilon}} H,\ \pi_L = \varepsilon P_L^{\frac{1}{\varepsilon}} L \tag{10}$$

The net present discounted values are expressed as follows: $\pi_H = rV_H - \dot{V}_H$ and $\pi_L = rV_L - \dot{V}_L$. r is market interest rate. V_H and V_L denote present discounted values of imported and domestic intermediates, respectively. The $\dot{V}$ term considers the fact that future profits may not equal current profits due to changing prices. π_H and π_L denote profits of two intermediates, respectively. Assuming steady state, let $\dot{V}_H$ and $\dot{V}_L$ terms are 0 (i.e., profits and the interest rate are constant in a steady state) (Acemoglu, 2002), thus $\pi_H = rV_H$ and $\pi_L = rV_L$, hence we get:

$$\frac{V_H}{V_L}=\frac{\pi_H/r}{\pi_L/r}=\frac{\varepsilon P_H^{\frac{1}{\varepsilon}}H}{\varepsilon P_L^{\frac{1}{\varepsilon}}L}=\left(\frac{P_H}{P_L}\right)^{\frac{1}{\varepsilon}}\left(\frac{H}{L}\right) \tag{11}$$

From Eqs. (8) and (9), we can reexpress Eq. (11) as:

$$\frac{V_H}{V_L}=\frac{[(1-\varepsilon)W_HH]/(rI_H)}{[(1-\varepsilon)W_LL]/(rI_L)}=\left(\frac{W_H}{W_L}\right)\left(\frac{H}{L}\right)\left(\frac{I_H}{I_L}\right)^{-1} \tag{12}$$

Substituting Eq. (8) into Eqs. (2) and (3) yield: $Y_H=\frac{1}{1-\varepsilon}P_H^{\frac{1-\varepsilon}{\varepsilon}}I_HHA_H$, $Y_L=\frac{1}{1-\varepsilon}P_L^{\frac{1-\varepsilon}{\varepsilon}}I_LLA_L$.

According to market-clearing condition, the relative price must satisfy:

$$\begin{aligned}\frac{P_H}{P_L}&=\left(\frac{\lambda}{1-\lambda}\right)\left(\frac{Y_H}{Y_L}\right)^{-\frac{1}{\sigma}}=\left(\frac{\lambda}{1-\lambda}\right)\left(\frac{\frac{1}{1-\varepsilon}P_H^{\frac{1-\varepsilon}{\varepsilon}}I_HHA_H}{\frac{1}{1-\varepsilon}P_L^{\frac{1-\varepsilon}{\varepsilon}}I_LLA_L}\right)^{\frac{-1}{\sigma}}\\&=\left(\frac{\lambda}{1-\lambda}\right)^{\frac{\sigma\varepsilon}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{I_H}{I_L}\right)^{-\frac{\varepsilon}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{H}{L}\right)^{-\frac{\varepsilon}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{A_H}{A_L}\right)^{-\frac{\varepsilon}{\sigma\varepsilon-\varepsilon+1}}\end{aligned} \tag{13}$$

From Eqs. (8) and (9), we derive: $\frac{W_H}{W_L}=\left(\frac{P_H}{P_L}\right)^{\frac{1}{\varepsilon}}\left(\frac{I_H}{I_L}\right)$. Substituting it into Eq. (12), we get:

$$\frac{V_H}{V_L}=\left(\frac{\lambda}{1-\lambda}\right)^{\frac{\sigma}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{I_H}{I_L}\right)^{-\frac{1}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{H}{L}\right)^{\frac{\sigma\varepsilon-\varepsilon}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{A_H}{A_L}\right)^{-\frac{1}{\sigma\varepsilon-\varepsilon+1}} \tag{14}$$

The skilled and unskilled labors are paid according to their marginal product values under equilibrium. Then, following market-clearing condition, we derive: $\frac{W_H}{W_L}=\frac{P_HA_H}{P_LA_L}$. Substituting it into Eq. (12), we get: $\frac{V_H}{V_L}=\left(\frac{P_H}{P_L}\right)\left(\frac{A_H}{A_L}\right)\left(\frac{H}{L}\right)\left(\frac{I_H}{I_L}\right)^{-1}$. From Eqs. (13) and (14), we derive: $\frac{V_H}{V_L}=\left(\frac{P_H}{P_L}\right)\left(\frac{A_H}{A_L}\right)\left(\frac{H}{L}\right)\left(\frac{I_H}{I_L}\right)^{-1}=\left(\frac{\lambda}{1-\lambda}\right)^{\frac{\sigma}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{I_H}{I_L}\right)^{-\frac{1}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{H}{L}\right)^{\frac{\sigma\varepsilon-\varepsilon}{\sigma\varepsilon-\varepsilon+1}}\left(\frac{A_H}{A_L}\right)^{-\frac{1}{\sigma\varepsilon-\varepsilon+1}}$, so the relative technical levels of skilled and unskilled labors can be obtained as follows:

$$A=\frac{A_H}{A_L}=\left(\frac{\lambda}{1-\lambda}\right)^{\frac{\sigma(1-\varepsilon)}{\sigma\varepsilon-2\varepsilon+2}}\left(\frac{I_H}{I_L}\right)^{\frac{\sigma\varepsilon}{\sigma\varepsilon-2\varepsilon+2}}\left(\frac{H}{L}\right)^{\frac{\varepsilon-1}{\sigma\varepsilon-2\varepsilon+2}} \tag{15}$$

Notice that the output elasticity of labor $\varepsilon\in(0,1)$. Accordingly, when $\sigma>0$, we derive $\frac{\sigma\varepsilon}{\sigma\varepsilon-2\varepsilon+2}>0$, so Eq. (15) implies given substitution elasticity of two intermediate products ($\sigma>0$), an increase in the degree of GVCs participation ($\frac{I_H}{I_L}$) will lead to an increase in skill-biased technological change ($\frac{A_H}{A_L}$).

2.3. Research sectors

The R&D sectors devote a total quantity of R&D investment Z, including Z_H in high-tech intensive sector and Z_L in low-tech intensive sector, to the production of new patented product designs, which lead to an increase in technological change A. The technological change in high-tech intensive sector relies only on domestic technology and R&D investment, while the technological change in low-tech intensive sector is affected not only by investment in domestic R&D but also by the spillover of technology arising from the imported intermediate products in high-tech intensive sectors. Therefore, the evolution of the technology gap across sectors depends on the relative rate of R&D investment in the high-tech intensive sector and technology diffusion towards the low-tech intensive sector. The evolution of the technological change in high-tech and low-tech intensive sectors can be specified as follows:

$$A_H=Z_HA_H,\ A_L=Z_LA_H^{\varphi}A_L^{1-\varphi} \tag{16}$$

where A_H and A_L denote the growth of the technological change in the two sectors, respectively. Z_H and Z_L denote the R&D investment in the two sectors, respectively. Then we can derive: $\frac{\partial LnA_H}{\partial LnA_L}=\vartheta\mu^{-\varphi}$, where $\mu=\frac{A_H}{A_L}$, $\vartheta=\frac{Z_H}{Z_L}$. φ governs the dispersion of the technology spillover from high-tech intensive sector to low-tech intensive sector.

2.4. Skill premium equilibrium

On the other hand, the first-order derivations of output to the skilled and unskilled labors yield the skilled and unskilled wages under the condition of competition, where there are an array of substitutable labors and each labor faces the competition of other labors.

From Eqs. (1)–(3), the wages of skilled and unskilled labors are as follows:

$$W_H=\frac{\partial Y(L,H)}{\partial H}=\lambda\left(\frac{\eta-1}{\eta}\right)A_H^{\frac{\eta-1}{\eta}}H^{-\frac{1}{\eta}} \tag{17}$$

$$W_L=\frac{\partial Y(L,H)}{\partial L}=(1-\lambda)\left(\frac{\eta-1}{\eta}\right)A_L^{\frac{\eta-1}{\eta}}L^{-\frac{1}{\eta}} \tag{18}$$

where W_H and W_L are the wages of skilled and unskilled labors, respectively. $\eta=\sigma\varepsilon-\varepsilon+1$ is the elasticity of substitution between the skilled and unskilled labors (Acemoglu, 2002).

From Eqs. (17) and (18), we can derive:

$$W=\frac{W_H}{W_L}=\frac{\lambda\left(\frac{\eta-1}{\eta}\right)A_H^{\frac{\eta-1}{\eta}}H^{-\frac{1}{\eta}}}{(1-\lambda)\left(\frac{\eta-1}{\eta}\right)A_L^{\frac{\eta-1}{\eta}}L^{-\frac{1}{\eta}}}=\left(\frac{\lambda}{1-\lambda}\right)\left(\frac{A_H}{A_L}\right)^{\frac{\eta-1}{\eta}}\left(\frac{H}{L}\right)^{-\left(\frac{1}{\eta}\right)} \tag{19}$$

Taking logarithm on both sides of Eq. (19), we can derive:

$$\frac{\partial Ln(W_H/W_L)}{\partial Ln(A_H/A_L)}=\frac{\eta-1}{\eta} \tag{20}$$

Notice that the elasticity of substitution between the skilled-unskilled labors $\eta=\sigma\varepsilon-\varepsilon+1$. If two intermediates are substitutes ($\sigma>1$) (skilled and unskilled labors are substitutes $\eta>1$), we derive $\phi=\frac{\eta-1}{\eta}>0$, so Eq. (20) implies the improvement in A_H, relative to A_L across sectors, leads to a rise in the relative productivity of the skilled labors and subsequently their wages. In the case of $\sigma<1(\eta<1)$, the relationship is reversed. When $\phi=0$, the technological change is Hicks-neutral. When $\phi>0$, the technological change is skill-biased.

Substituting Eq. (15) into Eq. (19), we can get:

$$W=\frac{W_H}{W_L}=\left(\frac{\lambda}{1-\lambda}\right)^{\frac{\eta^2+(1-\varepsilon)[\sigma(\eta-1)+\eta]}{\eta(\eta+1-\varepsilon)}}\left(\frac{I_H}{I_L}\right)^{\frac{\sigma\varepsilon(\eta-1)}{\eta(\eta+1-\varepsilon)}}\left(\frac{H}{L}\right)^{\frac{\varepsilon-2}{\eta+1-\varepsilon}} \tag{21}$$

Let us recall that $\eta=\sigma\varepsilon-\varepsilon+1$ and $\varepsilon\in(0,1)$, thus it is obvious that when $\sigma>1$, we get η>1, hence $\frac{\sigma\varepsilon(\eta-1)}{\eta(\eta+1-\varepsilon)}>0$, so Eq. (21) indicates there is the positive impact of GVCs participation, $\frac{I_H}{I_L}$, on skill premium, $\frac{W_H}{W_L}$, under the condition of the substitution elasticity of two intermediates ($\sigma>1$).

