Intermediate goods-skill complementarity and income distribution

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Abstract

The income share disparity between skilled and unskilled labor has been previously analyzed in relation to the elasticity of substitution between these factors and capital and changes in skill-biased technological changes. This study analyzes how the expansion of intermediate inputs affects change in the shares of skilled and unskilled labor, which has not been sufficiently analyzed in previous studies. After estimating the elasticity of substitution between four production factors, skilled labor, unskilled labor, capital, and intermediate goods, an analysis using a four-factor dynamic stochastic general equilibrium (DSGE) model with a three-level nested constant elasticity of substitution (CES) production function and factor-biased technological changes was conducted. It demonstrated that the characteristic change in the labor share was mainly related to changes in relative prices between intermediate goods and other factors and the intermediate goods-skill complementarity, which reflects the low elasticity of substitution between intermediate goods and skilled labor. The change in relative prices among production factors and elasticities of substitution are the main drivers of changing income distribution. In contrast to previous studies, our model allows the gross output and value-added deflators to move differently and thus could clarify the mechanism of the changing labor shares.

Key words: Income disparity between skilled and unskilled labor; Elasticity of substitution; Intermediate goods; Three-level nested CES

JEL Classification: D33; D58

1 Introduction

This study aimed to examine the effects of intermediate goods inputs on the widening gap between the income shares of skilled labor and unskilled labor, which previous studies have not yet fully elucidated. Widening income disparities have traditionally been discussed from two perspectives: disparity in the shares of skilled and unskilled labor and in the shares of capital and labor. However, the combined labor share of skilled and unskilled labor has stopped declining since the mid-1990s (Figure 1(a)). In contrast, the changes in

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income shares of skilled and unskilled labor and their wage bill ratio have become more pronounced. This study focused on this phenomenon (Figure 1(b)).

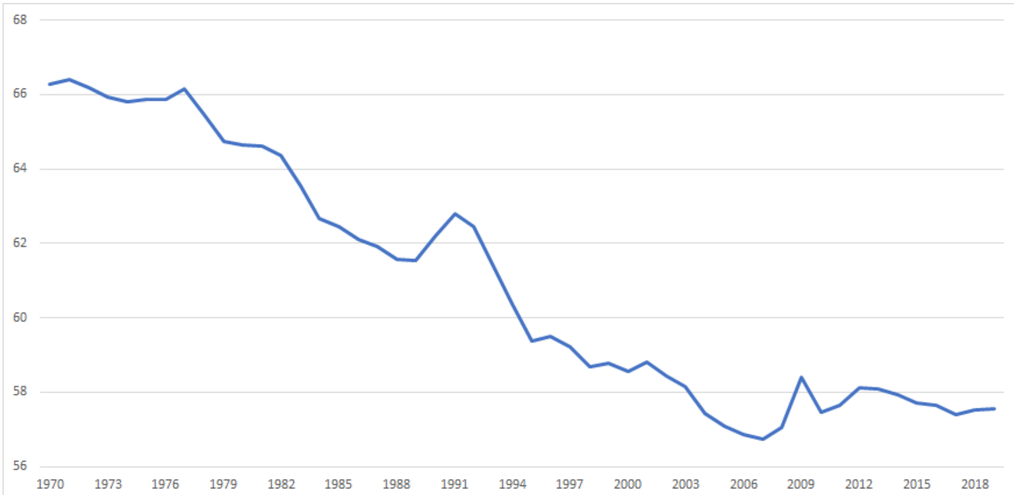

Fig. 1(a). Sample mean of labor income share.(%) Note: Sample countries are Australia, Belgium, Canada, Finland, France, India, Italy, Japan, Korea, Netherlands, Sweden, the United Kingdom and the United States. Data of these countries are available for the periods from 1970-2019 in Penn World Tables (ver. 10.0).

Regarding the mechanism underlying the widening gap between skilled and unskilled labor shares, previous studies have focused on two areas: (1) the capital-skill complementarity (CSC) and (2) skill-biased technological change (SBTC). In the CSC, the tendency to lower the prices of capital goods leads to their greater use, thereby increasing the demand for skilled labor, which is complementary to that of capital goods. If the total supply of labor is constant, the wage premium (the ratio of the wage of skilled labor over the wage of unskilled labor) rises. In SBTC, skilled labor-biased technological innovations improve the productivity of skilled labor, resulting in higher wage premiums. Considering the difference between the two concepts based on the productivity function, the CSC is related to the curvature of the isoquants, while SBTC originates from non-parallel shifts in those isoquants, such that it increases the input of skilled labor compared to unskilled labor.

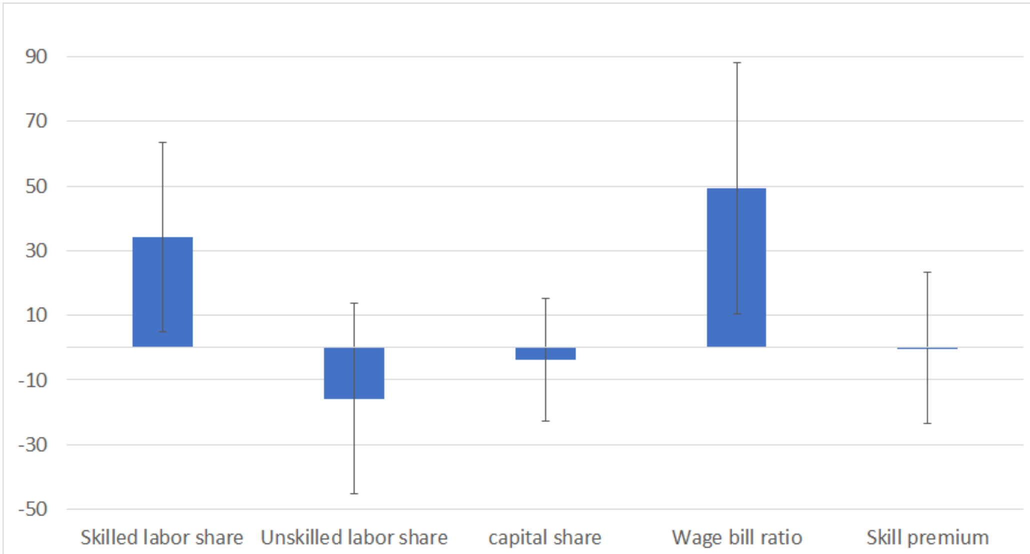

Fig. 1(b). Sample means of five indicators and their 90 % confidence intervals (%). Note: For 1995–2009, the percentage change over the 14-year period is presented. These data are collected for 31 developed and 9 developing countries from the WIOD Socio-Economic Account (2013 release). See Section 2.2 for the details.

Griliches (1969) originated the concept of the CSC and analyzed state-level data in the United States. Subsequently, Fallon and Layard (1975) used international data to conduct a more detailed analysis and demonstrated the existence of CSC. Parro (2013) and Burstein *et al.* (2013) used the dynamic stochastic general equilibrium (DSGE) model to test whether a drop in the price of capital goods and reduction in trade costs would lead to increased wage premiums through the CSC as a result of global capital goods trade. Regarding SBTC, Berman *et al.* (1998) summarized previous studies and concluded that SBTC was responsible for labor demand shifts to skilled labor and wage premiums in developed countries. In a recent study, Perez-Laborda and Perez-Sebastian (2020) analyzed the contributions of the CSC and SBTC to the wage premium for skilled labor by industry in the United States and concluded that both factors had an impact at the macro-aggregate level.

