How Biased is Skill-Biased Technical Change*

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In the presence of skill-biased technical change, changes in the skill composition of the labor force employed in a firm or an industry can contribute to growth. Important, then, is the extent to which we understand and can measure the skill bias in technical change. In this paper, we focus on an often misunderstood aspect of technical change and study how learning on the job - for labor of different skill levels - affects the effective *rate of technical change. We demonstrate that slower learning on the job, resulting in efficiency losses, by high-skilled labor means we underestimate the skill bias in technical change. First, we build a simple model that can explain how changes in the labor force skill composition can affect technical change and efficiency change. Monte Carlo simulations, calibrated to industry-level data for 40 countries and 31 industries over the period 1995-2009, show that our model can indeed explain the underestimation of skill-biased technical change. Our subsequent empirical analysis explains the discrepancy that has arisen between the marginal rate of technical substitution between labor of different skill levels and the relative wage paid to each, further illustrating that the skill bias in technical change is on average under estimated.*
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I. Introduction

Technical change, changes everything ... especially if it is skill biased. It is the source of increases in productivity (Solow, 1957), and in its simplest, neutral form means we can produce more today than we could yesterday, through the adoption of a better production technology. In its less simple form, technical change is not factor neutral, but dependent on changes in the mix of inputs employed. Its most poignant form is skill-biased technical change (SBTC), where a shift in production technology favors high-skilled labor over low-skilled labor by increasing high-skilled labor's relative productivity and thus relative demand. The underlying reasoning is that higher education can enhance

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a worker's ability to create, understand, learn, and adopt new technologial development (Nelson and Phelps, 1966). In this case, with the development of technology, more high-skilled workers will be needed to replace low-skilled workers. The result is increases in the skill premium, the ratio of the wages of skilled to unskilled workers, leading to an increase in wage inequality (Katz and Murphy, 1992; Autor, Katz and Krueger, 1998; Katz and Autor, 1999; Galor and Moav, 2000; Hornstein, Krusell and Violante, 2005).

SBTC can have a great impact on labor markets. It will increase the ratio of the marginal product of high-skilled over low-skilled labor, the marginal rate of technical substitution (MRTS). As a result, it changes how many low-skilled workers need to be replaced by one extra high-skilled worker, in order for firms to produce the same amount of output. In a perfectly competitive labor market, MRTS equals the relative price of inputs, in this case the wage ratio of high-skilled over low-skilled labor. SBTC changes the MRTS, and thereby also affects the wage differential between high-skilled and low-skilled labor. Indeed, the wages gap has widened in many countries over the past decades, in favor of high-skilled labor (Katz and Autor, 1999). At the same time, labor-saving technical change is the main explanation for the shift in demand away from unskilled and toward skilled labor in U.S. manufacturing during the 1980s (Berman, Bound and Griliches, 1994).

One of the aspects of SBTC that is less well understood is the role of learning on the job. The quality of labor forces depends not only on the education attainments but also on the experience. On-the-job learning can boost productivity and its effect would interact with the effects of SBTC. Black and Lynch (1996) find that there are adjustment costs related to the introduction of new skills, so the current training at the workplace will lower productivity in the short run and improve it after some time. We incorporate learning on the job for labor of different skill levels in a production model aimed at estimating technical change, including SBTC. Hiring and training new workers is not without costs, and hence involves a loss in efficiency. Newly-hired workers do not attain their full productivity as soon as they enter the labor market, but rather their productivity can stay temporarily below the productivity of experienced workers. If newly-hired labor has to learn on the job, some of the gains of replacing labor with one skill level for labor with another, better skill level, are - at least in the medium run - reduced by a loss in the efficiency with which each unit of labor contributes to producing output. We build a simple model that explains how changes in the composition of the labor force, the mix of high-, medium- and low-skilled labor, affect the efficiency of production. The key finding of our paper is that we end up with a biased estimate of SBTC if learning on the job leads to (temporary) efficiency losses that differ between skill levels. We demonstrate how important this bias is in explaining the wage gaps between labor of different skill levels as they have developed over a period of 15 years.

We contribute to the literature on SBTC in three ways. First, we derive the bias in the measurement of technical change in a simple production model with learning on the job that can easily be extended to accommodate many of the existing manners of measuring SBTC. Second, we use simulations to demonstrate how small differences in the speed of learning on the job for labor of different skill levels can already generate wage gap patterns similar to what we observe in practice for a rich data set covering 40 countries and 31 industries over the period 1995-2009. Third, we use the same data set to empirically measure the bias in skill-biased technical change, providing further evidence how the bias in the measurement SBTC can help explain the widening wage gap. **Ming, can we attach a simple number here????**.

We are not the first to tackle the measurement of SBTC. Although the literature on technical change is vast, most of if ignores the role of efficiency change. Baltagi and Griffin (1988) propose a procedure for calculating a general index of technical change, which replaces the time trend with time-specific dummies and can be both neutral and scale augmenting. Their approach can offer important advantages over the traditional time trend representation of technical change and attribute to the analysis of the determinants of technical change. Baltagi and Rich (2005) apply this general index approach to technical change between production and non-production labor in US manufacturing industries over the 1959-1996 period. They find that SBTC is significant and evident prior to 1983, predating the diffusion of personal computer technologies in the workplace and the dramatic changes of wage structure in the 1980s. However, they assume that all firms operate efficiently.

In Section II, we introduce a model that explains how inefficiencies from learning on the job by labor of different skill levels can bias the measurement of technical change. Section III explains how we can test this model empirically. In Section IV, we present results from simulating and estimating our model, respectively. To demonstrate the policy relevance of our results, we demonstrate their contribution to the debate on wage inequality in Section V. Some conclusions are drawn in Section VI.

II. Theoretical Model

Our objective is to analyze how skill-biased technical change is affected by differences in the manner in which labor of different skill levels becomes efficient.[1]

introduce a simple theoretical model can be influenced by efficiency change when they are entangled. In this section, we theoretically derive the bias in the measurement of technical change, especially skill-biased technical change. Before we show omitted variable bias in a production function parametrically in Section II.B, we first demonstrate technical change and efficiency change in

[1]In Appendix A, we reacquaint ourselves with the way we tend to measure and decompose total factor productivity (TFP) and its growth and explore the measurement of technical change in the existing literature.

production frontiers graphically. In Section A.A1, we revisit some approaches to measuring technical change and then in Section II.A, we developed a non-parametric model to distinguish the growth of output attributed to technical change and efficiency change.

A. Derivation of the Growth Equation

Following the previous non-parametric approach, we can demonstrate how efficiency change play a role in a traditional productivity model. With such a model, we do not need a specific parametric production function for an illustrative purpose. Sequentially, we will show that omitted efficiency change could bias estimations in a parametric function in Section II.B. Based on Hulten (1986)'s model, we adapt a traditional production model to a production frontier model. In a one output-multiple input setting, the general form of the aggregate production function is $Y_t = F(X_t, A_t)$, where Y_t is the scalar output at time t, X_t is a vector of input quantities used at time t, and A_t is a factor for technology. If not all outputs, given inputs, attain the maximum possible output level, we incorporate efficiency term and form the production frontier as

$$Y_t = F(X_t, A_t) \cdot TE_t, \tag{1}$$

where TE_t is technical efficiency at time t. Output Y_t achieves maximum output $F(X_t, A_t)$ when $TE_t = 1$.