The implication of combination of Eqs. (15), (19) and (21) is that given two substitutable intermediates $\sigma>1$, an increase in the degree of GVCs participation, $\frac{I_H}{I_L}$, will lead to an increase in skill-biased technological change, $\frac{A_H}{A_L}$ (seen in Eq. (15)), hence an increase in skill premium, $\frac{W_H}{W_L}$ (seen in Eq. (19)). In contrast, the relationship is reversed when $\sigma<0$. Therefore, skill-biased technological change $\frac{A_H}{A_L}$ is a mediating variable in the link between GVCs participation $\frac{I_H}{I_L}$ and skill premium $\frac{W_H}{W_L}$ (seen in Eq. (21)).

Proposition 1. *GVCs participation increases skill premium through skill-biased technological change channel.*

3. Methodology, variables and data description

3.1. Methodology

We use a PVAR model to consider the indirect contribution of GVCs participation shocks to skill premium via SBTC since PVAR model can separate the degree of impact of one endogenous variable on other endogenous variables by generalized forecast error variance decomposition analysis. The PVAR model is as follows:

$$Z_{it} = A(L)Z_{i(t-1)} + BX_{it} + \mu_i + \varepsilon_{it} \tag{22}$$

where $Z_{it} = [\Delta LnVS_{it}, \Delta LnTFP_{it}, \Delta Ln(W_H/W_L)_{it}]^{\mathrm{T}}$ $\cdot X_{it} = [\Delta Ln\widehat{O}_{it}, \Delta LnFDI_{it}, \Delta Ln(H/L)_{it}, \Delta LnSCALE_{it}]^{\mathrm{T}}$ $\cdot \mu_{it} = [\mu_i^{\Delta LnVS}, \mu_i^{\Delta LnTFP}, \mu_i^{\Delta Ln(W_H/W_L)}]^{\mathrm{T}} \cdot \varepsilon_{it} = [\varepsilon_{it}^{\Delta LnVS}, \varepsilon_{it}^{\Delta LnTFP}, \varepsilon_{it}^{\Delta Ln(W_H/W_L)}]^{\mathrm{T}}$. $A(L)$ is the lag operator. $(W_H/W_L)_{it}$ denotes the wage ratio of skilled-unskilled labors of sector i. TFP_{it} denotes the SBTC of sector i. VS_{it} denotes the extent to which sector i is embedded in GVCs. FDI_{it} is foreign direct investment. O_{it} is trade openness. $SCALE_{it}$ is enterprise number. $(H/L)_{it}$ is the relative skilled labor supply. ***i*** represents industry, and ***t*** represents year.

Endogeneity mainly includes omitted variables bias and reverse causality. We solve the endogeneity of omitted variables by including to the estimation equation additional control variables. The control variables in this paper are usually treated as exogenous variables, which are independent of the error term. However, it is possible that trade openness as one of the control variables and GVCs participation as the independent variable are determined jointly since both of them are connected to exports and imports. For example, a rise in the degree of trade openness results in an increase in the trade volume of imported intermediate products, which leads to higher GVCs participation. Conversely, the increased GVCs participation will cut down the trade cost of export thereby promoting trade openness. In order to correct this endogeneity,[1] we use the one-period lagged value of the growth of trade openness $\Delta LnO_{i,t-1}$ as an instrument for $\Delta LnO_{i,t}$, and estimate the predicted values $\Delta Ln\widehat{O}_{i,t}$ by regressing $\Delta LnO_{i,t}$ on $\Delta LnO_{i,t-1}$, then replace $\Delta LnO_{i,t}$ with its predicted values $\Delta Ln\widehat{O}_{i,t}$ in the PVAR model. On the other hand, regarding the endogeneity of reverse causality, GVCs participation could be endogenous in the sense that skill premium could have a reverse effect on GVCs participation. For example, skill premium will increase the demand and use of high-tech intermediate inputs, thus leading to a rise in the degree of GVCs participation. To solve the endogenous problems of reverse causality, we estimate the PVAR model by the two-step GMM, which is an instrumental variable method based on dynamic panel data. In this paper, we use the two-period or three-period lagged dependent variables as the instruments since lagged dependent variables are independent of the time difference of residual term.

As the results shown in Table 3, the Hansen test is used to test for the exogeneity of the control variables and the validity of over-identification in the estimations. The null hypothesis can't be rejected at the 10% significance level, which suggests the control variables in the estimations are exogenous and uncorrelated to the error term. Moreover, we find that including the control variables does not change the significance and coefficient size of the estimation results.

3.2. Variables

(1) Measurement of the degree of GVCs participation

The level of vertical specialization proposed by Hummels et al. (2001) is used to measure the degree of GVCs participation. The formula is as follows:

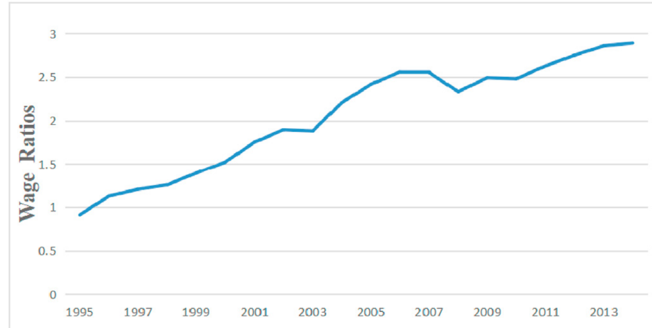

Fig. 1. The trend of wage ratio of skilled and unskilled labors. ***Notes***: The data are derived from *China Labor Statistical Yearbook*.

$$VS_j = V_j \Big/ X_j = \mu A^M \left(I - A^D\right)^{-1} X \Big/ X_j \tag{23}$$

where VS_j denotes vertical specialization index of a country's j industry. V_j denotes vertical specialized trade volume of a country's j industry. X_j denotes the total export volume of a country's j industry. μ represents a $1 \times$ N vector of 1's. N is the number of industries. A^M is the N $\times$ N import coefficient matrix. A^D represents the N $\times$ N domestic consumption matrix. X is the N $\times$ 1 vector of exports. $A^D + A^M = \tilde{A}$. $\tilde{A}$ is the direct consumption coefficient matrix.

(2) Measurement of skill-biased technological change

The measurement of skill-biased technological change (SBTC) is very difficult. Most of the studies use total factor productivity (TFP) as a proxy for SBTC. For example, Mallick and Sousa (2017) assumed TFP as a vector that includes two types of technology, hence uncovered a potentially 'skill-biased' characteristic of TFP by characterizing the link between TFP and the substitution degree of skilled and unskilled labor using US manufacturing industry data, thus found that the TFP in US was highly skill biased. Caron et al. (2020) provided a novel piece of evidence that supports the notion that TFP is skill biased using the GTAP5 dataset for the 1995–2010 period. The other measure index of SBTC in some studies is information technology, represented by computer penetration rate (Autor and Dorn, 2013). However, China lacks statistical data on this index at the industrial level. For example, the latest data of computer penetration rate published in the China Industry Business Performance Database are available before 2004. However, China's information technology has undergone great change in the past 10 years, so the data of information technology are out of date. Therefore, compared to other measure index, using the TFP as a proxy for SBTC is a relatively better choice.

Following Mallick and Sousa (2017), we use total factor productivity (TFP) to measure SBTC. TFP is estimated by Bayesian semi-parametric stochastic frontier approach in this paper (See Appendix A for details). According to Tsionas and Mallick (2019) and Feng et al. (2019), the kernel-based semi-parametric stochastic frontier model is specified as:

$$y_{it} = \beta_0 + \sum_{p=1}^{k} \beta_p x_{p,it} + \frac{1}{2}\sum_{p=1}^{k}\sum_{q=1}^{k} \beta_{pq} x_{p,it} x_{q,it} + \nu_{it} - u_{it} \tag{24}$$

where $y_{it}, x_{p,it}, x_{q,it}$ denote log of output, input p and input q, respectively. ν_{it} is noise component and is assumed to be independently and identically distributed as:

$$\nu_{it} \sim iidN\left(0, \sigma^2\right) \tag{25}$$

[1] There are uncontrollable variables that affect the independent variable, so GVCs participation, which appears as an independent variable in our model, is endogenous variable.

Table 1
Summary statistics on key indicators.