In the previous research, the CSC was more focused as a causing of increases in wage premiums and the share of skilled labor. In their seminal work, Krusell *et al.* (2000) also incorporated both the CSC and SBTC at the model stage, whereas SBTC was not considered in the actual estimation stage. The conclusions concerning the factors behind the income gap between skilled and unskilled labor have not yet been identified, with two mechanisms in mind.

Therefore, the relationship between the CSC, SBTC, and wage premiums and the labor share needs to be considered in terms of differences in time, country, and sector (Duffy *et al.*, 2004). Castex *et al.* (2022) performed the same estimation as Krusell *et al.* (2000) by expanding the estimation period and found that Krusell *et al.*'s CSC model could not reproduce actual labor share data from the beginning of the 2000s. They concluded that this was partly because of a reduced degree of CSC. The finding that the degree of complementarity between skilled labor and capital has decreased since the 2000s may reflect that conventional technology has been matured and become widespread; thus, skilled labor is not the only complemental production factor for capital. In addition, this change in the complementarity has intensified with new technological innovations, such as artificial intelligence and machine learning, in which conventionally defined skilled labor is unnecessary anymore.

Based on the previous studies discussed above, this study examined recent changes in the labor share from a different perspective than that of conventional research, which has focused on the relationship between capital and skilled and unskilled labor, centered on the CSC and SBTC. Intermediate goods input is another important production factor that remains to be studied. Since the mid-1990s, when the income share of skilled labor markedly increased, global supply chains have increased the share of intermediate goods in total trade from developed countries to developing countries (Figure 2). In addition, the share of intermediate goods in total production inputs in each country has also increased. Previous studies have shown that this has various macroeconomic effects, such as the correlation with the international business cycle. However, research on the impact of trade in intermediate goods on the labor share has not yet been sufficiently advanced compared with that on capital goods.

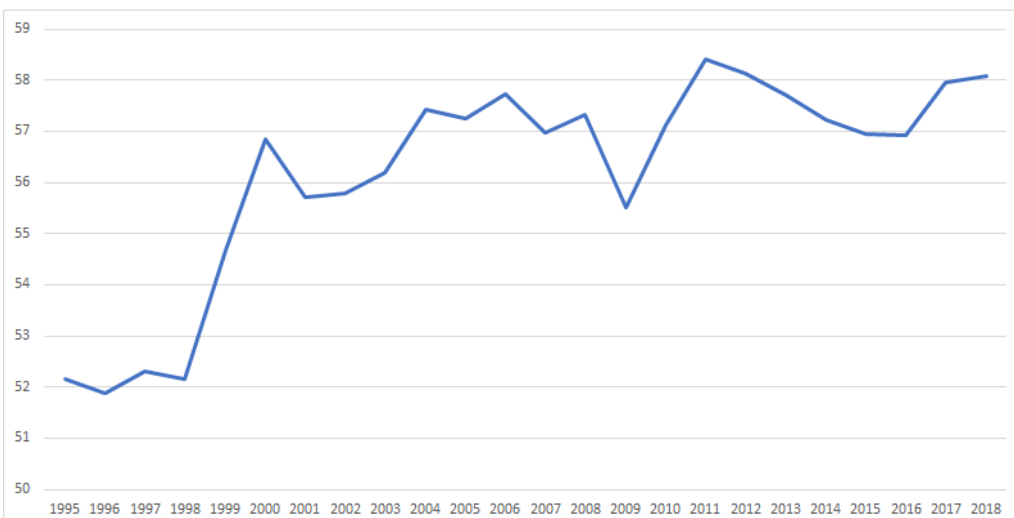

Fig. 2. The share of intermediate goods in total trade from developed to developing countries (%). Note: Data source is OECD TiVA Database

Kurokawa (2011) demonstrated a model of the mechanism by which wage premiums would arise, assuming that skilled labor and intermediate goods are complementary (i.e., the elasticity of substitution between these factors is less than one), as the expansion of the variation in intermediate goods through trade increases skilled workers' productivity at a pace that exceeds increases in final goods production. However, Kurokawa (2011) did not explicitly address capital. As described later, this study found that the widening disparity between the shares of skilled and unskilled labor is influenced by the elasticity of substitution between capital and labor and that between intermediate goods and other production factors. Kurokawa (2011) reported that the elasticity of substitution of skilled labor and intermediate goods was less than one, which was not an actual estimate. Previous studies have only made assumptions and do not provide examples of estimations.

Basco and Mestieri (2019) found that the more productive countries are, the more they import capital-intensive intermediate goods, resulting in faster accumulation of capital, increased income share of capital, and stagnation in the labor share. However, as this demonstrates, the disparity between the shares of skilled and unskilled labor has not been analyzed in their studies. Conversely, Arpaia *et al.* (2009) used the four-factor DSGE model with the three-level nested CES production function and production factor-biased technical changes, as in this study, and presented an analytical findings on the labor share under the assumption that gross output and value-added share the same deflator by reference to Bruno and Sachs (1985). According to their study, with all other things being equal, the labor share rises when the price of intermediate goods relative to that of gross output rises. This is because the elasticity of substitution between intermediate goods and the whole labor, including unskilled labor, is greater (the relationship is more substitute) than the elasticity of substitution between intermediate and capital goods. As a result, an increase in the relative price of intermediate goods will increase the labor demand relative to capital and increase the labor share rather than the capital share. However, Arpaia *et al.* (2009), like Basco and Mestieri (2019), did not analyze the disparity in the share of unskilled labor, and the assumption that gross output and value-added have the same deflator was inconsistent with the actual data. In this study, this constraint was removed and analyzed using a general equilibrium model.

From an empirical perspective, Crino (2012) analyzed the impact of imported intermediates on corporate skill upgrading using the propensity score matching method. The analysis demonstrated that the import of intermediate goods plays a role in increasing firms' demand for skilled labor. The study also noted that the background behind such mechanisms is that, by importing intermediate goods, companies will become engaged in activities that require a skilled labor force, such as developing new products, improving product quality, and incorporating research and development and new technologies.

Based on the previous studies described above, the present study can contribute to the current literature in several ways. First, we estimated the elasticity of substitution among four factors and the technological changes biased toward each factor. Second, we constructed a four-factor DSGE model with three-level nested CES and factor-biased technology using the estimated parameters and reproduced the actual data indicating that the shares of skilled and unskilled labor have changed dramatically in the context of a relatively stable wage premium, total labor share, and capital share. Third, through model simulations, we examined how the simulation results would change if the elasticity of substitution between multiple production factors changed. The analysis revealed that changes in relative prices between intermediate goods and other factors and complementary relationships between intermediate goods and skilled labor (intermediate goods-skill complementarity) determine changes in the shares of skilled and unskilled labor.

The elasticity of substitution between intermediate goods and other production factors plays an important role in analyzing the impact of intermediate goods on income distribution; however, it has not been previously estimated. To the best of our knowledge, Kiyota and Kurokawa (2019) provided the only estimate; however, they assumed the elasticity of substitution between capital and other factors of production is unity (i.e., assuming Cobb–Douglas technology). They did not estimate factor-biased technological changes. As Duffy *et al.* (2004) demonstrated, this restricted specification is undesirable when estimating nested CES functions. In this study, we calculated the rental price of capital using data from the Penn World Tables (PWT; ver. 10.0) and estimated the elasticity of substitution among four production factors, including intermediate goods and factor-biased technological changes under the specification of the three-level nested CES.