In an attempt to introduce SBTC, we consider three inputs: capital K_t, high-skilled labor H_t, and low-skilled labor L_t, so the production frontier will be

$$Y_t = f(K_t, A_H H_t, A_L L_t, A_t) \cdot TE_t, \tag{2}$$

where A_H and A_L denote factor-specific productivity of high and low skilled labor. A change in the ratio A_H/A_L is factor-biased technical change. Particularly, technical change is skill-biased if A_H/A_L increases.

Firstly, we show how neutral technical change is influenced by efficiency change. In order to account for output growth, we logarithmically differentiate equation (2) and obtain

$$\frac{\dot{Y}}{Y} = E_K\frac{\dot{K}}{K} + E_H\left[\frac{\dot{A_H}}{A_H} + \frac{\dot{H}}{H}\right] + E_L\left[\frac{\dot{A_L}}{A_L} + \frac{\dot{L}}{L}\right] + \frac{\dot{A}}{A} + \frac{\dot{TE}}{TE}, \tag{3}$$

where the dotted variables denote derivatives with respect to time, and the fractions, for example $\dot{Y}/Y$, indicate the growth rate (relative changes) of variables over time. E_K, E_H, and E_L are calculated as

$$E_K = \frac{\partial Y}{\partial K}\frac{K}{Y}, \quad E_H = \frac{\partial Y}{\partial H}\frac{H}{Y}, \quad \text{and} \quad E_L = \frac{\partial Y}{\partial L}\frac{L}{Y},$$

which demonstrate output elasticities with respect to capital, high-skilled, and low-skilled labor. We assume that inputs are paid the value of their marginal product, so output elasticities are equal to the income shares of each inputs.

As a result, total technical change can be measured as

$$\frac{\dot{Y}}{Y} - W_K \frac{\dot{K}}{K} - W_H \frac{\dot{H}}{H} - W_L \frac{\dot{L}}{L} - \frac{\dot{TE}}{TE},$$

where W_K, W_H, and W_L are the income shares of capital, high-skilled labor, and low-skilled labor respectively. It is equal to the sum of neutral and non-neutral technical change:

$$\frac{\dot{A}}{A} + W_H \frac{\dot{A_H}}{A_H} + W_L \frac{\dot{A_L}}{A_L},$$

where $\dot{A}/A$ is neutral technical change, and $\dot{A_H}/A_H$ and $\dot{A_L}/A_L$ are factor-augmenting technical change. If technical efficiency doesn't change over time, $\dot{TE}/TE$ will be eliminated. Otherwise, not accounting for efficiency change, technical change will be equal to the sum of real technical change and efficiency change. Moreover, technical change is skill-biased if

$$\frac{\dot{A_H}}{A_H} > \frac{\dot{A_L}}{A_L}. \tag{4}$$

It suggests that the growth rate of productivity of high-skilled workers is higher than that of low-skilled workers.

The further step is to demonstrate how effective labor affects SBTC. In our assumption, due to learning on the job, newly hired workers, the entrants, would have lower productivity than old experienced workers. In turn, new workers are less efficient and could influence the output changes. As a consequence, efficiency changes over time and it is correlated with the changes in labor inputs. There is a negative correlation between efficiency and the growth of new workers.

Based on our assumption, we denote the effective rates of high-skilled and low-skilled labor as

$$\eta_H = \frac{H_e}{H} \quad \text{and} \quad \eta_L = \frac{L_e}{L},$$

where H_e and L_e are effective corresponding skilled labor inputs, and they vary with the increase of newly hired labor. The more newly hired labor, the less effective. The effective rates of high-skilled and low-skilled labor are different from each other, depending on the percentage of newly hired workers with respect to their skilled levels and different learning process. In addition, we assume that the change of efficiency ($\dot{TE}/TE$) only comes from the effectiveness of labor inputs, so TE is input-oriented technical efficiency. Taking into account efficiency change of labor, we expect technical change to be

$$\frac{\dot{Y}}{Y} - W_K \frac{\dot{K}}{K} - W_H \left[\frac{\dot{\eta_H}}{\eta_H} + \frac{\dot{H}}{H} \right] - W_L \left[\frac{\dot{\eta_L}}{\eta_L} + \frac{\dot{L}}{L} \right],$$

where the effective rates, η_H and η_L, fluctuate with time and they are unobservable. Accordingly, the change of technical efficiency is considered as the weighted sum of efficiency change of different workers:

$$\frac{\dot{TE}}{TE} = W_H \frac{\dot{\eta_H}}{\eta_H} + W_L \frac{\dot{\eta_L}}{\eta_L}. \tag{5}$$

It is worth noting that to focus on labor changes, we suppose efficiency of capital remains constant and does not influence efficiency change. Therefore, ignoring efficiency change will result in

$$\frac{\dot{A'_H}}{A'_H} = \left[\frac{\dot{A_H}}{A_H} + \frac{\dot{\eta_H}}{\eta_H} \right] \quad \text{and} \quad \frac{\dot{A'_L}}{A'_L} = \left[\frac{\dot{A_L}}{A_L} + \frac{\dot{\eta_L}}{\eta_L} \right],$$

where $\dot{A'_H}/A'_H$ and $\dot{A'_L}/A'_L$ are estimated factor-augmenting technical change. Factor-augmenting technical change is biased by changes in efficiency attributed to inefficient new hires. If $\dot{\eta_H}/\eta_H > \dot{\eta_L}/\eta_L$, for example, the effective rate of high-skilled labor increases larger than that of low-skilled labor, SBTC is overestimated. On the contrary, if $\dot{\eta_H}/\eta_H < \dot{\eta_L}/\eta_L$, SBTC is underestimated.

B. Omitted Variable Bias

In the previous section, the non-parametric decomposition of the growth of output provides a convenient explanation of how efficiency change influences the measure of technical change. Although the non-parametric model can avoid any necessity to specify the production function, it has some restrictive assumptions and limitations, for example, the perfect competition in the input market is required. Therefore, in some situations, econometric estimations cannot be avoided. For instance, estimates of the underlying substitution elasticities and return-to-scale parameters are of great importance in their own right. Similarly, in the estimation of a parametric production function, omitted-variable bias will arise if we leave out inefficiency. In this section, we illustrate the omitted variable bias in a translog production function model, since a translog production function is flexible and is able to approximate the non-parametric model. Furthermore, we use Baltagi and Griffin (1988)'s general index method to measure technical change. We begin with a simple two-firm setting and then generalize our model to show how inefficient labor can contribute to a biased measurement of non-neutral (skill-biased) technical change.

A TWO-FIRM MODEL

For the purpose of simplicity, we consider a two-firm model with two inputs and one output. In this scenario, we define two firms as firm A and firm B, and suppose that they have different efficiency rates. Both of them have the same quantity of each input but different outputs. We assume that firm A is efficient and firm B is inefficient, which means that with the same quantities of inputs, the output of firm A is larger than that of firm B. Our assumptions can be expressed as following:

$$K_A = K_B, \qquad L_A = L_B, \qquad Y_A > Y_B,$$
$$Y_A = Y_A^* = Y_B^*,$$
$$Y_B = Y_B^* - u,$$

where K_A and K_B are capital inputs, L_A and L_B are labor inputs, and Y_A and Y_B are outputs for firm A and B respectively. Y_A^* and Y_B^* are the maximum feasible outputs for firm A and firm B separately and they are equal in our setting, because the inputs of capital and labor are the same for two firms. Since firm A is efficient, the output of firm A, Y_A, is equal to the maximum feasible output Y_A^*. All the inputs and outputs are specified in natural logarithms, so the variable u is the inefficiency term, which equals $Y_B^* - Y_B$.