Variable		cons	whol	tran	acco	fina	esta	leas	publ	educ	heal	othe	serv
Full sample													
TFP	Mean	2.100	2.814	2.074	2.453	5.196	0.493	2.782	3.076	2.726	2.703	0.787	2.473
	S.D.	0.171	0.699	0.272	0.215	1.933	0.106	0.322	0.710	0.603	0.350	0.065	1.361
VS	Mean	0.102	0.427	0.194	0.214	0.554	0.499	0.162	0.391	0.274	0.053	0.168	0.276
	S.D.	0.022	0.203	0.044	0.038	0.184	0.076	0.035	0.114	0.079	0.029	0.041	0.156
W_H/W_L	Mean	1.586	2.221	2.087	1.647	1.666	1.545	1.591	1.600	1.559	1.564	1.615	1.572
	S.D.	0.141	0.287	0.633	0.216	0.206	0.254	0.225	0.231	0.224	0.212	0.238	0.316
O	Mean	0.093	1.652	1.393	0.289	0.022	0.005	0.791	0.016	0.013	0.006	0.466	0.431
	S.D.	0.048	0.282	0.368	0.039	0.008	0.004	0.328	0.006	0.004	0.002	0.194	0.237
FDI	Mean	0.028	0.056	0.061	0.067	0.229	0.709	0.240	0.029	0.006	0.020	0.177	0.147
	S.D.	0.027	0.018	0.039	0.030	0.346	0.236	0.098	0.020	0.006	0.019	0.139	0.236
H/L	Mean	0.026	0.092	0.143	0.021	0.188	0.096	0.237	0.177	0.369	0.184	0.136	0.152
	S.D.	0.007	0.040	0.038	0.009	0.076	0.016	0.060	0.049	0.145	0.045	0.032	0.089
SCALE	Mean	2.500	0.241	1.538	0.832	2.881	0.717	0.437	0.070	0.166	0.309	0.407	0.918
	S.D.	0.663	0.032	0.177	0.239	2.191	0.218	0.091	0.027	0.045	0.146	0.108	0.509
GL	Mean	0.160	0.081	0.168	0.076	0.055	0.039	0.153	0.083	0.085	0.165	0.119	0.108
	S.D.	0.034	0.012	0.054	0.017	0.009	0.009	0.029	0.013	0.018	0.025	0.021	0.051
Obs							209						
Pre-WTO period													
TFP	Mean	1.952	2.265	1.833	2.258	3.730	0.405	2.511	2.470	2.230	2.398	0.743	2.072
	S.D.	0.030	0.186	0.124	0.094	0.372	0.028	0.093	0.250	0.192	0.132	0.015	0.870
VS	Mean	0.085	0.241	0.176	0.196	0.383	0.483	0.140	0.300	0.203	0.027	0.132	0.215
	S.D.	0.008	0.040	0.048	0.047	0.041	0.114	0.024	0.051	0.015	0.003	0.016	0.124
W_H/W_L	Mean	1.434	1.946	1.428	1.423	1.410	1.330	1.357	1.362	1.330	1.344	1.368	1.430
	S.D.	0.046	0.150	0.320	0.107	0.074	0.111	0.117	0.103	0.085	0.095	0.104	0.136
O	Mean	0.048	1.591	1.069	0.277	0.016	0.005	0.504	0.012	0.015	0.006	0.572	0.374
	S.D.	0.018	0.174	0.171	0.021	0.004	0.003	0.218	0.006	0.005	0.003	0.147	0.218
FDI	Mean	0.040	0.051	0.071	0.074	0.017	0.721	0.267	0.010	0.009	0.030	0.232	0.138
	S.D.	0.029	0.019	0.047	0.029	0.017	0.236	0.077	0.005	0.005	0.015	0.120	0.098
H/L	Mean	0.020	0.060	0.114	0.013	0.123	0.082	0.183	0.134	0.251	0.150	0.108	0.113
	S.D.	0.003	0.006	0.011	0.002	0.010	0.009	0.021	0.014	0.022	0.014	0.011	0.068
SCALE	Mean	1.893	0.218	1.497	0.611	1.053	0.893	0.451	0.047	0.139	0.211	0.327	0.667
	S.D.	0.348	0.015	0.247	0.041	0.160	0.205	0.130	0.006	0.016	0.047	0.042	0.597
GL	Mean	0.130	0.075	0.117	0.059	0.050	0.033	0.129	0.073	0.068	0.144	0.102	0.089
	S.D.	0.019	0.008	0.015	0.006	0.005	0.005	0.012	0.007	0.005	0.009	0.012	0.037
Obs							88						
Post-WTO period													
TFP	Mean	2.365	3.795	2.504	2.803	7.815	0.651	3.267	4.159	3.612	3.247	0.866	3.190
	S.D.	0.129	0.623	0.166	0.117	1.834	0.085	0.253	0.524	0.490	0.240	0.068	1.598
VS	Mean	0.116	0.586	0.209	0.230	0.700	0.512	0.181	0.469	0.335	0.075	0.199	0.328
	S.D.	0.020	0.131	0.036	0.021	0.109	0.019	0.033	0.092	0.054	0.019	0.027	0.193
W_H/W_L	Mean	2.086	3.030	3.536	2.282	2.356	2.147	2.233	2.252	2.191	2.177	2.284	2.364
	S.D.	0.071	0.189	0.319	0.112	0.119	0.155	0.112	0.128	0.134	0.117	0.130	0.185
O	Mean	0.132	1.704	1.671	0.300	0.027	0.005	1.036	0.018	0.010	0.006	0.375	0.480
	S.D.	0.023	0.356	0.226	0.049	0.006	0.004	0.153	0.004	0.002	0.007	0.190	0.277
FDI	Mean	0.050	0.061	0.096	0.095	0.022	0.899	0.327	0.015	0.016	0.044	0.294	0.185
	S.D.	0.005	0.018	0.006	0.014	0.397	0.134	0.042	0.016	0.002	0.008	0.085	0.217
H/L	Mean	0.032	0.119	0.169	0.027	0.244	0.108	0.285	0.214	0.471	0.213	0.160	0.186
	S.D.	0.004	0.037	0.034	0.008	0.058	0.008	0.036	0.036	0.124	0.042	0.021	0.108
SCALE	Mean	3.020	0.261	1.574	1.022	4.448	0.567	0.424	0.089	0.189	0.393	0.475	1.133
	S.D.	0.307	0.030	0.094	0.148	1.836	0.054	0.046	0.023	0.050	0.152	0.101	1.434
GL	Mean	0.202	0.089	0.241	0.100	0.062	0.047	0.187	0.098	0.110	0.194	0.143	0.134
	S.D.	0.017	0.012	0.028	0.008	0.009	0.009	0.022	0.010	0.010	0.020	0.015	0.056
Obs							121						

Notes: S.D.-Standard deviation. cons-construction industry, whol-wholesale and retail industry, acco-accommodation and catering industry, tran-transportation and communication industry, fina-finance industry, esta-real estate industry, leas-leasing and business industry, publ-public management and social organizations, educ-education, heal-health and social work, othe-other community societies and individuals, serv-service industry. *GL* is Grubel-Lloyd index. The data in the table are derived from *China Statistical Yearbook*, *China Labor Statistical Yearbook* and *World Input-output database* (WIOD).

u_{it} is the non-negative technical inefficiency component. Let $TE_{it} = \exp(-u_{it})$ be the technical efficiency, for i = 1, 2, …, N. The density estimator of u_{it} is modeled nonparametrically using the Rosenblatt-Parzen kernel density estimator:

$$p\left(u_{it}\middle|\mathbf{u}_{(it)}, \tau^2\right) = \frac{1}{(NT-1)u_{it}} \sum_{i=1:i\neq j}^{N} \sum_{r=1:r\neq t}^{T} \varphi\left(\frac{\ln u_{it} - \ln u_{jr}}{\tau}\right) I(u_{it} > 0) \tag{26}$$

where $\varphi(\cdot)$ is the standard Gaussian density function, $\mathbf{u}_{(it)}$ is the inefficiency vector without the it$^{\text{th}}$ element, τ is the bandwidth, and $I(\cdot)$ is an indicator function whose value is one for a true argument and zero otherwise.

When estimating TFP of the service industry, it involves output and three inputs. The output index of the service industry is expressed by the gross output of the service industry, converted to the constant price by the GDP deflator, using 1995 as the base year. The labor index of the service industry is expressed by the number of service industry employees. The capital index of the service industry is expressed by the real capital stock, using 1995 as the base year. The data of output, labor, capital and intermediate input are derived from the WIOD database.

(3) Measurement of skill premium

As shown in Eq. (21), there is a close relationship between skill

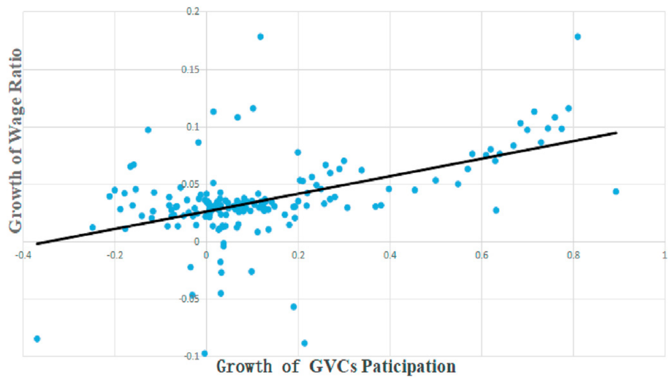

Fig. 2. GVCs participation and wage ratio.

premium and GVCs participation. Skill premium is expressed by the wage ratio of skilled and unskilled labors. The wage of skilled labor is expressed by the average wage per skilled labor with a college degree or above. The wage of unskilled labor is expressed by the average wage per unskilled labor with a degree below college.

(4) Control variables

Four control variables are adopted in the model. Foreign direct investment (*FDI*) is expressed by the ratio of total foreign investment to GDP, which reflects the amount of FDI. Trade openness (*O*) is expressed by the ratio of import and export trade to GDP, which reflects the degree of trade openness. Enterprise number (*SCALE*) is expressed by the number of the legal entity. The relative skilled labor supply (*H/L*) is represented by the ratio of the number of labors with a college degree or above to the number of labors with a degree below college.

3.3. Data descriptions

We use the panel data from China's service sectors for the estimation of the relationship among GVCs participation, SBTC and skill premium. The data consist of 11 service industries during the period 1995–2014. In terms of the classification criteria of the service industry in Industrial Classification for National Economic Activities (GB/4757-2002) and World Input-Output Database (WIOD), 11 service industries are selected as our research objects. Service sectors can be divided into two types on the basis of the ratio of capital per labor.[2] The high-tech service sectors include: the finance industry, leasing and business industry, transportation and communication industry, public management and social organizations industry, education industry, and health and social work industry. Low-tech service sectors include: the construction industry, real estate industry, wholesale and retail industry, accommodation and catering industry, and other community societies and individuals industry.

Since China fully participated in GVCs because of China's WTO accession in 2002, there may be a big change in productivity and wage caused by GVCs participation during the post-WTO accession period. In order to compare the effect of GVCs participation on skill premium between the pre-WTO and post-WTO accession period, the panel of 11 service industries spanning the period from 1995 to 2014 has been split into two sub-panels. The first sub-panel encompasses the pre-WTO accession period from 1995 to 2002, whereas the second sub-panel

Table 3
Describe two-step GMM results.