The mechanism by which the four-factor DSGE model with a three-level nested CES and factor-biased technological changes adopted in this study explains the disparity in the income shares between skilled and unskilled labor can be summarized as follows. We used Equation (1) as the benchmark model to explain the mechanism, although the three-layer structure of the CES function was estimated by varying the composition of each layer, as described in Section 2.

$$\begin{aligned} GO_t \;=\; & (\pi_3((\pi_2((\pi_1[K_t e^{g_K t}]^{-\rho_1} + (1-\pi_1)[L_{st} e^{g_{L_s} t}]^{-\rho_1})^{\frac{1}{-\rho_1}})^{-\rho_2} \\ & +(1-\pi_2)[L_{ut} e^{g_{L_u} t}]^{-\rho_2})^{\frac{1}{-\rho_2}})^{-\rho_3} + (1-\pi_3)[N_t e^{g_N t}]^{-\rho_3})^{\frac{1}{-\rho_3}} \end{aligned} \quad (1)$$

The first composite includes capital (K) and skilled labor (L_s), and the second combines the first composite and unskilled labor (L_u) (the second composite is equivalent to value-added). The third composite combines the second composite and intermediate input (N) (which is equivalent to gross output, GO), and the whole is a three-level nested CES.[1] In Equation (1), $\rho_x = \frac{1-\sigma_x}{\sigma_x}$ is the substitution parameter (with σ_x the elastisity of substitution) and π_x is the distribution parameter. In addition, g_x represents a factor-biased technological change in each production factor (assuming exponential technological growth).

SBTC, which is the starting point of the simulation, enhances the productivity of skilled labor and shifts the isoquant of the first composite closer to skilled labor. As a result, the input of skilled labor and its wage are substantially increased. In addition, the decrease in the prices of intermediate goods relative to skilled labor and other production factors, and thus an increase in the input of intermediate goods, contributes to the changes in relative income shares of production factors. While the first component of skilled labor and capital increases significantly owing to the complementary relationship with intermediate

[1] The baseline values for each variable required for normalization to estimate the elasticity of substitution are omitted here to avoid complexity. See Section 2 for details.

goods (i.e., the intermediate goods-skill complementarity is realized), the second component (value-added) including unskilled labor, which is a substitute for intermediate goods, only increases slightly. Consequently, the amount of unskilled labor input corresponding to the difference between the first and second components decreases. Through these processes, the income share of skilled labor increases, while the income share of unskilled labor decreases. The three-layer structure of each production factor with different elasticities of substitution allows us to accurately capture the changes in the actual shares of skilled and unskilled labor by changing the input balance among the production factors.

The remainder of this paper is organized as follows. Section 2 explains the estimation methods and results for the elasticity of substitution among the four factors and those for the estimation of factor-biased technological changes. Section 3 describes the DSGE model using the elasticity of substitutions and technological changes estimated in Section 2. Section 4 presents an overall summary.

2 Elasticity of substitution and production factor-biased technological change

2.1 Estimation method

This section describes the estimate of the elasticity of substitutions among production factors and production factor-biased technological changes based on the three-level nested CES function presented in Equation (1). The three-level nested CES function was estimated by varying the nesting structure; however, the estimation procedure is described here using Equation (1) as an example. Estimates were made as a system estimation method incorporating the first-order condition (FOC) of profit maximization and the CES function.

First, we estimated Equation (3), which represents the FOC of capital (K), and Equation (4), which represents the FOC of labor (L), which is the sum of skilled and unskilled labor (L_s, L_u). These equations are derived from Equation (2), representing real value-added (Y), where the elasticity of substitution between labor and capital (σ_Y) is $\sigma_Y = \frac{1}{1+\rho_Y}$. Overlined characters are baseline values required for normalization to estimate the elasticity of substitution, and here, we used the term mean values of variables. The following CES function estimates all use similar normalizations. $g_K t$ and $g_L t$ represent capital- and labor-biased technological changes, respectively. π is the distribution parameters calculated in the same manner as the baseline value of capital and labor. Equations (3) and (4) derive the elasticity of substitution between capital and labor and biased technological changes for each factor of production. Note that Equations (3) and (4) were estimated using the system approach in conjunction with the CES function, in which Equation (2) is modified as Equation (5). Compared to single-equation approaches in which Equations (3) and (4) were estimated separately, the benefits of the system approach in estimating Equations (3)–(5) in an integrated manner are that it reflects the information of both optimization behavior

(FOC) and technology (CES production function) (Klump *et al.*, 2004; Leon-Ledsma *et al.*, 2009; Klump *et al.*, 2011).

$$\frac{Y_t}{\overline{Y}} = \{\pi_Y(\frac{K_t}{\overline{K}}e^{g_K t})^{-\rho_Y} + (1-\pi_Y)(\frac{L_t}{\overline{L}}e^{g_L t})^{-\rho_Y}\}^{\frac{1}{-\rho_Y}} \tag{2}$$

$$d\ln(\frac{r_t}{P_{Yt}}) = (1+\rho_Y)d\ln(\frac{Y_t}{K_t}) - g_K\rho_Y \tag{3}$$

$$d\ln(\frac{w_{Lt}}{P_{Yt}}) = (1+\rho_Y)d\ln(\frac{Y_t}{L_t}) - g_L\rho_Y \tag{4}$$

$$d\ln(\frac{Y_t}{L_t}) = -\frac{1}{\rho_Y}d\ln[\pi_Y e^{\rho_Y(g_L-g_K)t}(\frac{K_t}{L_t}\frac{\overline{L}}{\overline{K}})^{-\rho_Y} + (1-\pi_Y)] + g_L \tag{5}$$

Next, we estimated the composite of capital and skilled labor, which is the first nest of Equation (1). Let R be the composite of this capital and skilled labor (Equation (6)). From Equation (6), we derived the FOC by differentiating R with capital and skilled labor, respectively, and estimated Equation (7) by using the ratio of wages for skilled labor (w_{Ls}) to the rental price of capital (r) as a dependent variable, using two explanatory variables: [1] the input ratio of skilled labor to capital and [2] the interaction term reflecting the difference between skilled- and capital-biased technological changes and the substitution parameter between these two factors ($(g_K - g_{L_S})\rho_R$). To reflect the structure of the CES function in Equation (6) in the estimation, Equation (7) was estimated using the system estimation method with Equation (8) modified from Equation (6). From the estimate of g_K derived from the system estimation in Equations (3)–(5) and estimations of Equations (7) and (8), ρ_R and skilled-biased technological changes (g_{L_S}) could be estimated. To prepare for the next estimation, we calculated the price of R (P_R), which is the composite of the rental price of capital and the skilled labor wage and paired with Equation (6) (Equation (9)).

$$\frac{R_t}{\overline{R}} = \{\pi_R(\frac{K_t}{\overline{K}}e^{g_K t})^{-\rho_R} + (1-\pi_R)(\frac{L_{st}}{\overline{L_s}}e^{g_{L_s} t})^{-\rho R}\}^{\frac{1}{-\rho_R}} \tag{6}$$

$$d\ln(\frac{w_{L_s t}}{r_t}) = (1+\rho_R)d\ln(\frac{K_t}{L_{st}}) + (g_K - g_{Ls})\rho_R \tag{7}$$

$$d\ln(\frac{R_t}{L_{st}}) = -\frac{1}{\rho_R}d\ln[\pi_R e^{\rho_R(g_{L_s}-g_K)t}(\frac{K_t}{L_{st}}\frac{\overline{L_s}}{\overline{K}})^{-\rho_R} + (1-\pi_R)] + g_{L_s} \tag{8}$$

$$\frac{P_{Rt}}{\overline{P_R}} = \{\pi_R(\frac{r_t}{\overline{r}}e^{g_K t})^{\frac{\rho_R}{1+\rho_R}} + (1-\pi_R)(\frac{w_{L_{st}}}{\overline{w_{L_s}}}e^{g_{L_s} t})^{\frac{\rho_R}{1+\rho_R}}\}^{\frac{1+\rho_R}{\rho_R}} \tag{9}$$