The production function for firm A is specified as

$$\begin{aligned} Y_A =& \boldsymbol{X}_A \beta_A \\ =& b_A + \sum \theta_{At} D_{At} + b_{AK} K_A + b_{AL} L_A \\ &+ \frac{1}{2} b_{AKK} (K_A)^2 + \frac{1}{2} b_{ALL} (L_A)^2 + b_{AKL} K_A L_A \\ &+ \sum b_{AKt} D_{At} K_A + \sum b_{ALt} D_{At} L_A, \end{aligned} \tag{6}$$

where b_A is a constant term, and D_{At}s are the time dummy variables, capturing the effects of technical change. The effects of non-neutral technical change (b_{AKt} and b_{ALt}) are also included in this specification.

For firm B, the production function is similar to that of firm A:

$$\begin{aligned} Y_B =& \boldsymbol{X}_B \beta_B - u \\ =& b_B + \sum \theta_{Bt} D_{Bt} + b_{BK} K_B + b_{BL} L_B \\ &+ \frac{1}{2} b_{BKK} (K_B)^2 + \frac{1}{2} b_{BLL} (L_B)^2 + b_{BKL} K_B L_B \\ &+ \sum b_{BKt} D_{Bt} K_B + \sum b_{BLt} D_{Bt} L_B - u, \end{aligned} \tag{7}$$

where the variables are the same, since both firms have the same quantities of inputs. If firm B is also efficient, which means that $u = 0$, then the coefficients must be the same for firm A and B, so the pooled OLS (POLS) estimator for panel data will be the same as the OLS estimator for each firm. The estimated coefficients of efficient firms are shown in the following:

$$\hat{\beta}_A = (\boldsymbol{X}'_A \boldsymbol{X}_A)^{-1} \boldsymbol{X}'_A Y_A,$$

$$\hat{\beta}^*_B = (\boldsymbol{X}'_B \boldsymbol{X}_B)^{-1} \boldsymbol{X}'_B Y^*_B,$$

$$\hat{\beta}^*_{POLS} = \hat{\beta}_A = \hat{\beta}^*_B,$$

where $\hat{\beta}^*_B$ is the estimator for efficient firm B, and $\hat{\beta}^*_{POLS}$ is the POLS estimator, assuming both firms are efficient. However, since firm B is inefficient, the estimator of coefficients should be different and can be expressed as:

$$\hat{\beta}_B = (\boldsymbol{X}'_B \boldsymbol{X}_B)^{-1} \boldsymbol{X}'_B Y^*_B - (\boldsymbol{X}'_B \boldsymbol{X}_B)^{-1} \boldsymbol{X}'_B u. \tag{8}$$

As long as $\mathrm{E}(X'_A u) \neq 0$, which is inevitable for $u \neq 0$, $\hat{\beta}_B$ is different from $\hat{\beta}^*_B$. As is shown previously, $\hat{\beta}_B$ will be smaller than $\hat{\beta}^*_B$, if $\mathrm{E}(X'_A u) > 0$, and otherwise $\hat{\beta}_B$ will be larger. All the derivations are contained in the appendix.

When the model is estimated with panel data for firms A and B, the POLS estimator $\hat{\beta}_{POLS}$ is also deviated from $\hat{\beta}^*_{POLS}$,

$$\begin{aligned} \hat{\beta}_{POLS} &= [\frac{1}{2}(\boldsymbol{X}'_A \boldsymbol{X}_A + \boldsymbol{X}'_B \boldsymbol{X}_B)]^{-1} [\frac{1}{2}(\boldsymbol{X}'_A Y_A + \boldsymbol{X}'_B Y_B)] \\ &= \hat{\beta}^*_{POLS} - \frac{1}{2}(\boldsymbol{X}'_A \boldsymbol{X}_A)^{-1} \boldsymbol{X}'_A u. \end{aligned} \tag{9}$$

The true coefficients $\hat{\beta}^*_{POLS}$ will be biased by $\frac{1}{2}(X'_A X_A)^{-1} X'_A u$. Whether the coefficients are overestimated or underestimated depends on the correlation between input X_A and inefficiency u. If X_A and u are positively correlated, the coefficients are underestimated. On the other hand, if X_A and u are negatively correlated, the coefficients are overestimated. Note that inefficiency u is time varying, otherwise it would be absorbed in the firm specific characteristics b_A or b_B.

In a similar case, all the conditions are the same, except firm A has inefficiency u_1 and firm B has inefficiency u_2 :

$$Y_A = Y^*_A - u_1,$$

$$Y_B = Y^*_B - u_2.$$

The estimation of the production function of each firm and the POLS estimator of the panel data have become:

$$
\begin{aligned}
\hat{\beta}_A &= (\boldsymbol{X}_A'\boldsymbol{X}_A)^{-1}\boldsymbol{X}_A'Y_A^* - (\boldsymbol{X}_A'\boldsymbol{X}_A)^{-1}\boldsymbol{X}_A'u_1,\\
\hat{\beta}_B &= (\boldsymbol{X}_B'\boldsymbol{X}_B)^{-1}\boldsymbol{X}_B'Y_B^* - (\boldsymbol{X}_B'\boldsymbol{X}_B)^{-1}\boldsymbol{X}_B'u_2,\\
\hat{\beta}_{POLS} &= (\boldsymbol{X}_A'\boldsymbol{X}_A)^{-1}\boldsymbol{X}_A'Y_A^* - \frac{1}{2}(\boldsymbol{X}_A'\boldsymbol{X}_A)^{-1}\boldsymbol{X}_A'(u_1+u_2).
\end{aligned} \tag{10}
$$

This result is analogous to the previous one: the existence of inefficiency can bias the calculation of the parameters by $\frac{1}{2}(\boldsymbol{X}_A'\boldsymbol{X}_A)^{-1}\boldsymbol{X}_A'(u_1+u_2)$. The larger inefficiency of firms, the larger estimation bias.

Given the estimation of the parameters in equations (9) and (10), it is possible to compute the rate of technical change for the pooled data and each firm respectively as

$$
\begin{aligned}
\dot{T}_t &= \theta_t - \theta_{t-1} + (b_{Kt} - b_{Kt-1})K + (b_{Lt} - b_{Lt-1})L,\\
\dot{T}_{At} &= \theta_{At} - \theta_{At-1} + (b_{AKt} - b_{AKt-1})K_A + (b_{ALt} - b_{ALt-1})L_A,\\
\dot{T}_{Bt} &= \theta_{Bt} - \theta_{Bt-1} + (b_{BKt} - b_{BKt-1})K_B + (b_{BLt} - b_{BLt-1})L_B.
\end{aligned} \tag{11}
$$