Variable	(1)		(2)	
	ΔLn*VS*	ΔLn*TFP*	ΔLn*VS*	ΔLn*TFP*
lag1_ΔLn*VS*	0.1997**	0.3816**	0.1903**	0.3770***
	(0.0851)	(0.1396)	(0.0846)	(0.1313)
lag1_ΔLn*TFP*	0.0109	0.2469**	0.0103	0.2371**
	(0.0086)	(0.1096)	(0.1046)	(0.1073)
ΔLn*O*			0.0202**	0.0088**
			(0.0098)	(0.0036)
Ln*FDI*			0.0184**	0.0136**
			(0.0076)	(0.0062)
ΔLn*H/L*			0.0240	0.0370**
			(0.0147)	(0.0155)
ΔLn*SCALE*			0.0389	0.0089
			(0.0490)	(0.0120)
Hansen test (p-value)	0.206		0.189	
Obs	209		209	

Notes: ***,** and * denote the significance levels of 1%, 5% and 10%, respectively. The numbers in parentheses are the standard deviations of the regression coefficients. The stability tests of the autoregressive processes show that all the eigenvalues lie inside the unit circle. The numbers of instruments (3-period lags) in two GMM estimators are 8 and 16, respectively.

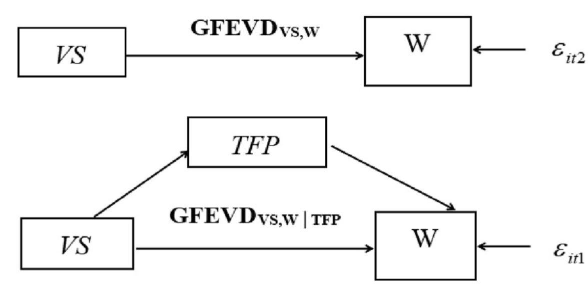

Fig. 3. Effect path diagram of mediation effect.

Table 2
Block Exogeneity Wald test results.

Variable	Excluded	Chi-sq	Prob.	Dependent variable	Excluded	Chi-sq	Prob.
ΔLn*VS*	ΔLn*TFP*	9.4092	0.0022***	ΔLn*FDI*	ΔLn*VS*	3.0419	0.0811*
	ΔLnW_H/W_L	9.9092	0.0016***		ΔLn*TFP*	3.0474	0.0809*
ΔLn*TFP*	ΔLn*VS*	0.2250	0.6353		ΔLn(W_H/W_L)	3.8933	0.0485**
	ΔLnW_H/W_L	12.3885	0.0004***	ΔLn(*H/L*)	ΔLn*VS*	0.2909	0.0646*
ΔLn(W_H/W_L)	ΔLn*VS*	0.8993	0.3430		ΔLn*TFP*	9.6329	0.0019***
	ΔLn*TFP*	0.2585	0.6111		ΔLn(W_H/W_L)	14.0881	0.0009***
ΔLn*O*	ΔLn*VS*	2.8934	0.0889*	ΔLn*SCALE*	ΔLn*VS*	0.5195	0.0712*
	ΔLn*TFP*	4.1885	0.0407**		ΔLn*TFP*	1.1979	0.0492**
	ΔLn(W_H/W_L)	2.7932	0.0920*		ΔLn(W_H/W_L)	11.5281	0.0031***

Notes: ***,** and * denote the significance levels of 1%, 5% and 10%, respectively.

[2] Feng, X.H., 2018. Effect of intra-industry trade on skill premium in manufacturing in China. China Econ. Rev. 47, 206–218.

Table 4
Describe GFEVD result of full sample.

Variable	Full model			Benchmark model	
	(1)	(2)	(3)	(4)	(5)
	ΔLn*VS*	ΔLn*TFP*	$\Delta\text{Ln}(W_H/W_L)$	ΔLn*VS*	$\Delta\text{Ln}(W_H/W_L)$
lag1_ΔLn*VS*	0.1867**	0.3701**	0.0164*	0.2553**	0.1141**
	(0.0931)	(0.1435)	(0.0092)	(0.1221)	(0.0458)
lag1_ΔLn*TFP*	0.0078	0.2049**	0.1602**		
	(0.0101)	(0.1011)	(0.0703)		
lag1_$\Delta\text{Ln}(W_H/W_L)$	0.1309	0.0612	0.1974**	0.1163	0.2171**
	(0.1702)	(0.0486)	(0.0968)	(0.1677)	(0.0860)
ΔLn*O*	0.0184**	0.0079**	0.0099**	0.0208**	0.0103**
	(0.0090)	(0.0037)	(0.0043)	(0.0101)	(0.046)
ΔLn*FDI*	0.0172**	0.0102**	0.0117**	0.0178**	0.0109*
	(0.0079)	(0.0048)	(0.0051)	(0.0078)	(0.0049)
ΔLn(*H*/*L*)	0.0218	0.0290**	0.0646**	0.0232	0.0691**
	(0.0289)	(0.0141)	(0.0318)	(0.0149)	(0.0343)
ΔLn(*SCALE*)	0.0381	0.0078	0.0263**	0.0353	0.0299**
	(0.0209)	(0.0317)	(0.0130)	(0.1862)	(0.0142)
Hansen test (p-value)	0.202			0.239	
$\text{GFEVD}_{\text{VS,W}}$	0.0956			0.4364	
	(0.0195)			(0.0558)	
$\text{GFEVD}_{\text{VS,W}}-\text{GFEVD}_{\text{VS,W\|TFP}}$			0.3408***		
(5)–(3)			(0.0412)		
Rate of mediation effect			78.1%		
1-(3)/(5)					
Obs			209		

Notes: ***,** and * denote the significance levels of 1%, 5% and 10%, respectively. The numbers in parentheses are the standard deviations. The stability tests of the autoregressive processes show that all the eigenvalues lie inside the unit circle. The numbers of instruments (3-period lags) in two models are 30 and 16, respectively.

covers the post-WTO accession period from 2003 to 2014. Furthermore, we look to examine the differences in terms of the effect of GVCs participation on skill premium between the pre-WTO and post-WTO accession period.

The import coefficient matrix, domestic consumption matrix, direct consumption matrix, export and import data are provided by WIOD covered the years 1995–2014. The data of FDI, trade openness, and the number of legal entity are derived from the *China Statistical Yearbook*, and the number and wages of skilled and unskilled labors are derived from the *China Labor Statistical Yearbook*.

The first panel of Table 1 reports the summary statistics for the full sample. It shows that the TFP of the service industry averages around 2.473. The highest is the finance industry (up to 5.196), the lowest is the real estate industry (only 0.493). The relative wage ratio of skilled and unskilled labors varies with a range from 1.545 to 2.221. We find that the relative wage ratio of the service industries with higher marketization is also higher than others, such as the wholesale and retail industry, transportation and communication industry. As shown in Fig. 2, the higher growth of GVCs participation, the higher growth of wage ratio.

The second and third panels of the table present descriptive statistics

Table 5
Describe GFEVD result of high-tech sample.

Variable	Full model			Benchmark model	
	(1)	(2)	(3)	(4)	(5)
	ΔLn*VS*	ΔLn*TFP*	$\Delta\text{Ln}(W_H/W_L)$	ΔLn*VS*	$\Delta\text{Ln}(W_H/W_L)$
lag1_ΔLn*VS*	0.2346**	0.3670***	0.0147*	0.1647**	0.1381**
	(0.1025)	(0.0229)	(0.0082)	(0.0823)	(0.0565)
lag1_ΔLn*TFP*	0.0016	0.1909***	0.1594***		
	(0.0019)	(0.0598)	(0.0123)		
lag1_$\Delta\text{Ln}(W_H/W_L)$	0.0807	0.0310	0.1910***	0.0048	0.2088**
	(0.0684)	(0.0403)	(0.0576)	(0.0121)	(0.0829)
ΔLn*O*	0.0247**	0.0091**	0.0075**	0.0261**	0.0042**
	(0.0119)	(0.0044)	(0.0035)	(0.0128)	(0.0019)
ΔLn*FDI*	0.0185**	0.0111**	0.0178**	0.0189**	0.0182**
	(0.0088)	(0.0046)	(0.0082)	(0.0088)	(0.0085)
ΔLn(*H*/*L*)	0.0667	0.0344**	0.0661**	−0.0076	0.0303***
	(0.0357)	(0.0162)	(0.0329)	(0.0148)	(0.0019)
ΔLn(*SCALE*)	0.0155	0.0035*	0.0222**	0.0066	0.0359***
	(0.0099)	(0.0015)	(0.0105)	(0.0047)	(0.0130)
Hansen test (p-value)		0.233		0.247	
$\text{GFEVD}_{\text{VS,W}}$		0.0939		0.5151	
		(0.0207)		(0.0791)	
$\text{GFEVD}_{\text{VS,W}}-\text{GFEVD}_{\text{VS,W\|TFP}}$			0.4212***		
(5)–(3)			(0.0210)		
Rate of mediation effect			81.8%		
1-(3)/(5)					
Obs			114		

Notes: ***,** and * denote the significance levels of 1%, 5% and 10%, respectively. The numbers in parentheses are the standard deviations. The stability tests of the autoregressive processes show that all the eigenvalues lie inside the unit circle. The numbers of instruments (3-period lags) in two models are 30 and 16, respectively.

Table 6
Describe GFEVD result of low-tech sample.

Variable	Full model			Benchmark model	
	(1)	(2)	(3)	(4)	(5)
	ΔLn*VS*	ΔLn*TFP*	$\Delta\text{Ln}(W_H/W_L)$	ΔLn*VS*	$\Delta\text{Ln}(W_H/W_L)$
lag1_ΔLn*VS*	0.1460**	0.3860**	0.0173*	0.2261**	0.1246*
	(0.0698)	(0.1782)	(0.0077)	(0.1121)	(0.0043)
lag1_ΔLn*TFP*	0.0120	0.1920***	0.1648**		
	(0.0126)	(0.0168)	(0.0718)		
lag1_$\Delta\text{Ln}(W_H/W_L)$	0.1387	0.0183	0.2354***	0.1245	0.2573**
	(0.1493)	(0.0486)	(0.0458)	(0.1550)	(0.0315)
ΔLn*O*	0.0209**	0.0044**	0.0062*	0.0284*	0.0058*
	(0.0095)	(0.020)	(0.0033)	(0.0140)	(0.0030)
ΔLn*FDI*	0.0301**	0.0148***	0.0146**	0.0204**	0.0144**
	(0.0149)	(0.0040)	(0.0065)	(0.0101)	(0.0069)
ΔLn(*H/L*)	0.0001	0.0134***	0.0490***	0.0003	0.0509***
	(0.0030)	(0.0028)	(0.0039)	(0.0034)	(0.0018)
ΔLn(*SCALE*)	−0.0108	0.0044*	0.0284***	−0.0103	0.0401***
	(0.0222)	(0.0025)	(0.0013)	(0.0121)	(0.0026)
Hansen test (p-value)		0.237		0.248	
$\text{GFEVD}_{\text{VS,W}}$		0.1005		0.4020	
		(0.0231)		(0.0373)	
$\text{GFEVD}_{\text{VS,W}}-\text{GFEVD}_{\text{VS,W}\mid\text{TFP}}$ (5)–(3)			0.3015***		
			(0.0386)		
Rate of mediation effect 1-(3)/(5)			75.0%		
Obs			95		

Notes: ***,** and * denote the significance levels of 1%, 5% and 10%, respectively. The numbers in parentheses are the standard deviations. The stability tests of the autoregressive processes show that all the eigenvalues lie inside the unit circle. The numbers of instruments (3-period lags) in two models are 30 and 16, respectively.