Next, we defined Q as the composite of R and unskilled labor corresponding to the second nested part of Equation (1) (Equation (10)). As in the case of R, we derived the FOC by differentiating Q using R and unskilled labor and estimate Equation (11), where the ratio of R's price (P_R) to the wage of unskilled labor (w_{Lu}) is the dependent variable, and unskilled labor and R's input ratio, and the interaction term of unskilled labor-biased technological change (g_{Lu}) and ρ_Q reflecting the elasticity of substitution between R and unskilled labor are the explanatory variables. We again estimated the system of Equations (11) and (12), transforming Equation (10), and estimated unskilled labor-biased technological change (g_{Lu}) andρ_Q. To prepare for the next estimation, we calculated the price of Q (P_Q). P_Q is the composite of the price of R (P_R) and the wage of unskilled labor (w_{Lu}), which is paired with Equation (10) (Equation (13)).

$$\frac{Q_t}{\overline{Q}} = \{\pi_Q(\frac{R_t}{\overline{R}})^{-\rho_Q} + (1-\pi_Q)(\frac{L_{ut}}{\overline{L_u}}e^{g_{Lu}t})^{-\rho_Q}\}^{\frac{1}{-\rho_Q}} \tag{10}$$

$$d\ln(\frac{P_{Rt}}{w_{L_{ut}}}) = (1+\rho_Q)d\ln(\frac{L_{ut}}{R_t}) + g_{Lu}\rho_Q \tag{11}$$

$$d\ln(\frac{Q_t}{L_{ut}}) = -\frac{1}{\rho_Q}d\ln[\pi_Q e^{\rho_Q g_{Lu}t}(\frac{R_t}{L_{ut}}\frac{\overline{L_u}}{\overline{R}})^{-\rho_Q} + (1-\pi_Q)] + g_{L_u} \tag{12}$$

$$\frac{P_{Qt}}{\overline{P_Q}} = \{\pi_Q(\frac{P_{Rt}}{\overline{P_R}})^{\frac{\rho_Q}{1+\rho_Q}} + (1-\pi_Q)(\frac{w_{L_{ut}}}{\overline{w_{L_u}}}e^{g_{Lu}t})^{\frac{\rho_Q}{1+\rho_Q}}\}^{\frac{1+\rho_Q}{\rho_Q}} \tag{13}$$

The third level at the top of Equation (1) is the composite of Q and the intermediate good N, which is equivalent to the real gross output (GO) (Equation (14)). By differentiating Equation (14) with Q and N and estimating Equation (15), where the price ratio of Q to intermediate good N is an explanatory variable, we could estimate the elasticity of substitution between Q and intermediate goods ($\sigma_{GO} = \frac{1}{1+\rho_{GO}}$) and intermediate goods-biased technological change (g_N). In this case, Equation (15) was estimated simultaneously with Equation (16) transformed from Equation (14).

$$\frac{GO_t}{\overline{GO}} = \{\pi_{GO}(\frac{Q_t}{\overline{Q}})^{-\rho_{GO}} + (1-\pi_{GO})(\frac{N_t}{\overline{N}}e^{g_N t})^{-\rho_{GO}}\}^{\frac{1}{-\rho_{GO}}} \tag{14}$$

$$d\ln(\frac{P_{Qt}}{P_{Nt}}) = (1+\rho_{GO})d\ln(\frac{N_t}{Q_t}) + g_N\rho_{GO} \tag{15}$$

$$d\ln(\frac{GO_t}{N_t}) = -\frac{1}{\rho_{GO}}d\ln[\pi_{GO}e^{\rho_{GO}g_N t}(\frac{Q_t}{N_t}\frac{\overline{N}}{\overline{Q}})^{-\rho_{GO}} + (1-\pi_{GO})] + g_N \tag{16}$$

These estimations were conducted in stages, and the results estimated in the previous stage (layer) were used in the subsequent estimation. Therefore, the above nine estimation equations (Equations (3)–(5), (7), (8), (11), (12), (15), and (16)) were conducted as one system estimation.

2.2 Data

Data from the WIOD Socio-Economic Account (WIDO, 2013 release) and PWT (ver. 10.0) were used for the estimations. Data for real & nominal gross output, real & nominal intermediate inputs, real & nominal value added, total hours worked by persons engaged, hours worked by high-skilled persons engaged, hours worked by medium- and low-skilled persons engaged, labor compensation, high-skilled labor compensation, medium- and low-skilled labor compensation, and capital compensation were obtained from the WIOD, and data for capital stock, real internal rate of return, and price level of capital stock from the PWT.These data are collected for 40 countries: 31 developed and 9 developing countries that are subject to the WIOD. The developed countries are Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Taiwan, the United Kingdom, and the United States. The developing countries are Brazil, Bulgaria, China, India, Indonesia, Russia, Mexico, Romania, and Turkey.

The WIOD classifies skilled and unskilled labor by the educational level (International Standard Classification of Education, ISCED) of workers: high-skilled labor corresponds to ISCED categories 5 and 6, middle-skilled to ISCED categories 3 and 4, and low-skilled to ISCED categories 1 and 2 (Timmer *et al.*, 2015). The rental price of capital was calculated by multiplying the real internal rate of return by the price level of capital stock according to Inklaar and Woltjer (2019).

2.3 Estimation results

To address the endogeneity of the explanatory variables, estimates were conducted using the generalized method of moments. The lag value of the explanatory variables was used as the instrumental variable. In addition to Equation (1), the three-level nested CES function was replaced by a hierarchical structure to test the five patterns. When Equation (1) is written as Model 1 (((K Ls) Lu) N), the other four patterns are Model 2 (((K Ls) N)) Lu), Model 3 (((Ls N) K) Lu), Model 4 (((K N) Ls) Lu), and Model 5 ((K Ls) Lu). Model 5 is a conventional two-level CES function, without intermediate goods. The results of previous studies indicated that the elasticity of substitution between unskilled labor and capital is relatively high (i.e., the CSC). Therefore, Lu is structured outside the composites of K and Ls.

Table 1(a) Estimation results

	Model 1		Model 2		Model 3		Model 4		Model 5	
c(1)	1.4847	***	0.8107	***	-1.2029	***	1.1500	***	0.7657	***
	(0.2011)		(0.1168)		(0.0978)		(0.2832)		(0.1022)	
c(2)	-0.0214	**	-0.0182	**	-0.0081	***	-0.0271	**	-0.0190	***
	(0.0108)		(0.0049)		(0.0017)		(0.0118)		(0.0065)	
c(3)	-0.0087	**	0.0030		0.0023	**	-0.0018		0.0035	**
	(0.0036)		(0.0020)		(0.0011)		(0.0033)		(0.0016)	
c(4)	-0.4262	***	-0.5687	**	-0.5626	**	-1.0692	***	-0.4893	**
	(0.1261)		(0.2801)		(0.2530)		(0.1259)		(0.2180)	
c(5)	-0.0216	***	0.0418	***	0.0183		0.0123	*	0.0421	***
	(0.0076)		(0.0099)		(0.0072)		(0.1192)		(0.0077)	
c(6)	-0.0704	***	-0.6128	***	-0.6557	***	-0.3150	***	-0.2696	*
	(0.0130)		(0.0227)		(0.0784)		(0.1192)		(0.1527)	
c(7)	-0.0002	**	0.0000		0.0002	**	-0.0001		0.0000	
	(0.0001)		(0.0001)		(0.0001)		(0.0001)		(0.0012)	
c(8)	-0.9722	***	-0.2000	*	-0.3053	**	-0.2898	**		
	(0.0480)		(0.1179)		(0.1379)		(0.1375)			
c(9)	0.0000		-0.0003		-0.0014		0.0006			
	(0.0000)		(0.0011)		(0.0013)		(0.0008)			