If the estimation above is biased by ignoring inefficiency, the estimates of technical change would be largely biased. To determine the biases in technical change, we need to calculate the subsets of variables. In the first case that only firm B is inefficient, $\hat{\beta}_{POLS}$ is a $(3T+3)\times 1$ matrix,

$$
\hat{\beta}_{POLS}' = (\hat{b}_0, \hat{\theta}_2, \cdots, \hat{\theta}_T, \hat{b}_K, \hat{b}_L, \hat{b}_{KK}, \hat{b}_{LL}, \hat{b}_{KL}, \hat{b}_{K2}, \cdots, \hat{b}_{KT}, \hat{b}_{L2}, \cdots, \hat{b}_{LT}),
$$

and X_A is a $T\times(3T+3)$ matrix. $(X_A'X_A)^{-1}X_A'$ is denoted as a $(3T+3)\times T$ matrix Z. For the period from $t-1$ to t, the estimated parameters are calculated as

$$
\begin{aligned}
\hat{\theta}_{t-1} &= \theta_{t-1} - \frac{1}{2}Z_{row(t-1)}u,\\
\hat{\theta}_t &= \theta_t - \frac{1}{2}Z_{rowt}u,\\
\hat{b}_{Kt-1} &= b_{Kt-1} - \frac{1}{2}Z_{row(T+3+t)}u,\\
\hat{b}_{Kt} &= b_{Kt} - \frac{1}{2}Z_{row(T+4+t)}u,\\
\hat{b}_{Lt-1} &= b_{Lt-1} - \frac{1}{2}Z_{row(2T+2+t)}u,\\
\hat{b}_{Lt} &= b_{Lt} - \frac{1}{2}Z_{row(2T+3+t)}u.
\end{aligned} \tag{12}
$$

The biased technical change will be

$$\dot{T}_t = \theta_t - \theta_{t-1} - \frac{1}{2}(Z_{rowt} - Z_{row(t-1)})u + (b_{Kt} - b_{Kt-1})K \\ - \frac{1}{2}(Z_{row(T+4+t)} - Z_{row(T+3+t)})uK + (b_{Lt} - b_{Lt-1})L \\ - \frac{1}{2}(Z_{row(2T+3+t)} - Z_{row(2T+2+t)})uL. \tag{13}$$

The direction of the bias depends on $(Z_{rowt} - Z_{row(t-1)})$, $(Z_{row(T+4+t)} - Z_{row(T+3+t)})$, and $(Z_{row(2T+3+t)} - Z_{row(2T+2+t)})$.

A General Model

Based on panel data, the previous two-firm model can be easily generalized to an extensive model of many firms. In this section, we apply a more general model to illustrate the bias in the measurement of technical change due to the omission of inefficiency. If we miss out an important variable, it is more likely that not only our model is poorly specified but also the estimated parameters are biased. If there are correlations between explanatory variables and the omitted variable, bias and inconsistency will occur from the OLS estimates. With the objective of determining the effect of omitted variable on the estimated production function and technical change, we omit the subsets of variables from the model. The true model is supposed to be

$$y_{it} = \alpha_0 + \alpha_1 x_{it} - u_{it} + v_{it} \qquad (i = 1, \cdots, N; \quad t = 1, \cdots, T), \tag{14}$$

where u_{it} denotes technical inefficiency, $v_{it} \sim N[0, \sigma_v^2]$ represents the noise term, and they are independent of each other. This means that the true model is a stochastic production frontier. If we overlook efficiency and estimate a production function model instead, then the misspecification will be

$$y_{it} = \beta_0 + \beta_1 x_{it} + \epsilon_{it}, \tag{15}$$

where

$$\epsilon_{it} = -u_{it} + v_{it}. \tag{16}$$

The omitted variable u_{it} is assumed as a function of explanatory variable x_{it} in a conditional or auxiliary regression

$$u_{it} = \gamma x_{it} + w_{it}. \tag{17}$$

The OLS estimator $\hat{\beta}_1$ of parameter β_1 is biased and inconsistent, since it is correlated with u_{it} and therefore with ϵ_{it}. The variance-covariance matrix of x, denoted by Σ_x (which is $T \times T$), is the same across individuals but otherwise of general form over time. In vector form, the model becomes

$$y = \beta_0 + \beta_1 x + \epsilon, \quad \epsilon = v - u, \tag{18}$$

where

$$v' = (v_{11}, \cdots, v_{N1}, \cdots, v_{1T}, \cdots, v_{NT}),$$
$$u' = (u_{11}, \cdots, u_{N1}, \cdots, u_{1T}, \cdots, u_{NT}).$$

Now consider any matrix P that eliminates the individual effects; P must satisfy $P\iota_T = 0$. For instance, one of such matrices is $P = I_T - (\iota_T \iota_T'/T)$ and the corresponding estimator is the within estimator. Let $Q = P'P$. Generally, for any Q, the estimator $\hat{\beta}_1$ is given by

$$\begin{aligned} \hat{\beta}_1 =& x'(Q \otimes I_N)y/x'(Q \otimes I_N)x \\ =& \beta_1 + x'(Q \otimes I_N)(v-u)/x'(Q \otimes I_N)x. \end{aligned} \tag{19}$$

For a fixed T, taking probability limits as the limit of expectations of the numerator and denominators as $N \to \infty$, we get

$$\begin{aligned} \frac{1}{N}\left[x'(Q \otimes I_N)(v-u)\right] &= -\frac{1}{N}\text{tr}[(Q \otimes I_N)\text{cov}(x'u)] = -\gamma \text{tr}(Q\Sigma_x), \\ \frac{1}{N}\left[x'(Q \otimes I_N)x\right] &= \frac{1}{N}\text{tr}[(Q \otimes I_N)(\Sigma_x \otimes I_N)] = \text{tr}(Q\Sigma_x), \end{aligned} \tag{20}$$

and

$$\begin{aligned} \text{plim}\hat{\beta}_1 =& \beta_1 - \text{tr}[(Q\text{cov}(x'u)]/\text{tr}(Q\Sigma_x) \\ =& \beta_1 - \gamma[\text{tr}(Q\Sigma_x)/\text{tr}(Q\Sigma_x)] \\ =& \beta_1 - \gamma. \end{aligned} \tag{21}$$

The correlation γ between x and u determines the direction of the bias. If $\gamma > 0$, which means they are positively correlated, the bias will be downward. On the contrary, if $\gamma < 0$, the negative correlation will lead to an upward bias. In particular, inefficiency u is time varying, so the bias in technical change is determined by how inefficiency changes over time.

III. Methodology

What remains, is how we can estimate technical change and efficiency change empirically. Some research has decomposed the productivity change into technical change and efficiency change by a non-parametric index approach (Fare et al., 1994; Maudos, Pastor and Serrano, 2000; Banker, Chang and Natarajan, 2005), but not often by parametric estimation (Feng and Serletis, 2010). Nevertheless, the non-parametric approach does not provide as much insight into the production technology and individual behaviors as the parametric stochastic frontier analysis (SFA) does. Therefore, the SFA approach is naturally applied to estimate both technical change and efficiency. The general stochastic frontier model with panel data can be written as

(22)
$$y_{it} = \alpha_i + \boldsymbol{\beta}' \boldsymbol{x}_{it} + A(t) + \sum \psi A(t) \boldsymbol{x}_{it} + v_{it} \pm u_{it}, \quad i = 1, \cdots, N, \quad t = 1, \cdots, T,$$

where y_{it} is the observed performance of individual i in the period t, and α_i is a vector of dummy variables, which captures any firm or unit specific characteristics. The vector $\boldsymbol{x}_{it}$ contains variables of input quantities or output and input prices. Based on Baltagi and Griffin (1988)'s general index method, time dummy variables $A(t)$ are incorporated in the production frontier to capture neutral technical change and the interactions between time dummies and inputs $\psi A(t)\boldsymbol{x}_{it}$ present non-neutral technical change. The coefficient ψ is cumulative factor-specific technical change (non-neutral technical change). The error term ϵ_{it} is specified as $v_{it} \pm u_{it}$, where v_{it} is the statistical "noise" component and is assumed to be independently and identically distributed, and $u_{it} \geqslant 0$ represents technical inefficiency. The sign of u_{it} depends on whether the frontier describes production (-) or cost (+). The stochastic frontier model proposed by Aigner, Lovell and Schmidt (1977) makes the following distributional assumptions:

$$v_{it} \sim N[0, \sigma_v^2],$$
$$u_{it} \sim N^+[0, \sigma_u^2] \perp v_{it}.$$

Other distributional assumptions, for example the normal exponential, the normal truncated normal [Stevenson (1980)] or the normal-gamma [Greene (1990)] model are often considered. The SFA model is usually specified in logs, so the degree of technical efficiency of producer i in each period is derived from $TE_{it} = \exp(-u_{it})$.