Table 7
Describe result of alternative independent variable.

Variable	ΔLn(*GL*)	ΔLn*TFP*	$\Delta\text{Ln}(W_H/W_L)$
lag1_ΔLn(*GL*)	0.2517***	0.2069***	0.0172*
	(0.0722)	(0.0615)	(0.0096)
lag1_ΔLn*TFP*	0.0183	0.1680***	0.1291**
	(0.0232)	(0.0605)	(0.0513)
lag1_$\Delta\text{Ln}(W_H/W_L)$	0.1017	0.0257	0.2368**
	(0.1163)	(0.0224)	(0.943)
ΔLn*O*	0.0173*	0.0061**	0.0096**
	(0.094)	(0.0028)	(0.0045)
ΔLn*FDI*	0.0177	0.0237***	0.0128**
	(0.0161)	(0.0057)	(0.0049)
ΔLn(*H/L*)	0.0107	0.0325**	0.0362**
	(0.0531)	(0.0150)	(0.0174)
ΔLn(*SCALE*)	0.0702	0.0038	0.0217**
	(0.1557)	(0.0265)	(0.0099)
Hansen test (p-value)		0.244	
$\text{GFEVD}_{\text{VS,W}}$		0.0972	
		(0.0288)	
$\text{GFEVD}_{\text{VS,W}}-\text{GFEVD}_{\text{VS,W}\mid\text{TFP}}$		0.3128***	
		(0.0306)	
Rate of mediation effect		76.3%	
Obs		209	

Notes: ***,** and * denote the significance levels of 1%, 5% and 10%, respectively. The numbers in parentheses are the standard deviations. The stability tests of the autoregressive processes show that all the eigenvalues lie inside the unit circle. The number of instruments (3-period lags) is 30.

for the pre-WTO sample and post-WTO sample, respectively. As one would expect, we find that the post-WTO sample is more productive (3.190 vs 2.072), has the higher relative wage ratio (2.364 vs 1.430), deepens globalization (0.328 vs 0.215), obtains more FDI to GDP (0.185 vs 0.138), has the higher trade openness (0.480 vs 0.374), higher relative skilled labor supply (0.186 vs 0.113), larger enterprise number (1.133 vs 0.667), and higher Grubel-Lloyd index (0.134 vs 0.089). The same conclusion can be drawn with consideration for other sub-sectors.

4. Analysis of empirical results

According to the results and based on the recommended model and moment selection criteria (MMSC) developed by Andrews and Lu (2001) for GMM estimators, the first-order PVAR is the most preferred model since it has the lowest MMSC-BIC (Bayesian Information Criterion) value and the lowest MMSC-HQIC (Hannan-Quinn information criterion) value (See Table C.1 and Table C.2). The CIPS test results show the series are stationary (See Table B).

4.1. Block exogeneity tests

The block exogeneity Wald test is considered as 'a chronological ordering of movements of variables' method, which can identify whether the change of one variable is related to the change of the previous values of another variables. In this paper, it is supposed that the change in GVCs participation appears to lead to productivity improving and skill premium increasing and vice versa. Therefore, we use the block exogeneity Wald test to investigate the relationships of these three variables.

Table 2 shows the results of the block exogeneity Wald test for our sample of China's service industry. The causality is detected from *VS* to *TFP, VS* to W_H/W_L and *TFP* to W_H/W_L. Furthermore, there is no causality from W_H/W_L to *VS* and W_H/W_L to *TFP*. The causality from *O* to *VS*, *TFP* and W_H/W_L are obtained. The causality from *FDI*, or *SCALE*, or *H/L* to *VS*, *TFP* and W_H/W_L are also found. Therefore, it is proved that the wage ratio of skilled and unskilled labors (W_H/W_L) is affected by the GVCs participation (*VS*), SBTC (*TFP*), trade openness (*O*), foreign direct investment (*FDI*), enterprise number (*SCALE*) and relative skilled labor supply (*H/L*).

4.2. SBTC effect

The PVAR model is firstly estimated via the two-step GMM estimator developed by Binder et al. (2005) for short PVAR and extended by Sigmund and Ferstl (2019) with the Helmert transformation and the Windmeijer (2005) correction for finite sample bias. The Helmert forward mean-differencing transformation controls for fixed effects while preserving the orthogonality between the endogenous variables and their lags, allowing the latter to be used as instruments in GMM

Table 8
Describe results of pre-WTO period and post-WTO period samples.

Variable	pre-WTO period			post-WTO period		
	(1)	(2)	(3)	(4)	(5)	(6)
	ΔLn*VS*	ΔLn*TFP*	ΔLn(W_H/W_L)	ΔLn*VS*	ΔLn*TFP*	ΔLn(W_H/W_L)
lag1_ΔLn*VS*	0.0944**	0.1527**	0.0174*	0.1532**	0.5061***	0.0179*
	(0.0415)	(0.0362)	(0.0099)	(0.0616)	(0.0931)	(0.0093)
lag1_ΔLn*TFP*	0.0052	0.1410**	0.1686***	0.0067	0.2507***	0.1681***
	(0.0191)	(0.0608)	(0.0342)	(0.0251)	(0.0795)	(0.0335)
lag1_ΔLn(W_H/W_L)	0.0820	0.0143	0.2278**	0.2208	0.0789	0.2065**
	(0.0973)	(0.0525)	(0.0995)	(0.1904)	(0.0763)	(0.0826)
ΔLn*O*	0.0252**	0.0094**	0.0078***	0.0128**	0.0077*	0.0106*
	(0.0118)	(0.0043)	(0.0003)	(0.0059)	(0.0041)	(0.0061)
ΔLn*FDI*	0.0333	0.0136**	0.3210**	0.0289**	0.0146**	0.1311**
	(0.0422)	(0.0066)	(0.1576)	(0.0123)	(0.0072)	(0.0642)
ΔLn(*H/L*)	0.0011	0.0158**	0.0098**	0.0080	0.0748**	0.0603**
	(0.0009)	(0.0062)	(0.0046)	(0.0262)	(0.0366)	(0.0298)
ΔLn(*SCALE*)	0.0754	−0.0126	0.0239**	−0.0693	0.0147	0.0201**
	(0.1690)	(0.0420)	(0.0108)	(0.0819)	(0.0212)	(0.0094)
Hansen test (p-value)		0.225			0.216	
$GFEVD_{VS,W}$		0.0656			0.0693	
		(0.0164)			(0.0159)	
$GFEVD_{VS,W}-GFEVD_{VS,W\|TFP}$		0.2743***			0.4156***	
		(0.0268)			(0.0293)	
Rate of mediation effect		80.7%			85.7%	
Obs		88			121	

Notes: ***,** and * denote the significance levels of 1%, 5% and 10%, respectively. The numbers in parentheses are the standard deviations. The stability tests of the autoregressive processes show that all the eigenvalues lie inside the unit circle. The number of instruments (3-period lags) is 30.

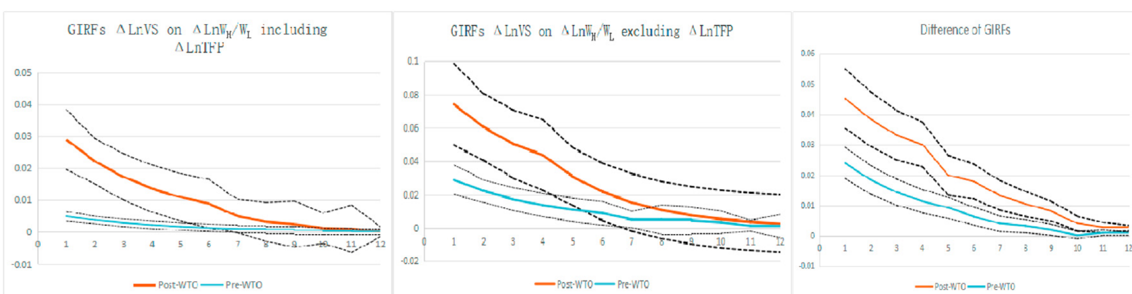

Fig. 4. GIRFs during the pre-WTO and post-WTO period. ***Notes***: The solid line shows the impulse responses. The dashed lines indicate 90% confidence band around the estimate.

estimators. If 'T' gets large relative to 'N' (long panels), the instrument count becomes very large which may result in poor small sample properties of the estimator and hypothesis tests (Breitung, 2015). In order to reduce the number of moment conditions, following Sigmund and Ferstl (2019), we combine the two approaches to instrument containment: using only the two-period or three-period lags and collapsing instruments (Roodman, 2009). The joint validity of the instruments is checked by the standard Hansen test of over-identifying restrictions. This method is known to yield consistent estimates in panel data settings. Since the Hansen statistic in Table 3 is greater than 10%, therefore, the null hypothesis can't be rejected, which suggests that both the control variables and instruments are orthogonal and validity.

Table 3 shows a statistically significant and positive effect of ΔLn*VS* on ΔLn*TFP* in the first GMM estimator with the estimated coefficient of 0.3816. In the second GMM estimator after including control variables, the impact of ΔLn*VS* on ΔLn*TFP* doesn't change the significance as well as the coefficient size of the estimation results, with the coefficient of 0.3770. We find that the SBTC effect is always positive, which may lead to the positive effect of ΔLn*VS* on ΔLn(W_H/W_L).