Model 1		Model 2		Model 3		Model 4		Model 5	
σ_{KLs}	$-\frac{1}{c(4)}$	σ_{KLs}	$-\frac{1}{c(4)}$	σ_{NLs}	$-\frac{1}{c(4)}$	σ_{KN}	$-\frac{1}{c(4)}$	σ_{KLs}	$-\frac{1}{c(4)}$
σ_{RLu}	$-\frac{1}{c(6)}$	σ_{RN}	$-\frac{1}{c(6)}$	σ_{RK}	$-\frac{1}{c(6)}$	σ_{RLs}	$-\frac{1}{c(6)}$	σ_{RLu}	$-\frac{1}{c(6)}$
σ_{QN}	$-\frac{1}{c(8)}$	σ_{QLu}	$-\frac{1}{c(8)}$	σ_{QLu}	$-\frac{1}{c(8)}$	σ_{QLu}	$-\frac{1}{c(8)}$		
g_K	$-\frac{c(2)}{c(1)-1}$					g_K	$-\frac{c(2)}{c(1)-1}$		
g_{Ls}	$g_K+\frac{c(5)}{c(4)+1}$	g_{Ls}	$g_K+\frac{c(5)}{c(4)+1}$	g_{Ls}	$g_K+\frac{c(5)}{c(4)+1}$			g_{Ls}	$g_K+\frac{c(5)}{c(4)+1}$
g_{Lu}	$\frac{c(7)}{-c(6)-1}$								
						g_N	$g_K+\frac{c(5)}{c(4)+1}$		
$A=K$		$A=K$		$A=N$		$A=K$			
$B=L_s$		$B=L_s$		$B=L_s$		$B=N$			
$C=L_u$		$C=N$		$C=K$		$C=L_s$			
$D=N$		$D=L_u$		$D=L_u$		$D=L_u$			

Standard errors are in parentheses. ***, **, and * indicate that they are significant at the 1%, 5%, and 10% levels.

Table 1(b) Estimated elasticities of substitution (point and interval estimates)

Model 1			
		5%	95%
σ_{KLs}	2.35	1.58	4.57
σ_{RLu}	14.21	10.91	20.39
σ_{QN}	1.03	0.95	1.12

Model 2			
		5%	95%
σ_{KLs}	1.76	0.97	9.27
σ_{RN}	1.63	1.54	1.74
σ_{QLu}	5.00	2.54	166.65

Model 3			
		5%	95%
σ_{NLs}	1.78	1.02	6.83
σ_{RK}	1.53	1.27	1.90
σ_{QLu}	3.28	1.88	12.76

Model 4			
		5%	95%
σ_{KN}	0.94	0.78	1.16
σ_{RLs}	3.17	1.96	8.41
σ_{QLu}	3.45	1.94	15.69

Model 5			
		5%	95%
σ_{KLs}	2.04	1.18	7.65
σ_{YLu}	3.71	1.92	54.07

Table 1(a) presents the estimation results. With Models 1–5 presented in order from the left edge of the table, the results of both point and interval estimations are shown (Figure 1(b)). The model simulation in the next Section 3 sets the parameters to reproduce the data within the range of these interval estimations.

The estimated coefficients c(1)–c(9) listed in Table 1(a) are included in the equations below. Variables A, B, C, and D are defined differently depending on the model (see the definitions in Table 1(a)):

For Models 1, 2, and 4, the estimated equations are as follows:

$$d\ln(\frac{r_t}{P_{Yt}}) = c(1) * d\ln(\frac{Y_t}{K_t}) + c(2) \tag{a}$$

$$d\ln(\frac{w_{Lt}}{P_{Yt}}) = c(1) * d\ln(\frac{Y_t}{L_t}) + c(3) \tag{b}$$

$$d\ln(\frac{Y_t}{L_t}) = -\frac{1}{c(1)-1} * d\ln[\pi_Y e^{(c(2)-c(3))}(\frac{K_t}{L_t}\frac{\overline{L}}{\overline{K}})^{-(c(1)-1)} + (1-\pi_Y)] - \frac{c(3)}{c(1)-1} \tag{c}$$

$$d\ln(\frac{P_{Bt}}{P_{At}}) = c(4) * d\ln(\frac{A_t}{B_t}) + c(5) \tag{d}$$

$$d\ln(\frac{R_t}{B_t}) = -\frac{1}{c(4)-1} * d\ln[\pi_R e^{-c(5)}(\frac{A_t}{B_t}\frac{\overline{B}}{\overline{A}})^{-(c(4)-1)} + (1-\pi_R)] + (\frac{c(5)}{c(4)-1} - \frac{c(2)}{c(1)-1}) \tag{e}$$

$$d\ln(\frac{P_{Rt}}{P_{Ct}}) = c(6) * d\ln(\frac{C_t}{R_t}) + c(7) \tag{f}$$

$$d\ln(\frac{Q_t}{C_t}) = -\frac{1}{c(6)-1} * d\ln[\pi_Q e^{c(7)}(\frac{R_t}{C_t}\frac{\overline{C}}{\overline{R}})^{-(c(6)-1)} + (1-\pi_Q)] + \frac{c(7)}{c(6)-1} \quad \text{(g)}$$

$$d\ln(\frac{P_{Qt}}{P_{Dt}}) = c(8) * d\ln(\frac{D_t}{Q_t}) + c(9) \quad \text{(h)}$$

$$d\ln(\frac{GO_t}{D_t}) = -\frac{1}{c(8)-1} * d\ln[\pi_{GO} e^{c(9)}(\frac{Q_t}{D_t}\frac{\overline{D}}{\overline{Q}})^{-(c(8)-1)} + (1-\pi_{GO})] + \frac{c(9)}{c(8)-1} \quad \text{(i)}$$

For Model 3, the estimated equations are following [j], [k] [l] and above-described equations [d]-[i]:

$$d\ln(\frac{P_{Nt}}{P_{GOt}}) = c(1) * d\ln(\frac{GO_t}{N_t}) + c(2) \quad \text{(j)}$$

$$d\ln(\frac{P_{Yt}}{P_{GOt}}) = c(1) * d\ln(\frac{GO_t}{Y_t}) + c(3) \quad \text{(k)}$$

$$d\ln(\frac{GO_t}{N_t}) = -\frac{1}{c(1)-1} * d\ln[\pi_{GO} e^{c(2)}(\frac{Y_t}{N_t}\frac{\overline{N}}{\overline{Y}})^{-(c(1)-1)} + (1-\pi_{GO})] - \frac{c(2)}{c(1)-1} \quad \text{(l)}$$