The following step is how to estimate efficiency change. There is an increasing use of time-varying technical efficiency specifications in the estimation of production frontier models based on panel data. When the time periods become longer, it is implausible to assume technical inefficiency remains constant through time. The longer the panel, the more likely technical efficiency varies over time. In the previous combined model (equation (22)), if inefficiency (u_{it}) is constant, it can be absorbed in the firm-specific dummies and cannot affect TFP growth. Otherwise, time-varying inefficiency should be considered. Karagiannis, Midmore and Tzouvelekas (2002) suggested an approach that uses a general index method to model technical change along the production function, and a quadratic function of the time trend, as in the Cornwell, Schmidt and Sickles (1990)'s model, to capture the temporal pattern of technical inefficiency. In their setting, it is possible to identify the effect of technical change and the effect of changes in time-varying technical inefficiency without any distributional assumptions.

In order to estimate a time-varying technical efficiency model, two approaches have been pursued: Greene (2005b)'s "true" fixed-effects (TFE) model and Wang and Ho (2010)'s model. The latter proposes a class of stochastic frontier models to solve the incidental parameters problem in the former. Wang and Ho (2010) show that we can seperate heteroskedasticity and technical efficiency by performing the first-difference and within transformation on the model. The time-varying inefficiency term u_{it} is specified as

$$\begin{aligned} u_{it} &= h_{it} u_i^*, \\ h_{it} &= f(\boldsymbol{z}_{it}' \delta), \\ u_i^* &\sim N^+[\mu, \sigma_u^2], \qquad i = 1, \cdots, N, \qquad t = 1, \cdots, T. \end{aligned} \tag{23}$$

The term h_{it} is a positive function of a vector of variables $\boldsymbol{z}_{it}$, which explains inefficiency u_{it}. This model is developed from Wang and Schmidt (2002)'s scaling property model, which is adapted to a time-varying specification.

In our theoretical analysis in Section II.A and II.B, time-varying inefficiency is determined by the changes in labor inputs. In particular, the change of technical efficiency can be explained by the change of efficient workers with different skill levels. According to equation (5), we can construct a relation between total efficiency change and efficiency change of labor with different skill levels. As a starting point, total efficiency is supposed to be the weighted sum of efficiency of different types of labor:

$$TE_t = W_H \eta_{Ht} + W_M \eta_{Mt} + W_L \eta_{Lt}, \tag{24}$$

where TE_t is total efficiency at time t, W_{Ht}, W_{Mt}, and W_{Lt} are weights, and η_{Ht}, η_{Mt}, and η_{Lt} are the efficiency index of high, medium, and low skilled workers respectively. As stated in equation (5), the weights could be the shares in total labor compensation, because if labor is paid for the value of their marginal product, output elasticities are equal to the income shares of different types of labor. To start with a simple model, we assume that the weights do not change over time. Then, the change of efficiency from period t to period $t+1$ is

$$\begin{aligned} \Delta TE_{t+1} =& TE_{t+1} - TE_t \\ =& W_H \Delta \eta_{Ht+1} + W_M \Delta \eta_{Mt+1} + W_L \Delta \eta_{Lt+1}, \end{aligned} \tag{25}$$

which is the weighted sum of efficiency change of different labor inputs. Efficiency change of labor is

$$\Delta \eta_{jt+1} = \lambda_{jt+1} \eta_{jt} - \eta_{jt}, \qquad j = H, M, L, \tag{26}$$

where j denotes skill types H, M, or L, which present high-, medium-, and low-skilled labor separately. The variable λ_{jt+1} is the percentage change of the efficiency index, which is determined by the change of the composition of different workers and inefficiency of newly hired workers. In order to derive λ_{jt+1}, we need to dive into how the adjustment of labor inputs would affect efficiency.

For illustrative purpose, we show the derivation of λ_{Ht+1} for high-skilled labor, and it is the same for medium- and low-skilled labor. High-skilled labor input (H_t) can be decomposed into three components: (1) workers who remain in the labor force, (2) workers who leave the labor force, and (3) new workers who just enter the labor force. In our model, we assume that ω_t^H percent high-skilled labor is retained at time $t+1$, correspondingly $1-\omega_t^H$ percent leave the labor force, and the growth rate of new labor force is g_{t+1}^H. An additional assumption is that newly hired workers can only be τ_H percent as efficient as experienced workers due to the learning on the job. Moreover, there is a supplementary assumption that the remaining labor force will increase efficiency at a rate of φ_H. Therefore, the total percentage change of efficiency is

$$\lambda_{Ht+1} = \frac{g_{t+1}^H \tau_H \eta_{Ht} + \omega_t^H \varphi_H \eta_{Ht}}{g_{t+1}^H \eta_{Ht} + \omega_t^H \eta_{Ht}}, \tag{27}$$

where $\tau_H \leqslant 1$, and $\varphi_H \geqslant 1$. At this stage, we suppose that τ_H and φ_H stay constant over time. As a result, the higher growth rate of newly hired labor will reduce efficiency, and on the other hand, the higher remaining rate of labor force will raise efficiency.

In general, total efficiency can be expressed as

$$TE_t = W_H \eta_H \lambda_{Ht} + W_M \eta_M \lambda_{Mt} + W_L \eta_L \lambda_{Lt}, \tag{28}$$

where

$$\lambda_{jt} = \frac{\tau_j g_t^j}{g_t^j + \omega_{t-1}^j} + \frac{\varphi_j \omega_t^j}{g_t^j + \omega_{t-1}^j}, \qquad j = H, M, L. \tag{29}$$

It is reasonable that λ_{jt} varies among different types of labor and changes over time. Accordingly, the determinants of efficiency are the relative growth rate of new workers and the relative remaining rate of labor, which in turn determine inefficiency as well. Because inefficiency u_{it} can be roughly approximated by $1 - TE_t$, the determinants can be the explanatory variables z_{it} in a function h_{it}. However, considering the limitation of the data, we can not observe the growth rate g_t^j and the remaining rate ω_t^j separately and directly. Instead, we can only observe labor inputs and calculate the changes. The general changes of labor inputs (r_t^j) are equal to

$$r_t^j = g_t^j + \omega_t^j, \qquad j = H, M, L, \tag{30}$$

where r_t^j can be calculated as the ratio of the labor input at time t to the labor input at time $t-1$. Because both of the rates (g_t^j and ω_t^j) are positively correlated with the changes in labor inputs (r_t^j), we still can account for efficiency change. Thus, we are able to estimate the average compound effects of labor adjustments on efficiency change without separating the distinct effects. Following Wang and Ho (2010)'s model, we can specify a function of explanatory variables as

$$h_{it} = \delta_1 r_{it}^H + \delta_2 r_{it}^M + \delta_3 r_{it}^L, \tag{31}$$

where r_{it} is the growth rate of high-, medium-, and low-skilled labor at time t.