4.3. Mediation effect

What is the mechanism of GVCs participation on skill premium? The above literature has confirmed that the skill premium is influenced by GVCs participation or SBTC. According to the technology diffusion model, the firms participating in GVCs have a higher productivity than the firms non-participating in GVCs (i.e., positive SBTC effect). As a result, the firms participating in GVCs increase the demand and hence wage ratio of skilled labors owing to technology-skill complementarity. In view of this, we will investigate whether GVCs participation affects skill premium through the SBTC channel, and to what extent the SBTC explains the effect of GVCs participation on skill premium.

According to the principle of mediation effect, and considering potential endogeneity among *TFP*, *VS* and W_H/W_L, and allowing for lagged impacts at the same time, we estimate the following two PVAR models: full PVAR model (including *TFP*) and benchmark PVAR model (excluding *TFP*). The full PVAR model is as follows:

$$\begin{pmatrix} \Delta LnVS_{it} \\ \Delta LnTFP_{it} \\ \Delta Ln(W_H/W_L)_{it} \end{pmatrix} = A_1(L)\begin{pmatrix} \Delta LnVS_{it-1} \\ \Delta LnTFP_{it-1} \\ \Delta Ln(W_H/W_L)_{it-1} \end{pmatrix} + B_1X_{it} + \mu_{i1} + \varepsilon_{it1} \quad (27)$$

The benchmark PVAR model is then as follows:

$$\begin{pmatrix} \Delta LnVS_{it} \\ \Delta Ln(W_H/W_L)_{it} \end{pmatrix} = A_2(L)\begin{pmatrix} \Delta LnVS_{it-1} \\ \Delta Ln(W_H/W_L)_{it-1} \end{pmatrix} + B_2X_{it} + \mu_{i2} + \varepsilon_{it2} \quad (28)$$

where $A_1(L)$ and $A_2(L)$ are the lag operators, respectively. $X_{it} =$

$[\Delta Ln\widehat{O}_{it}, \Delta LnFDI_{it}, \Delta Ln(H/L)_{it}, \Delta LnSCALE_{it}]^{\mathrm{T}}$. μ_{i1} and μ_{i2} denote individual effect variable vectors of the two models, respectively. ε_{it1} and ε_{it2} denote disturbance terms vectors of the two models, respectively. Let $W \equiv W_H/W_L$.

Based on the PVAR parameters, we derive the generalized forecast error variance decomposition estimates. The GFEVD shows how much each endogenous variable can be explained by the shocks of other variables, accessing the contribution of each structural shock to the change of endogenous variables. However, GFEVD can't distinguish the indirect (mediation) contributions from the total contributions. In order to show the mediation effect of SBTC in the relationship between GVCs participation and skill premium, we use the principle of the mediation effect. Mediation effect can be assessed by comparing the relationship between the independent variable and the dependent variable before and after adjustment for the mediating variable. As shown in Fig. 3, $\mathrm{GFEVD}_{\mathrm{VS,W|TFP}}$ is the direct contributions of *VS* shock on W_H/W_L in the full PVAR model (including *TFP*). $\mathrm{GFEVD}_{\mathrm{VS,W}}$ is the total contributions of *VS* shock on W_H/W_L in the benchmark PVAR model (excluding *TFP*). A method based on GFEVDs (H_0: $\mathrm{GFEVD}_{\mathrm{VS,W}} - \mathrm{GFEVD}_{\mathrm{VS,W|TFP}} = 0$) compares the GFEVD between *VS* and W_H/W_L before and after it is adjusted for *TFP*. $\mathrm{GFEVD}_{\mathrm{VS,W}} - \mathrm{GFEVD}_{\mathrm{VS,W|TFP}}$ is considered as the mediation effect of *TFP* in the link between *VS* and W_H/W_L. The rate of mediation effect is mediation effect divided by total effect, that is, $(\mathrm{GFEVD}_{\mathrm{VS,W}} - \mathrm{GFEVD}_{\mathrm{VS,W|TFP}})/\mathrm{GFEVD}_{\mathrm{VS,W}}$.

The three key requirements of the mediation effect analysis are met. Firstly, causal interpretation between GVCs participation, SBTC and skill premium must be assumed. From the existing literature, we know that there is the causal interpretation among these three variables. Secondly, no unmeasured confounding is assumed. To control for confounding for these relationships, the measured covariates must be included in the models (VanderWeele, 2015). In practice, we use the variables which affect both GVCs participation and skill premium and the variables which affect both productivity and skill premium as the elements of the collection of control variables. Thirdly, no error in mediator measurement should be assumed. In our paper, the mediator is measured by TFP. Chen et al. (2018) found that the magnitudes of estimation biases depend on the correlations between the variables which are used to estimate TFP (that is, capital, labor and intermediate input) and the regressors in the mediator model when using TFP as one of the dependent variables. Fortunately, we see that the capital, labor and intermediate input are all insignificantly correlated with the regressors in the mediator model (see Table D). Furthermore, our results remain robust when the mediator (i.e., SBTC) is calculated by TFP and information technology, respectively.[3] Therefore, the requirement of no error in mediator measurement is met.

According to the model selection criteria by Andrews and Lu (2001), the first-order PVAR model (27) and model (28) are chosen in Table 4. Using China's service industry data, we estimate the parameters of Eq. (21) by the industry fixed effect, and then get the substitution elasticity between two intermediates $\sigma = 1.82$ and the substitution elasticity between two labors $\eta = 1.33$. Both of them are greater than 1, which implies an increase in GVCs participation (*VS*) will lead to an increase in skilled-unskilled wage ratio (W_H/W_L). Moreover, the results from Table 4 show the effect of $\Delta\mathrm{Ln}VS$ on $\Delta\mathrm{Ln}(W_H/W_L)$ will decrease significantly after including the $\Delta\mathrm{Ln}TFP$ variable (from 0.1141 to 0.0164), suggesting that the effect of GVCs participation on skill premium is influenced by SBTC.

As far as the mechanism of GVCs participation on skill premium is concerned, we use the GFEVD and the mediation effect principle to investigate to what extent the SBTC explains the effect of GVCs participation on skill premium. Using the PVAR parameters, the relative importance of the response of $\Delta\mathrm{Ln}(W_H/W_L)$ to $\Delta\mathrm{Ln}VS$ is established based on GFEVD values in the two models. We derive $\mathrm{GFEVD}_{\mathrm{VS,W|TFP}}$ and $\mathrm{GFEVD}_{\mathrm{VS,W}}$ estimators from 1 to 16 years, which reduces sensitivity to short-term fluctuations. We then average $\mathrm{GFEVD}_{\mathrm{VS,W|TFP}}$, $\mathrm{GFEVD}_{\mathrm{VS,W}}$ and their difference. And then we get the rate of the mediation effect. Table 4 reveals that the GVCs participation (*VS*) affecting skill premium (W_H/W_L) indirectly via the channel of SBTC (*TFP*), accounts for 78.1%. It also suggests that the SBTC (*TFP*) adds significant explanatory power to the wage ratio, compared with the benchmark model. In the benchmark model, $\Delta\mathrm{Ln}VS$ explains 43.64% of the variation in wage ratio. After adding $\Delta\mathrm{Ln}TFP$, $\Delta\mathrm{Ln}VS$ accounts for only 9.56% of the total variation in wage ratio. Therefore, the findings not only reveal evidence of *TFP* explaining a significant proportion of variance in wage ratio, but also confirm the mediation effect of *TFP* in the predictive relationship between *VS* and W_H/W_L. Thus, the mediation role of the SBTC hypothesis is also supported.

For the sub-samples of service sectors in Tables 5 and 6, the significant mediation effect indicates that the results are robust. GVCs participation can explain 51.5% variation of wage ratio in the high-tech service sectors, while this number is 40.2% in the low-tech service sectors. The mediation effect of SBTC in the high-tech service sectors is greater than the effect in the low-tech service sectors (81.8% vs 75.0%). The main reason is that the high-tech service sectors tend to use more imported intermediate inputs and skilled labors in the process of the deepening of globalization, leading to a big increase in technology and hence skill premium, whereas the low-tech service sectors tend to use more domestic intermediate inputs and unskilled labors for cost saving, thus resulting in a small increase in technology and hence skill premium.

4.4. Robustness checks

In view of the potential endogeneity caused by the measurement error, we recalculate the degree of GVCs participation to ensure robustness. The Grubel-Lloyd index is used to measure the degree of the GVCs participation(Grubel and Lloyd, 1975). The results from the Grubel-Lloyd index reported in Table 7 are similar to those of Table 4. The mediation effect of SBTC is 76.3%.

$$GL_{it} = 1 - \frac{|X_{it} - M_{it}|}{X_{it} + M_{it}} \tag{29}$$

where X_i and M_i denote export volume and import volume of sector i, respectively.

We explore the robustness of our results by distinguishing samples between the pre-WTO and post-WTO periods. The first order PVAR is the preferred model based on MMSC-BIC and MMSC-HQIC in both cases (for pre-WTO and post-WTO periods) (See Table C.2). Results of Table 8 show a statistically significant and positive effect of $\Delta\mathrm{Ln}VS$ on $\Delta\mathrm{Ln}(W_H/W_L)$ with the estimated coefficient of 0.0174 during the pre-WTO accession period, while during the post-WTO accession period, the estimated coefficient increases to 0.0179. Meanwhile, the estimated coefficient of $\Delta\mathrm{Ln}VS$ on $\Delta\mathrm{Ln}TFP$ rises dramatically from 0.1527 during pre-WTO accession period to 0.5061 during post-WTO accession period. Accordingly, GVCs participation can explain 33.99% variation of wage ratio during pre-WTO accession period, while this number is 48.49% during post-WTO accession period. The mediation effect of the SBTC during the post-WTO accession period is a little bit greater than the effect during the pre-WTO accession period (85.7% vs 80.7%). The significant mediation effect indicates that the results are robust. These results are consistent with the findings supporting that adding SBTC into the trade model will strengthen the effect of GVCs participation on skill premium. We replicate our main findings with the alternative measure of GVCs participation and find alternative measure does not change significance and coefficient size of the estimation results. Since the Hansen statistics are greater than 10%, therefore, the null hypothesis can't be rejected, which suggests the validity of the instruments.