For Model 5, the estimated equations are as following [m]-[p] and above-described equations [a]-[c]:

$$d\ln(\frac{w_{Lst}}{r_t}) = c(4) * d\ln(\frac{K_t}{L_{st}}) + c(5) \quad \text{(m)}$$

$$d\ln(\frac{R_t}{L_{st}}) = -\frac{1}{c(4)-1} * d\ln[\pi_R e^{-c(5)}(\frac{K_t}{L_{st}}\frac{\overline{L_s}}{\overline{K}})^{-(c(4)-1)} + (1-\pi_R)] + (\frac{c(5)}{c(4)-1} - \frac{c(2)}{c(1)-1}) \quad \text{(n)}$$

$$d\ln(\frac{P_{Rt}}{L_{ut}}) = c(6) * d\ln(\frac{L_{ut}}{R_t}) + c(7) \quad \text{(o)}$$

$$d\ln(\frac{Y_t}{L_{ut}}) = -\frac{1}{c(6)-1} * d\ln[\pi_Q e^{c(7)}(\frac{R_t}{L_{ut}}\frac{\overline{L_u}}{\overline{R}})^{-(c(6)-1)} + (1-\pi_Q)] + \frac{c(7)}{c(6)-1} \quad \text{(p)}$$

The estimated elasticity of substitution between unskilled labor and other factors of production is greatest, which is consistent with previous studies (Table 1(b)). For production factor-biased technological changes, SBTCs (g_{L_s}) were estimated to be significantly positive, as expected, in common with most models. Regarding other technological changes, notably, the three biased technological changes of capital, skill, and unskilled labor were estimated to be significant in Model 1 (Table 1(a)).

3 Simulation with DSGE models

Using the elasticity of substitutions and parameters of technological changes estimated in the previous chapter, we constructed and simulated DSGE models. We examined the extent to which actual changes in the labor shares, wage premiums and wage bill ratios could be reproduced using the estimated parameters. Simultaneously, we examined how the results changed when the parameters were changed. To apply factor-biased technological changes to the model, we adopted non-stationary technology (i.e., technology following a random walk with drift).

3.1 Model

The model structure is described below. The representative consumer has preferences for consumption (C_t) and leisure ($1-L_t$, where L_t is the amount of work), as shown (Equation (17)). Of these, v takes the following form (Equation (18)). Consumers have capital stock and choose the level of its utilization. Consumers lend capital services (the product of utilization and capital) to firms. The consumer's problem consists of choosing consumption, investment (I_t), labor (L_t), capital stock (K_{t+1}), capital utilization (u_t) and bond (B_{t+1}) as follows:

$$u(C_t, L_t) = \frac{(C_t v(1-L_t))^{1-\sigma} - 1}{1-\sigma} \tag{17}$$

$$v(1-L_t) = \exp(\theta\frac{(1-L_t)^{1-\xi} - 1}{1-\xi}) \tag{18}$$

$$\max\{\sum_{t=0}^{\infty}\beta^t u(C_t, L_t)\} \tag{19}$$

$$C_t + I_t + B_{t+1} \leq w_t L_t + r_t u_t K_t + (1 + r_{t-1})B_t \tag{20}$$

$$K_{t+1} = [1-\delta(u_t)]K_t + I_t[1 - S(\frac{I_t}{I_{t-1}})] \tag{21}$$

Equation (20) is the consumer's budget constraint and Equation (21) is the law of motion of capital, where r_t is the rental price of capital, δ is the capital depreciation rate, u_t is the capital utilization rate, and S is the investment adjustment cost. The overall work comprises skilled and unskilled labor ($L_t = L_{st} + L_{ut}$); however, both skilled and unskilled works have the same effect on consumer preferences. The capital depreciation rate is expressed as a function of the capital utilization rate, as shown in Equation (22). The investment adjustment cost is expressed as Equation (23).

$$\delta(u_t) = \delta_0 + \delta_1(u_t - 1) + \frac{\delta_2}{2}(u_t - 1)^2 \tag{22}$$

$$S(\frac{I_t}{I_{t-1}}) = \frac{\kappa}{2}(\frac{I_t}{I_{t-1}} - 1)^2 \tag{23}$$

The representative firm produces output (GO) using Equation (1). It acts as though it gets to choose the volumes of production factors and capital utilization even though the consumer can choose the component of labor (skilled and unskilled), utilization and capital. The firm's problem is:

$$\max\ GO_t - w_{Lst}L_{st} - w_{Lut}L_{ut} - r_t u_t K_t - P_{Nt}N_t \tag{24}$$

where N_t is the intermediate goods input and P_{Nt} is its prices.

The real value-added is defined in Equation (2) and also expressed as $Y_t = w_{Lst}L_{st} + w_{Lut}L_{ut} + r_t u_t K_t$. Finally, the relationship between GO_t, real value added (Y_t), and intermediate input (N_t) is expressed as Equation (25). As noted above, Arpaia *et al.*'s (2009) hypothesis that the deflators of gross output and value-added (P_{GOt}, P_{Yt}) are identical is inconsistent with the actual data; therefore, this study revises this constraint.

$$GO_t = \frac{P_{Yt}}{P_{GOt}}Y_t + \frac{P_{Nt}}{P_{GOt}}N_t \qquad (\frac{\partial GO_t/\partial K_t}{\partial Y_t/\partial K_t} = \frac{P_{Yt}}{P_{GOt}}) \tag{25}$$

To characterize the consumer's problem, we set up the Lagrangian with two constraints:

$$\begin{aligned}\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t [&\frac{(C_t v(1-L_t))^{1-\sigma} - 1}{1-\sigma} \\ &+ \lambda_t\{w_t L_t + r_t u_t K_t + (1 + r_{t-1})B_t - C_t - I_t - B_{t+1}\} \\ &+ \mu_t\{I_t[1 - \frac{\kappa}{2}(\frac{I_t}{I_{t-1}} - 1)^2] + [1 - \delta(u_t)]K_t - K_{t+1}\}]\end{aligned} \tag{26}$$

The equilibrium conditions for the consumer can be written as follows:

$$\lambda_t = C_t^{-\sigma}(\exp((\theta\frac{(1-L_t)^{1-\xi} - 1}{1-\xi}))^{1-\sigma} \tag{27}$$

$$\begin{aligned}\lambda_t &= \mu_t\{1-\frac{\kappa}{2}(\frac{I_t}{I_{t-1}}-1)^2-\kappa(\frac{I_t}{I_{t-1}}-1)\frac{I_t}{I_{t-1}}\} \\ &\quad +\beta E_t\mu_{t+1}\kappa(\frac{I_{t+1}}{I_t}-1)(\frac{I_{t+1}}{I_t})^2\end{aligned} \tag{28}$$

$$\lambda_t w_t = \{C_t \exp(\theta\frac{(1-L_t)^{1-\xi}-1}{1-\xi})\}^{-\sigma}C_t\theta$$
$$\exp(\theta\frac{(1-L_t)^{1-\xi}-1}{1-\xi})(1-L_t)^{-\xi} \tag{29}$$

$$\mu_t = \beta\lambda_{t+1}[\{r_{t+1}u_{t+1}+\delta(u_{t+1})\}+\beta\mu_{t+1}(1-\delta(u_{t+1}))] \tag{30}$$

$$\mu_t\delta^{'}(u_t) = \lambda_t r_t \tag{31}$$

$$\lambda_t = \beta E_{t+1}\lambda_{t+1}(1+r_t) \tag{32}$$

For the firm, the equilibrium conditions are:

$$\frac{\partial GO_t}{\partial L_{st}} = \frac{w_{L_{st}}}{P_{GOt}} \tag{33}$$

$$\frac{\partial GO_t}{\partial L_{ut}} = \frac{w_{L_{ut}}}{P_{GOt}} \tag{34}$$

$$\frac{\partial GO_t}{\partial (u_t K_t)} = \frac{r_t}{P_{GOt}} \tag{35}$$

$$\frac{\partial GO_t}{\partial N_t} = \frac{P_{Nt}}{P_{GOt}} \tag{36}$$

The next equation (37) describes technology.

$$g_t = \exp(g_z)\exp(\varepsilon_t) \tag{37}$$

The technological shock represents non-stationary technology. The technological change biased toward different production factors estimated in the previous chapter is assumed to have a deterministic trend. The DSGE model in this chapter uses the estimated deterministic trend and defines technological shock (A_t) as the random walk technology with drift as follows:

$$\frac{A_t}{A_{t-1}} = g_t \tag{38}$$

In Equation (37), $\exp(g_z)$ is the deterministic trend and $\exp(\varepsilon_t)$ is the stochastic trend. We used the following analytical procedure. We divided nonstationary variables (all variables excluding stationary variables: labor (L_t, L_{st}, L_{ut}) and interest rate (r_t) by A_t, and simulated the log-linearized model. To generate the levels of these non-stationary variables, we then added back the response of A_t (i.e., $\ln(A_t) = \sum g_t$) to the responses of those variables.