Summing up, we have adopted a SFA method and developed an empirical model that allow us to distinguish technical change and efficiency change. In the next section, we display our data and estimation model.

IV. Empirical Results and Simulation

A. Data Description and Estimation Procedure

We begin this section with the description of data. To analyze SBTC, we use the industry data of the Socio-economic accounts of the World Input-Output Database (WIOD), which categorize labor into high-, meidum- and low-skilled levels. It consists of 18600 observations covering 27 EU countries and 13 other major countries in the world for the period from 1995 to 2009. The original data set has 34 industries, however, some industries are less likely to be affected by technical change or SBTC, namely, real estate, construction, and hotels and restaurants. We drop those industries and obtain a panel observed for 31 industries. Timmer et al. (2015) fully described the usage of the data, and it can be obtained from the WIOD website. The details of the industries and the countries that are included can be found in Table B2 and Table B1 in Appendix B. Table B2 displays the name of the countries, the acronym, and the number i of the countries we generate in our analysis. Table B1 presents the name of the industries, the specific code, and the number j of the industries we generate for illustrative purpose.

The variables used in the model include one output and four inputs. Table B3 in Appendix B shows the variables we adopt from the World Input-Output Database (WIOD) and how we construct output and input variables. We convert all the national currency into US dollar by the provided exchange rates from WIOD website. All the values are adjusted to 1995 price levels. Output Y_{ijt} is the real value added, calculated as the gross value added (VA) devided by its price indice (VA_P). We use real fixed capital stock (K_GFCF) as capital input K_{ijt}. High-, medium-, and low-skilled labor inputs are the hours worked by the respective skill type of labor, which are calculated as total hours worked by persons engaged (H_EMP) multiplied by corresponding shares in total hours. The key variables employed in the estimation are as following:

Y_{ijt} =real value added (in millions);
K_{ijt} =real fixed capital stock (in millions);
HS_{ijt} =hours worked by high-skilled labor (in millions);
MS_{ijt} =hours worked by medium-skilled labor (in millions);
LS_{ijt} =hours worked by low-skilled labor (in millions).
D_{ij} =country-industry pair specific dummy variable, $i = 2, \cdots, 40$, $j = 2, \cdots, 31$;
D_t =time dummy variable, $i = 2, \cdots, 15$;

HS_{ijt}, MS_{ijt}, and LS_{ijt} are the high-, medium-, and low-skilled labor inputs. Labor skill types are classified on the basis of educational attainment levels as defined in the International Standard Classification of Education (ISCED): low-skilled (ISCED categories 1 and 2), medium-skilled (ISCED 3 and 4) and high-skilled (ISCED 5 and 6). All the values are expressed in millions. Table B4 in Appendix B demonstrates the descriptive statistics for these variables in natural logarithms. The standard deviations of all the variables are fairly large, which means there is heterogeneity across countries and industries. We control for country-industry pair fixed-effects, because the same industry may have different characteristics in different countries.

Based on the sufficient data, we firstly estimate a production function without inefficiency term u, using the fixed-effects regression. Secondly, we applied Wang and Ho (2010)'s model to estimate a SFA model with time-varying efficiency. We choose a translog specification of production function to identify different types of labor-augmenting technical change, due to its flexibility. Our interest at this point focuses on the estimates of high-, medium-, and low-skilled labor-augmenting technical change. The production frontier model will be:

(32)
$$\begin{aligned}\ln Y =&\alpha_0 + \sum \alpha_{ij} D_{ij} + \sum \alpha_t D_t + \alpha_k \ln K + \alpha_h \ln HS + \alpha_m \ln MS \\ &+ \alpha_l \ln LS + \frac{1}{2}\alpha_{kk}(\ln K)^2 + \frac{1}{2}\alpha_{hh}(\ln HS)^2 + \frac{1}{2}\alpha_{mm}(\ln MS)^2 \\ &+ \frac{1}{2}\alpha_{ll}(\ln LS)^2 + \alpha_{kh} \ln K \ln HS + \alpha_{km} \ln K \ln MS + \alpha_{kl} \ln K \ln LS \\ &+ \alpha_{hm} \ln HS \ln MS + \alpha_{hl} \ln HS \ln LS + \alpha_{ml} \ln MS \ln LS + \sum \alpha_{kt} D_t \ln K \\ &+ \sum \alpha_{ht} D_t \ln HS + \sum \alpha_{mt} D_t \ln MS + \sum \alpha_{lt} D_t \ln LS + v - u,\end{aligned}$$

In the above equation, we omit subscripts of variables for simplicity, and we omit three dummy variables to avoid multicollinearity. As in equation (31), u is specified as

(33)
$$u = f(\delta_1 \ln HS + \delta_2 \ln MS + \delta_3 \ln LS) N^+[0, \sigma_u^2].$$

We use natural logarithms of labor inputs instead of the ratio between the input at period t and at period $t-1$, because the effects of labor changes will give the same results. In addition, we impose that inefficiency follows a half-normal distribution and we let the determinants only affect the variance.

SBTC is the difference between high-skilled labor-augmenting technical change and relatively lower-skilled labor-augmenting technical change, involving unequal responses between specific types of labor. In order to compare high-, medium-, and low-skilled labor specific technical change, we took the differences between the high- and the medium-skilled ($SBTC_{hm}$), the high- and the low-skilled labor ($SBTC_{hl}$), and the medium- and the low-skilled labor ($SBTC_{ml}$). The rates of SBTC are calculated as:

$$\begin{aligned} SBTC_{hm} &= \alpha_{ht} - \alpha_{mt}, \\ SBTC_{hl} &= \alpha_{ht} - \alpha_{lt}, \\ SBTC_{ml} &= \alpha_{mt} - \alpha_{lt}, \end{aligned} \tag{34}$$

where t corresponds to each time period. We use the general index approach to measure technical change and non-neutral technical change, because it provides a more flexible time path, which is not constrained to fit a particular functional (linear, quadratic, other) pattern (Baltagi and Rich, 2005). Subsequently, we show our results in the next section.

B. *Skill-Biased Technical Change*

In this section, we present the estimation results with several objectives in mind. Our goal is to illustrate how the change of labor composition would affect efficiency change and therefore affect technical change, especially SBTC. The effect of accounting for efficiency change is statistically and economically significant.

Table 1 summarizes the parameter estimates for both the fixed-effects production function and the stochastic production frontier. Because coefficients in a translog model are not directly interpretable, estimation results are converted into output elasticities ($\partial \ln Y / \partial \ln X$). Reported elasticities are evaluated at the sample means of the variables and they are all different from zero at the 1% significance level. The elasticity for medium-skilled labor is -0.059 in the fixed-effects model, which indicates that medium-skilled labor is not efficient. On the contrary, it is 0.992 in the stochastic frontier model. Indeed, the output elasticities for all the inputs have increased after accounting for efficiency change. However, the elasticity for capital does not differ much between two models.