In addition, we add the structural break test to check the stability of the parameter estimates across pre-WTO and post-WTO accession

[3] Due to limited space, the data are not shown.

periods. If a structural break occurs, the parameter takes different values during pre-WTO and post-WTO accession periods. We use the model and moment selection criteria developed by Andrews and Lu (2001) to choose between the no-break and the break models. The smaller values for MMSC-BIC and MMSC-HQIC are obtained when no structural break is assumed. The value of MMSC-BIC is smaller for the model with no-break (−109.9 versus −97.16 for the model with a structural break), and the value of MMSC-HQIC is also smaller for the model with no-break (−75.55 versus −68.32 for the model with a structural break). We find no evidence of the existence of a structural break. Accordingly, the parameter estimates are stable during pre-WTO and post-WTO accession periods.

After the PVAR is estimated by the two-step GMM, the structural error terms are identified. The general impulse response functions (GIRFs), which can be obtained by the PVMA representation of the model, are generated. The results of GIRFs to capture the long run impact of $\Delta \mathrm{Ln}VS$ on $\Delta \mathrm{Ln}(W_H/W_L)$ including or excluding $\Delta \mathrm{Ln}TFP$, which are calculated with 500 bootstrap resampling for the estimated models, are given in Fig. 4.

Following a shock to $\Delta \mathrm{Ln}VS$, the estimated cumulative impact on $\Delta \mathrm{Ln}(W_H/W_L)$ declines by the twelfth year, after which it is essentially zero. The GIRFs increase from the pre-WTO to the post-WTO period. During the post-WTO accession period, the response of $\Delta \mathrm{Ln}(W_H/W_L)$ to $\Delta \mathrm{Ln}VS$ is substantial, longer lasting, and more pronounced compared to that in the pre-WTO period.

The differences of GIRFs of $\Delta \mathrm{Ln}VS$ on $\Delta \mathrm{Ln}(W_H/W_L)$ including and excluding $\Delta \mathrm{Ln}TFP$ are calculated. We are able to establish a clear statistical distinction between the pre-WTO period and the post-WTO period as the confidence intervals of the resulting GIRFs differences are very distinct. Fig. 4 shows the SBTC adds statistically significant meaningful explanatory power for the effect of GVCs participation on skill premium after China's accession into WTO. These findings confirm the importance of the SBTC on the relationship between GVCs participation and skill premium.

5. Conclusions

Different from the existing literature in what regards the skill premium is affected by GVCs participation or SBTC alone, this paper combines the above literature into one framework to unveil the mediating role of SBTC in the impact of GVCs participation on skill premium. It argues, using a two-intermediates choice model with endogenous SBTC, GVCs participation contributes to a small change of skill premium, while contributes a lot to it after adding the mediating role of SBTC into the trade model. After that, the model is estimated using China's service industry data by mediation effect analysis based on panel vector autoregression. The empirical results show the indirect effect of GVCs participation on skill premium via SBTC. The positive mediating effect of SBTC is more pronounced in the high-tech service sectors than low-tech service sectors. Our findings may be in the interest of understanding evolution of technical progress in China and complements a number of papers on the economic impact of China's globalization and wage reform. Furthermore, with this paper, we wish to convey the idea of the positive SBTC effect is crucial for the rising skill premium in developing countries.

Our findings have important policy implications. Since accelerating SBTC development is so important for rising skill premium in developing countries, it is crucial for policy makers to consider how developing countries with few abundant technological elements boost SBTC improvement. Active integration into GVCs is an important development strategy for developing countries in terms of accelerating the development of SBTC, through which the domestic firms take advantage of technology spillover and transmit it into overall technology improvement. At the same time, it is particularly important to improve technology absorption ability by investment on R&D and education to achieve technical spillover and the abundant technology stock accumulation. Hence, we recommend that policies should be a bias towards the firms, which focus more on technological innovation rather than pure imitation processes, so as to encourage domestic firms to enhance SBTC development and promote self-innovation capability. In addition, policy makers should pay attention to the unemployment of unskilled labors due to the adjustment of labor skill structure alongside SBTC development, and support them by unemployment compensation, job training and subsistence allowances. Finally, the government needs to strengthen the protection of intellectual property rights, which will spur firms to widely share their knowledge.

Our study has two limitations. The first limitation is to use industry data to perform the empirical estimates. Studies based on firm-level data will broaden the applicability of our results and provide additional insight into the nexus between GVCs participation and skill premium. But until now, firm-level data of China's service industry have not been available. The second limitation is not to explore the channels other than SBTC through which participating in GVCs affects the skill premium. We want to know whether there are other mediating channels in addition to the existence of SBTC, and if it exists, what would the corresponding mechanism be?

Declaration of competing interest

No conflict of interest exits in the submission of this manuscript, and manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed.

Acknowledgements

We are grateful to Sushanta Mallick and two anonymous referees for useful comments and suggestions. Errors remain our responsibility.

This work was supported by the National Social Science Foundation of China (Grant No. 20BJY096) and the National Natural Science Foundation of China (Grant No. 71873040).

Appendix A. Measurement of TFP by Bayesian semi-parametric stochastic frontier

The parameters to be estimated for the model are in the vector $(\beta, h, \tau^2, \mathbf{u})$, where $\beta \equiv (\beta_0, \beta_1, ..., \beta_k, \beta_{11}, \beta_{12}, ..., \beta_{kk})$. In order to carry out kernel-based semi-parametric stochastic frontier analysis, the prior distribution of model parameters is selected firstly. For β, h and τ^2, we use the following priors:

$$p(\beta) \propto 1 \tag{A1}$$

$$p(\beta) \propto \frac{1}{h}, \text{ where } h = \frac{1}{\sigma^2} \tag{A2}$$

$$p(\tau^2) = [\Gamma(\theta_1)\theta_2^{\theta_1}]^{-1}\left(\frac{1}{\tau^2}\right)^{\theta_1+1}\exp\left(-\frac{1}{\tau^2\theta_2}\right) \tag{A3}$$

where the shape parameter $\theta_1 = 1$ and the scale parameter $\theta_2 = 1/0.05$.

The density of is approximated by

$$p\left(u_{it}\middle|\mathbf{u}_{(it)}, \tau^2\right) = \frac{1}{(NT-1)u_{it}} \sum_{i=1:i\neq j}^{N} \sum_{r=1:r\neq t}^{T} \varphi\left(\frac{ln\ u_{it} - ln\ u_{jr}}{\tau}\right) I(u_{it} > 0) \tag{A4}$$

The likelihood function is shown to be:

$$L\left(y\middle|\beta, h, \tau^2, \mathbf{u}\right) = \prod_{i=1}^{N}\prod_{t=1}^{T} \frac{h^{NT/2}}{(2\pi)^{NT/2}} \left\{ \exp\left[-\frac{h}{2}\left(y_{it} - \beta_0 - \sum_{p-1}^{k} \beta_p x_{p,it} - \frac{1}{2}\sum_{p=1}^{k}\sum_{q=1}^{k}\beta_{pq}x_{p,it}x_{q,it} + u_{it}\right)^2 \right] \right\} \tag{A5}$$

In order to simulate from the joint posterior density, we use a Gibbs sampler with data augmentation which involves drawing sequentially from the full conditional posterior densities of parameters. The full conditional posterior densities are:

$$p\left(\beta\middle|y, h, \tau^2, \mathbf{u}\right) \propto f_{\text{Normal}}\left(\beta\middle|\overline{\beta}, \overline{\mathbf{V}}\right) \tag{A6}$$

$$p\left(h\middle|y, \beta, \mathbf{u}, \tau^2\right) \propto f_{\text{Gamma}}\left(h\middle|\overline{\nu}, \overline{s}^2\right) \tag{A7}$$

$$p\left(\tau^2\middle|y, \beta, h, \mathbf{u}\right) \propto \left(\frac{1}{\tau^2}\right)^{\theta_1+1} \exp\left(-\frac{1}{\tau^2\theta_2}\right) \prod_{i=1}^{N}\prod_{t=1}^{T} p\left(u_{it}\middle|\mathbf{u}_{(it)}, \tau^2\right) \tag{A8}$$

$$p\left(\mathbf{u}\middle|y, \beta, h, \tau^2\right) \propto \prod_{i=1}^{N}\prod_{t=1}^{T} \left\{ \exp\left[-\frac{h}{2}\tilde{\delta}_{it}^2\right] \right\} \prod_{i=1}^{N}\prod_{t=1}^{T} p\left(u_{it}\middle|\mathbf{u}_{(it)}, \tau^2\right) \tag{A9}$$

where f_{Normal} and f_{Gamma} denote the normal and the Gamma distribution, respectively.

$$\overline{\mathbf{V}} = \left(h\sum_{i=1}^{N}\sum_{t=1}^{T} x_{p,it}x_{q,it} \right)^{-1}_{(k+1)\times(k+1)} \tag{A10}$$

$$\overline{\beta} = \overline{\mathbf{V}}\left(h\sum_{i=1}^{N}\sum_{t=1}^{T} x_{p,it}(y_{it} + u_{it}) \right)_{(k+1)\times 1} \tag{A11}$$

$$\overline{\nu} = NT/2 \tag{A12}$$

$$\overline{s}^2 = \frac{1}{2}\left[\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \beta_0 - \sum_{p=1}^{k}\beta_p x_{p,it} - \frac{1}{2}\sum_{p=1}^{k}\sum_{q=1}^{k}\beta_{pq}x_{p,it}x_{q,it} + u_{it} \right)^2 \right] \tag{A13}$$

$$\tilde{\delta}_{it} = y_{it} - \beta_0 - \sum_{p=1}^{k}\beta_p x_{p,it} - \frac{1}{2}\sum_{p=1}^{k}\sum_{q=1}^{k}\beta_{pq}x_{p,it}x_{q,it} + u_{it} \tag{A14}$$

Appendix B. Panel unit root tests

Table B
Panel unit root tests:1995–2014.

Variable	ΔLn*VS*	ΔLn*TFP*	ΔLn(W_H/W_L)	ΔLn*O*	ΔLn*FDI*	ΔLn(H/L)	ΔLn*SCALE*
Pesaran CD Test	10.422***	9.278***	21.445***	5.489***	6.485***	4.683***	12.487***
CIPS	−3.464***	−3.771***	−3.343***	−3.211***	−3.590***	−2.775***	−3.179***
Result	stationary	stationary	stationary	stationary	stationary	stationary	stationary

Notes: For the Pesaran CD test (Pesaran, 2004), the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. The CIPS tests (Pesaran, 2007) are estimated with an intercept term and automatically selected lag length. *** denotes the significance levels of 1%.