3.2 Calibration

This section describes the parameters used in the simulation. Key parameters other than the elasticity of substitutions estimated in Section 2 are summarized in Table 2.

Table 2 Calibration

Parameters	Description	Value
β	discount factor	0.99
δ_2	capital utilization parameter	0.50
κ	degree of adjustment cost	0.05
ξ	inverse of the Frish elasticity	0.25
n^*	steady-state hours to work	0.30
σ	risk aversion	2.00

3.3 Simulation results

Simulations were performed on the five models assumed in Section 2, which estimate the elasticity of substitution: Model 1 (((K Ls) Lu) N), Model 2 (((K Ls) N) Lu), Model 3 (((Ls N) K) Lu), Model 4 (((K N) Ls) Lu)), and Model 5 ((K Ls) Lu). Model 1 was used for three types of simulations because production factor-biased technological changes were estimated to be significant for three parameters: skilled labor, unskilled labor, and capital. In Model 4, technological changes estimated as significant in the Section 2 were for intermediate goods and capital; thus, these technologies were adopted. All other models were simulated based on skilled labor-biased technological changes. The size of the shock in Equation (37) was set such that the result of the factor share obtained by the simulation in Model 1 (benchmark model) would match the share obtained by the data.

The simulation results are presented in Table 3. For each model, simulation results are shown for five indicators: skilled labor share ($\frac{w_{Ls}L_s}{Y}$), unskilled labor share ($\frac{w_{Lu}L_u}{Y}$), capital share ($\frac{ruK}{Y}$), wage bill ratio for skilled and unskilled labor ($\frac{w_{Ls}L_s}{w_{Lu}L_u}$), and skill premium ($\frac{w_{Ls}}{w_{Lu}}$). All are the primary indicators referenced in relevant prior studies. The right edge of the table represents the value calculated from the data. For 1995–2009, the percentage change over the 14-year period is presented. The elasticity value of the substitution adopted is indicated in the bottom row.

Table 3 Simulation results: growth rates of five indicators (%)

	Model 1 (L_s)	Model 1 (L_u)	Model 1 (K)	Model 2 (L_s)	Model 3 (L_s)	Model 4 (K)	Model 4 (N)	Model 5 (L_s)	Data
Skilled labor share	36.15	29.36	4.79	2.29	22.89	24.08	20.97	0.61	34.20
Unskilled labor share	-12.89	-10.65	-1.38	-1.36	-7.76	-8.15	-6.34	-0.20	-15.75
Capital share	0.65	0.71	0.50	1.91	0.80	0.79	-0.26	3.80	-3.74
Wage bill ratio	49.04	40.02	6.18	3.65	30.64	32.23	27.31	0.81	51.62
Skill premium	-9.25	8.15	-0.86	0.39	37.03	-38.77	-14.86	-0.54	-0.23
Elasticities of	σ_{KLs}= 4.57	σ_{KLs}= 4.57	σ_{KLs}= 4.57	σ_{KLs}= 0.97	σ_{LsN}= 2.55	σ_{KN}= 0.95	σ_{KN}= 0.95	σ_{KLs}= 2.04	
substitution adopted	σ_{RLu}= 20.39	σ_{RLu}= 20.39	σ_{RLu}= 20.39	σ_{RN}= 1.63	σ_{RK}= 1.53	σ_{RLs}= 3.17	σ_{RLs}= 3.17	σ_{YLu}= 5.00	
for simulation	σ_{QN}= 1.03	σ_{QN}= 1.03	σ_{QN}= 1.03	σ_{QLu}= 6.00	σ_{QLu}= 3.00	σ_{KLu}= 1.94	σ_{KLu}= 1.94		

Note: The factor-biased technological change adopted in each simulation is in parentheses.

First, we examined Models 1-4, which account for intermediate input. In baseline Model 1, data are reproduced for almost all indicators in the simulation of skilled and unskilled labor shocks. Decreases in the prices of intermediate goods relative to other factors of production, and thus increases in the input of intermediate goods, contributes to increases in the relative income share of skilled labor, which are complementary to intermediate goods. Thus, the intermediate goods-skill complementarity holds (σ_{LsN} is calculated as 0.80 in the model 1 simulation with skilled labor shock). Accordingly, the first component, which is a composite of skilled labor and capital, increased significantly, while the second component including unskilled labor, which is a substitute for intermediate goods, increased slightly, thereby reducing the input of unskilled labor, corresponding to the difference between the first and second components (σ_{L_uN} is calculated as 1.08). In the case of simulation with unskilled labor shock, the same mechanism works (σ_{LsN} is 0.83, and σ_{L_uN} is 1.07). Capital had a relatively high elasticity of substitution to skilled labor of 4.57; however, capital input did not decrease significantly. The elasticity of substitution between the first composite and unskilled labor was greater (20.39); therefore, capital inputs were maintained through an increase in the second composite (a composite of capital, skilled labor, and unskilled labor) and a significant reduction in unskilled labor. Thus, the change in share of capital remained small, as the data indicate. This is so-called the net substitution effect a la Berndt and Wood (1979).

For capital-biased technological change in Models 1, the overall change was small compared with the data. Unless the average annual rate of increase in technological shock in the simulation is unrealistically high, changes in each indicator cannot be matched to the data. Models 2-4 share a common feature, in that the wage bill ratio and/or skill premium cannot match the data. This may be attributed to the difference in the elasticity of substitution between unskilled labor and other production factors. In Model 1, unskilled labor is in the second component of the CES function, and the elasticity of substitution with the first component is 20.39, which is large. Thus, the change in the wage ratio (skill premium) was relatively small, while the wage bill ratio greatly increased.

In this study, it is important to consider how intermediate inputs relate to changes in the income share of production factors. Accordingly, the results of Model 5 ((K Ls) Lu), which does not include intermediate goods, are important to examine. In Model 5, the overall range of change is much smaller than that of models that consider intermediate goods.

The large change in each variable in the model that incorporates intermediate goods is attributable to the large change in the relative prices between intermediate goods and value-added deflators. As described in Section 1, a decrease in the price of intermediate goods relative to that of the second composite (value-added) of Model 1, and thus an increase in the input of intermediate goods, plays a role in stimulating changes in other production factors. In the simulation, the price of intermediate goods relative to the value-added deflator declines by 2.24% (2.23% in the data). However, in Model 5, which does not consider intermediate goods, the absolute value of changes in the relative prices of wages for skilled and unskilled labor and the rental price of capital, which comprise the value added, were small. The relative wage of skilled labor to unskilled labor (skill premium) decreases only by 0.54% in Model 5, which is lower than that in other models that incorporate intermediate goods.