Moreover, estimated neutral technical change and input-specific technical change are the average annual index changes across the period from 1996 to 2009. Estimates of SBTC are given as simple means across the annual values as well. Neutral technical change is consistently negative and statistically significant in both models. This coincides with the recent productivity slowdown, which is common to all industrialized countries and common to most industries as well (Hornstein, Krusell and Violante, 2005). Meanwhile, capital-specific technical change is positive and significant on average. Medium-skilled labor specific technical change shows a positive and higher average rate than the other input factors, while both high- and low-skilled labor experience average annual decreases related to technical change across the alternative specifications. As a consequence, skill-neutral technical change between high- and medium-skilled labor ($SBTC_{hm}$) and that between medium- and low-skilled labor ($SBTC_{ml}$) are rejected at the 1% significance level. SBTC between high- and low-skilled labor ($SBTC_{hl}$) is positive at 0.3% to 0.34% per year in both specifications, implying that technical change favors high-skilled relatively to low-skilled workers. Although the average estimates of $SBTC_{hl}$ are slightly dissimilar, the fixed-effects specification can not reject skill neutrality, on the other hand, the stochastic frontier yields a significant result.

Furthermore, in the lower part of Table 1, the determinants of inefficiency and variance are examined, since the stochastic frontier includes an inefficiency function as equation (33). The estimates of inefficiency parameters are reported as the means of the marginal effects. A positive estimate shows that the variable has a negative effect on efficiency. The average marginal effects of all three types of labor are positive and statistically significant at the 1% level, which means that the growing of all three categories of labor will reduce efficiency. Specifically, the marginal effect of the growing medium-skilled labor is the highest, and high-skilled labor has the second highest impact. This is consistent with our model, because the weight of medium-skilled labor is the highest. As in equation (28), the parameters represent the product of weights and inefficiency change of one percent change of labor. Consequently, one percent change of medium-skilled labor will increase 8.36% of inefficiency index, making production more inefficient. This can also explain the negative output elasticity of medium-skilled labor in the production function model. A likelihood ratio test is performed and indicates that the null hypothesis of no technical inefficiency is rejected. A full set of parameter estimates is in Table B5 and Table B6 in Appendix B.

In order to distinguish the distinction between the alternative models and discover the effect of accounting for efficiency change, an effective comparison of the cumulative effects of technical change is displayed in Figure 1. Each graph is categorized by different skill levels of labor, and each series represents the time path of the cumulative labor-augmenting technical change from 1995 to 2009. The trends of each type of labor-augmenting technical change are similar across different models, however, there are some divergences. As is analyzed before, technology favors medium-skilled labor, of which the cumulative technical change has increased to almost 14% in 2009 without considering efficiency. Meanwhile, both the rates of high-skilled and low-skilled labor-augmenting technical change have decreased over time. Technical change harmed low-skilled workers more than the other two skill levels, which dropped about 10% in 2009 in both models. This is a departure from previous studies, which document a phenomenon of the polarization of the labor market. Some studies find the growth of wages and employment occur in both high-education, high-wage occupations and low-education, low-wage occupations(Autor, Levy and Murnane (2003), Autor, Katz and Kearney (2006), Autor and Dorn (2013), Goos, Manning and Salomons (2014), Bárány and Siegel (2018)). The explanation for the polarization is that information and computer technologies substitute for medium-skilled workers. This is not completely contrasting to our result, because medium-skilled workers can work more productively with fewer hours but become less efficient in general. If technologies have replaced medium-skilled workers, they may need to find lower-skilled jobs and become less efficient. The production frontier model showed higher rates of labor-augmenting technical change in the both high-skilled and low-skilled labor cases and on the contrary presented lower rates in the medium-skilled labor case. From the previous analysis in Section II, it is possible that without considering inefficiency change, the estimated rates of high-skilled and low-skilled labor specific technical change are underestimated, and medium-skilled labor-augmenting technical change is overestimated. In general, all three types of labor-specific technical change have a smaller magnitude after disentangling technical change and efficiency change.

On the basis of Figure 1, we focus more on the differences between skill levels. Figure 2 examines the cumulative effects of SBTC across two models. Especially, we mainly focus on how much technical change favors high-skilled labor, so we omit the estimation of $SBTC_{ml}$, and present the estimated $SBTC_{hm}$ and $SBTC_{hl}$. Not surprisingly, $SBTC_{hm}$ has been declining and $SBTC_{hl}$ has been inclining. $SBTC_{hl}$ appears to become positive after 2000. This accords with the results of other literature, which only found positive SBTC before 1983 (e.g.Baltagi and Rich (2005)). Most importantly, $SBTC_{hm}$ is underestimated and $SBTC_{hl}$ is overestimated over time, when efficiency change is not considered. This supports the previous result and our model that high-skilled labor has a smaller effect on efficiency change than medium-skilled labor, and a larger impact on efficiency change than low-skilled labor. Overall, high-skilled labor dose not benefit from technology development.

Considering the general index approach supports point-to-point tests for SBTC effects (Baltagi and Rich, 2005). In Table 2, we provide the results of SBTC for sub-periods. As Baltagi and Rich (2005), we form the expressions $(\alpha_{ht} - \alpha_{mt}) - (\alpha_{h,t-q} - \alpha_{m,t-q})$ and $(\alpha_{ht} - \alpha_{lt}) - (\alpha_{h,t-q} - \alpha_{l,t-q})$, where $t - q$ represents the earlier comparison year. Generally, the estimates of $SBTC_{hm}$ across alternative models are negative in all sub-periods and significant during most of the time except 2007-2009. However, the degrees of fluctuations vary over time. Both models display skill-neutral technical change between high- and low-skilled labor, except during the period from 2003 to 2006, $SBTC_{hl}$ is significant at the 1% level and positive at around 3% to 4%. During the financial crisis from 2007 to 2009, there is no evidence of SBTC. The evident deviation between two models appears during the full sample period from 1995 to 2009. This is because when the time periods become longer, efficiency is more likely to change over time.

Table 1—: Parameter estimates in different models

Parameter	Production function Estimate	Production function Std. Err.	Stochastic frontier Estimate	Stochastic frontier Std. Err.
Output elasticities				
Capital	0.7003***	(0.0139)	0.7288***	(0.0081)
High-skilled labor	0.1784***	(0.0170)	0.4298***	(0.0249)
Medium-skilled labor	−0.0586***	(0.0210)	0.9917***	(0.0451)
Low-skilled labor	0.1359***	(0.0151)	0.3123***	(0.0229)
Technical change				
Neutral	−0.0504***	(0.0056)	−0.0447***	(0.0028)
Capital specific	0.0048***	(0.0008)	0.0054***	(0.0004)
High-skilled labor specific	−0.0042***	(0.0016)	−0.0039***	(0.0009)
Medium-skilled labor specific	0.0085***	(0.0018)	0.0065***	(0.0010)
Low-skilled labor specific	−0.0072***	(0.0011)	−0.0073***	(0.0006)
Skill-biased technical change				
High-skilled vs. Medium-skilled	−0.0128***	(0.0032)	−0.0104***	(0.0018)
High-skilled vs. Low-skilled	0.0030	(0.0019)	0.0034***	(0.0011)
Medium-skilled vs. Low-skilled	0.0158***	(0.0026)	0.0138***	(0.0013)
Inefficiency determinants				
High-skilled labor			0.0256***	(0.0125)
Medium-skilled labor			0.0836***	(0.0408)
Low-skilled labor			0.0177***	(0.0087)
Observations	17595		17595	
R^2 from OLS	0.9925			
Log-likelihood	2090.0606		3758.7927	

Note: This table compares the estimates of parameters between a production function model and a stochastic frontier model. Output elasticities are evaluated at the sample means of the variables. Values for technical change represent average annual index changes based on full sample estimates. Skill-biased technical change is calculated as equation (34) and presented as average annual index changes. The determinants of inefficiency and variance are examined based on equation (33). The estimates of inefficiency parameters are reported as the means of the marginal effects. A positive estimate shows that the variable has a negative effect on efficiency. The standard errors are in the parentheses and are computed using the Delta method. Estimates of the parameters for country-industry pair fixed-effects are not reported in the table to save space. */**/*** signifies statistical significance at the 10/5/1% level.