Appendix C. PVAR lag order selection

Table C.1
PVAR lag order selection criteria used in Table 3.

lag	Excluding control variables		Including control variables	
	BIC	HQIC	BIC	HQIC
1	−24.87	−15.85	−47.79	−32.84
2	−18.80	−13.00	−37.45	−25.93

Table C.2
PVAR lag order selection criteria used in Tables 4–8

lag	Full sample		High-tech		Low-tech		GL		Pre-WTO		Post-WTO	
	BIC	HQIC	BIC	HQIC	BIC	HQIC	BIC	HQIC	BIC	HQIC	BIC	HQIC
1	−109.9	−75.55	−95.65	−68.83	−92.16	−67.04	−105.9	−71.59	−81.10	−58.35	−91.31	−66.59
2	−93.64	−64.83	−81.20	−58.85	−78.24	−57.29	−91.20	−62.39	−69.93	−52.57	−74.75	−55.37

Appendix D. Correlation coefficients

Table D
Correlation coefficients.

Variable	$\Delta\text{Ln}VS$	$\Delta\text{Ln}TFP$	$\Delta\text{Ln}(W_H/W_L)$	$\Delta\text{Ln}O$	$\Delta\text{Ln}FDI$	$\Delta\text{Ln}(H/L)$	$\Delta\text{Ln}SCALE$
$\Delta\text{Ln}K$	−0.103	−0.1067	0.063	0.1367	0.0982	−0.1344	0.0022
$\Delta\text{Ln}L$	0.0306	−0.0961	−0.1067	−0.0173	0.0857	0.0132	0.0726
$\Delta\text{Ln}M$	0.056	0.1267	0.0807	0.126	−0.1362	−0.0426	0.1007

Notes: *K*, *L* and *M* denote capital, labor and intermediate input, respectively. All the correlation coefficients are insignificantly different from zero ($p > 0.01$).

References

Acemoglu, D., 1998. Why do new technologies complement skills? Directed technical change and wage inequality. Q. J. Econ. 113 (4), 1055–1089.
Acemoglu, D., 2002. Technical change, inequality, and the labor market. J. Econ. Lit. 40 (1), 7–72.
Acemoglu, D., Gancia, G.A., Zilibotti, F., 2015. Offshoring and directed technical change. Am. Econ. J. Macroecon. 7 (3), 84–122.
Afonso, O., Neves, P.C., Thompson, M., 2016. The skill premium and economic growth with costly investment, complementarities and international trade of intermediate goods. Jpn. World Econ. 37–38, 73–86.
Andrews, D., Lu, B., 2001. Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. J. Econom. 101 (1), 123–164.
Anwar, S., Sun, S.Z., Valadkhani, A., 2013. International outsourcing of skill intensive tasks and wage inequality. Econ. Modell. 31, 590–597.
Autor, D.H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. Am. Econ. Rev. 103 (5), 1553–1597.
Autor, D.H., Katz, L.F., Kearney, M.S., 2008. Trends in US wage inequality: revising the revisionists. Rev. Econ. Stat. 90 (2), 300–323.
Avalos, A., Savvides, A., 2006. The manufacturing wage inequality in Latin America and East Asia: openness, technology transfer, and labor supply. Rev. Dev. Econ. 10 (4), 553–576.
Basu, P., Guariglia, A., 2007. Foreign direct investment, inequality, and growth. J. Macroecon. 29 (4), 824–839.
Binder, M., Hsiao, C., Pesaran, M.H., 2005. Estimation and inference in short panel vector autoregressions with unit roots and cointegration. Econom. Theor. 21 (4), 795–837.
Borrs, L., Knauth, F., 2021. Trade, technology, and the channels of wage inequality. Eur. Econ. Rev. 131 (C), 1–28.
Breitung, J., 2015. The analysis of macroeconomic panel data. In: Baltagi, B.H. (Ed.), The Oxford Handbook of Panel Data. Oxford University Press, New York, pp. 453–492.
Burstein, A., Vogel, J., 2017. International trade, technology, and the skill premium. J. Polit. Econ. 125 (5), 1356–1412.
Caron, J., Fally, T., Markusen, J., 2020. Per capita income and the demand for skills. J. Int. Econ. 123 (C), 1–18.
Caselli, M., 2014. Trade, skill-biased technical change and wages in Mexican manufacturing. Appl. Econ. 46 (3), 336–348.
Chaudhuri, S., Banerjee, D., 2010. Foreign capital inflow, skilled-unskilled wage inequality and unemployment of unskilled labour in a fair wage model. Econ. Modell. 27 (1), 477–486.
Chen, T., Chen, X., Wang, C., Xiang, X., 2018. Export behavior and firm innovation: new method and evidence. Econ. Lett. 170, 76–78.
Chongvilaivan, A., Thangavelu, S.M., 2012. Does outsourcing provision lead to wage inequality? New evidence from Thailand's establishment-level data. Rev. Int. Econ. 20 (2), 364–376.
Chowdhury, S.R., 2010. Technology and outsourcing: an explanation to the rising wage gap. Econ. Modell. 27, 380–387.
Egger, H., Egger, P., Kreickemeier, U., 2013. Trade, wages and profits. Eur. Econ. Rev. 64, 332–350.
Feenstra, R.C., Hanson, G.H., 1996. Globalization, outsourcing, and wage inequality. Am. Econ. Rev. 86 (2), 240–245.
Feng, G., Wang, C., Zhang, X., 2019. Estimation of inefficiency in stochastic frontier models: a Bayesian kernel approach. J. Prod. Anal. 51 (1), 1–19.
Goel, M., 2017. Offshoring-effects on technology and implications for the labor market. Eur. Econ. Rev. 98 (C), 217–239.
Goldberg, P.K., Khandelwal, A., Pavcnik, N., Topalova, P., 2009. Trade liberalization and new imported inputs. Am. Econ. Rev. 99 (2), 494–500.
Goldberg, P.K., Pavcnik, N., 2005. Trade, wages, and the political economy of trade protection: evidence from the Colombian trade reforms. J. Int. Econ. 66 (1), 75–105.
Grubel, H.G., Lloyd, P.J., 1975. Intra-Industry Trade: The Theory and Measurement of International Trade in Differentiated Products. Macmillan, London.
Helpman, E., Krugman, P., 1985. Market Structure and Foreign Trade: Increasing Returns, Imperfect Competition, and the International Economy. MIT Press, Cambridge, MA.
Hummels, D., Ishii, J., Yi, K.M., 2001. The nature and growth of vertical specialization in world trade. J. Int. Econ. 54 (1), 75–96.
Li, S., Pan, S., Chi, S., 2016. North–South FDI and directed technical change. Econ. Modell. 59, 425–435.
Mallick, S.K., Sousa, R.M., 2017. The skill premium effect of technological change: new evidence from United States manufacturing. Int. Lab. Rev. 156 (1), 113–131.
Mallick, S.K., Yang, Y., 2013. Productivity performance of export market entry and exit: evidence from Indian firms. Rev. Int. Econ. 21 (4), 809–824.
Marouani, M.A., Nilsson, B., 2016. The labor market effects of skill-biased technological change in Malaysia. Econ. Modell. 57, 55–75.
Mehta, A., Hasan, R., 2012. The effects of trade and services liberalization on wage inequality in India. Int. Rev. Econ. Finance 23, 75–90.
Orazio, A., Goldberg, P.K., Pavcnik, N., 2004. Trade reforms and wage inequality in Colombia. J. Dev. Econ. 74 (2), 331–366.
Parteka, A., Wolszczak-Derlacz, J., 2015. Impact of offshoring on wages and wage convergence in the EU27. J. Econ. Inequal. 3 (3), 325–350.
Pesaran, M.H., 2004. General diagnostic tests for cross section dependence in panels. Working Papers in Economics No. 0435. University of Cambridge.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econom. 22 (2), 265–312.
Roodman, D., 2009. A Note on the theme of too many instruments. Oxf. Bull. Econ. Stat. 71 (1), 135–158.

Shen, C.M., Zheng, J.H., 2020. Does global value chains participation really promote skill-biased technological change? Theory and evidence from China. Econ. Modell. 86, 10–18.
Sigmund, M., Ferstl, R., 2019. Panel vector autoregression in R with the package panelvar. Q. Rev. Econ. Financ. https://doi.org/10.1016/j.qref.2019.01.001. In press.
Stolper, W.F., Samuelson, P.A., 1941. Protection and real wages. Rev. Econ. Stud. 9 (1), 58–73.
Stringfellow, A., Teagarden, M.B., Nie, W., 2008. Invisible costs in offshoring services work. J. Oper. Manag. 26 (2), 164–179.
Tsionas, M.G., Mallick, S.K., 2019. A Bayesian semiparametric approach to stochastic frontiers and productivity. Eur. J. Oper. Res. 274, 391–402.
VanderWeele, T., 2015. Explanation in Causal Inference: Methods for Mediation and Interaction. Oxford University Press, New York.
Vannoorenberghe, G., 2011. Trade between symmetric countries, heterogeneous firms, and the skill premium. Can. J. Econ. 44 (1), 148–170.
Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. J. Econom. 126 (1), 25–51.
Zeira, J., 2007. Wage inequality, technology and trade. J. Econ. Theor. 137 (1), 79–103.

Huijuan Li is an associate professor of economics at school of management in Guangzhou University. She holds a B.A. (2000) and a M.A. (2003) from South China Normal University, and a Ph.D from Sun Yat-sen University (2013). Her research specializes in the fields of industrial economics and international economics.

Weihong Cai is an associate professor of economics at school of finance in Guangdong University of Foreign Studies. He holds a B.A. (1997) and a M.A. (2000) from Sun Yat-sen University, and a Ph.D from Huazhong University of Science and Technology (2012). His research fields involve quantitative economics and finance.

Wenxiu Li is a professor of economics at school of Economics & Trade in Guangdong University of Finance. She holds a Ph.D (2006) from Wuhan University, a Post-Doc (2009) from Sun Yat-sen University and a Post-Doc (2013) from Chinese Academy of Social Sciences. Her research fields involve industrial economics and international economics.