As noted above, in this study, we revised the assumption that the gross output and value added share the same deflator, as was posited in previous studies and adopted the specification in Equation (25). This shows that the model revision plays an important role in data replication.

Figures 3–5 show the results of the simulation (Model $1(L_s)$). The responses of the following three indicators in the model simulations with skilled-biased technological changes are plotted in Figures 3–5. Figure 3 shows the rate of change in the skilled labor income share, Figure 4 shows the rate of change in the unskilled labor income share, Figure 5 shows the rate of change in the capital income share. The x-axis depicts the elasticity of substitution between capital and skilled labor, the y-axis is the elasticity of substitution between value added (composite of skilled labor, unskilled labor, and capital) and intermediate goods and the z-axis depicts the rate of change for each variable. Figures 3–5 show that, when the elasticity between skilled labor and capital decreases along the x-axis, the results of the simulations change. When the elasticity of substitution between skilled labor and capital decreases, the relative increase in skilled labor to capital turns to increase the relative income share of capital. The increase in the rate of change in capital share also leads to the decrease in the rate of change in skilled labor share in the context of a relatively stable unskilled share. This mechanism of changing factor shares is attributable to the three-layer structure of CES function where unskilled labor input is in the different component from skilled labor and capital.

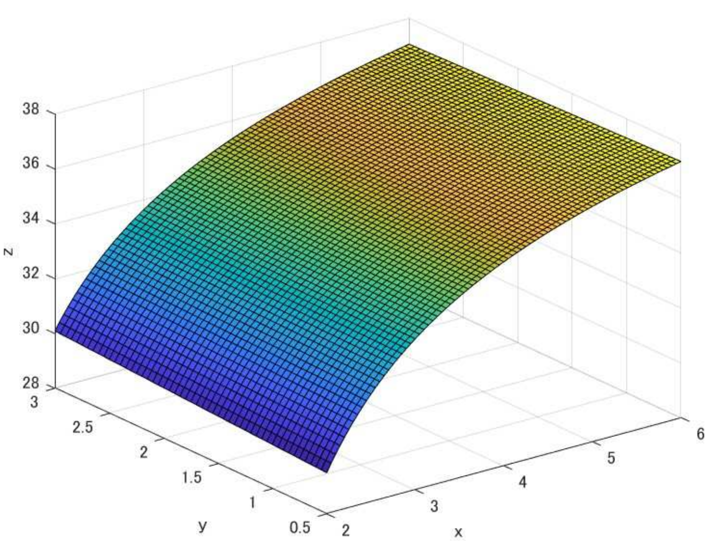

Fig. 3. The rate of change in the skilled labor income share (%, z-axis), the elasticity of substitution between capital and skilled labor (%, x-axis), and the elasticity of substitution between value-added and

intermediate goods (%, y-axis)

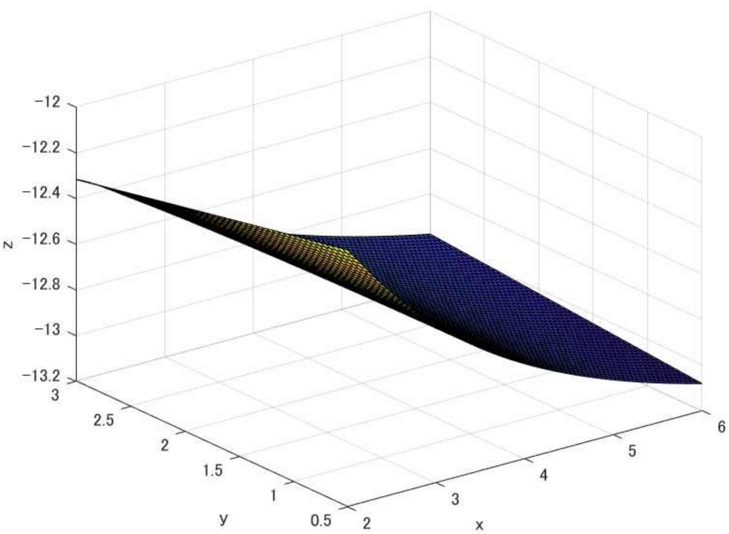

Fig. 4. The rate of change in the unskilled labor income share (%, z-axis), the elasticity of substitution between capital and skilled labor (%, x-axis), and the elasticity of substitution between value-added and intermediate goods (%, y-axis)

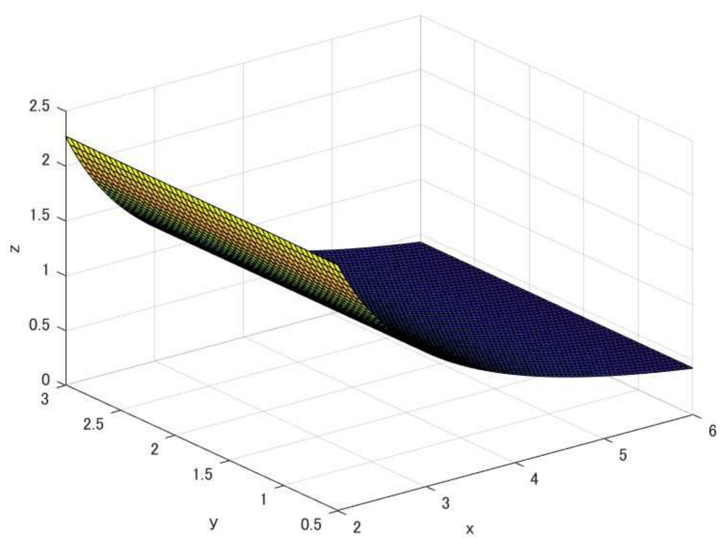

Fig. 5. The rate of change in the capital income share (%, z-axis), the elasticity of substitution between capital and skilled labor (%, x-axis), and the elasticity of substitution between value-added and intermediate goods (%, y-axis)

4 Conclusion

In this study, we analyzed the effects of the expansion of intermediate inputs on changes in the income disparity between skilled and unskilled labor, which was not sufficiently analyzed in previous studies. After estimating the elasticity of substitution among the four production factors of skilled labor, unskilled labor, capital, and intermediate goods, an analysis using a four-factor DSGE model with three-level nested CES and factor-biased technological changes was conducted. It demonstrated that the characteristic changes in the labor share in recent years were mainly related to the elasticity of substitution between intermediate goods and other factors, particularly the low elasticity of substitution between intermediate goods and skilled labor. The latter is the so-called intermediate goods-skill complementarity.

Decreases in the price of intermediate goods relative to other production factors and increases in the input of intermediate goods have a major impact on increases in the income share of skilled labor, which are complementary to intermediate goods. This property of an intermediate goods-skill complementarity plays a major role in stimulating changes in other variables in the model. The conventional three-factor model that does not consider intermediate goods fails to reproduce increases in the share of skilled labor and decreases in the share of unskilled labor. The main contribution of this study to the literature is an estimate of the elasticity of substitution among the four production factors and the technological changes biased toward each factor. Second, this study constructs a four-factor DSGE model using estimated parameters to reproduce the actual data showing that the shares of skilled and unskilled labor have changed dramatically in the context of a relatively stable wage premium, total labor share, and capital share. When intermediate goods were incorporated into the model, the assumption made in previous studies that the gross output and value added have the same deflator was revised, and the two deflators were allowed to move differently. Thus, the model simulation could reproduce the data.

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