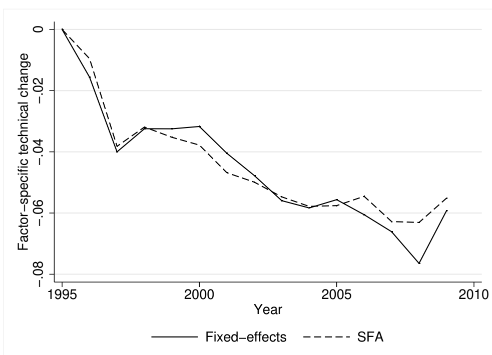
Table 2—: Skill-biased technical change in different models

	Production function				Stochastic frontier			
Period	$SBTC_{hm}$	Std. Err.	$SBTC_{hl}$	Std. Err.	$SBTC_{hm}$	Std. Err.	$SBTC_{hl}$	Std. Err.
1995-1998	−0.0476*	(0.0281)	−0.0067	(0.0176)	−0.0391**	(0.0173)	−0.0083	(0.0104)
1999-2002	−0.0652***	(0.0178)	0.0105	(0.0106)	−0.0705***	(0.0179)	0.0064	(0.0108)
2003-2006	−0.0593***	(0.0196)	0.0334***	(0.0112)	−0.0320*	(0.0186)	0.0386***	(0.0113)
2007-2009	−0.0068	(0.0386)	0.0045	(0.0202)	−0.0040	(0.0217)	0.0108	(0.0127)
1995-2009	−0.1789***	(0.0451)	0.0416	(0.0264)	−0.1456***	(0.0248)	0.0474***	(0.0150)

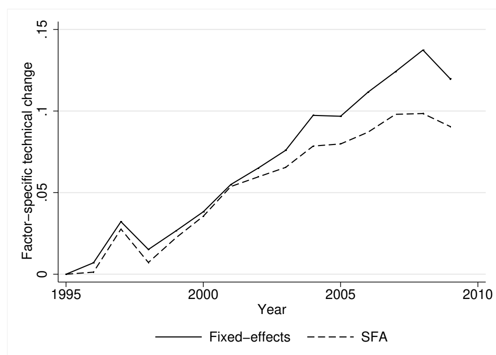
Note: This table compares the estimates of SBTC in sub-periods between a production function model and a stochastic frontier model. SBTC are presented as point-to-point estimates. $SBTC_{hm}$ is the difference of high- and medium-skilled specific technical change. $SBTC_{hl}$ is the difference of high- and low-skilled specific technical change. The standard errors are in the parentheses and are computed using the Delta method. */**/*** signifies statistical significance at the 10/5/1% level.

Figure 1. : Paths of Cumulative Labor-Augmenting Technical Change

(a) High-skilled labor



(b) Medium-skilled labor



(c) Low-skilled labor

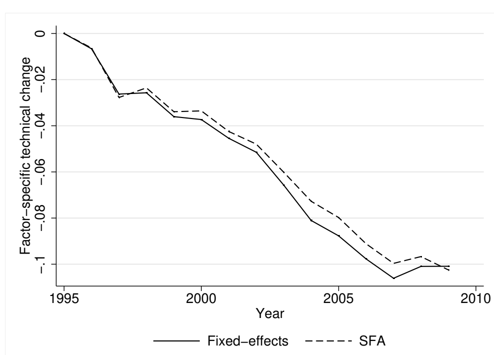
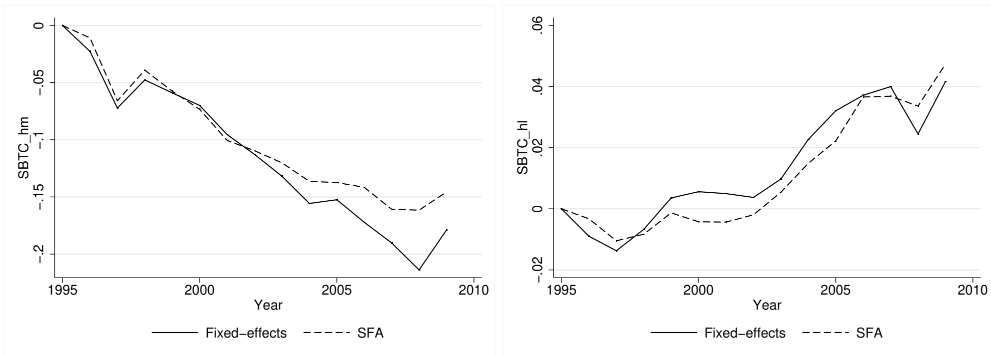


Figure 2. : Paths of cumulative skill-biased technical change

(a) High- versus medium-skilled labor

(b) High- versus low-skill labor



C. *Efficiency Change*

Based on the stochastic production frontier estimation, efficiency change is separated from technical change. As is shown in Figure 3a, the distribution of estimated efficiency index shows very low efficiency estimates, most of which lower than 0.2. This may be because that fixed-effects may capture time invariant inefficiency and we use inputs as determinants. Figure 3b displays the estimated annual average efficiency index, which also shows very low average efficiency estimates. The estimated yearly average efficiency went up and down, peaked at around 2.055% and dropped to almost 2.048% in 2008. This coincides with the financial crisis in 2008. Additionally, Figure 4 plots technical efficiency versus high-, medium-, and low-skilled labor. All of three types of labor seem to have negative influences on technical efficiency, which accords with our model.

Furthermore, in our assumption, the change of labor can influence efficiency change. To find the relations, we calculate the first differences of labor inputs and efficiency and make a correlation matrix among the growth rates of labor inputs and efficiency change. We can observe from Table 3 that the growth rates of high-, medium-, and low-skilled labor are positively and significantly correlated with each other. Moreover, the growth rates of high-skilled (-0.0415), medium-skilled (-0.1042) and low-skilled (-0.1001) labor are all negatively correlated with efficiency change. This can provide some evidence for the previous theory that the growing number of newly hired high- and medium-skilled workers may reduce efficiency and the declining number of low-skilled workers may raise efficiency. As is illustrated in our model, the positive correlation between changes in labor inputs and efficiency change can result in the overestimation of labor-augmenting technical change, and on the contrary, the negative correlation can bring about the underestimation of labor-augmenting technical change. As a consequence, it can indicate that without considering efficiency change, the production function model may underestimate the rates of labor specific technical change, as is shown in Figure 1. This finding is also consistent with our assumption that the changes in labor inputs due to the growing newly hired workers can reduce efficiency rates. Remarkably, the results also suggest that the increases in medium-skilled labor have a larger negative effect on efficiency change, compared with that of high- and low-skilled labor. This confirms the earlier analysis that the different effects of the changes in different labor types can bias the estimation of SBTC. In the next section, we use the estimated results of both models to discover the influence of SBTC on wage gaps.

Figure 3. : Efficiency distribution and annual change

(a) Efficiency distribution (b) Estimated yearly average efficiency

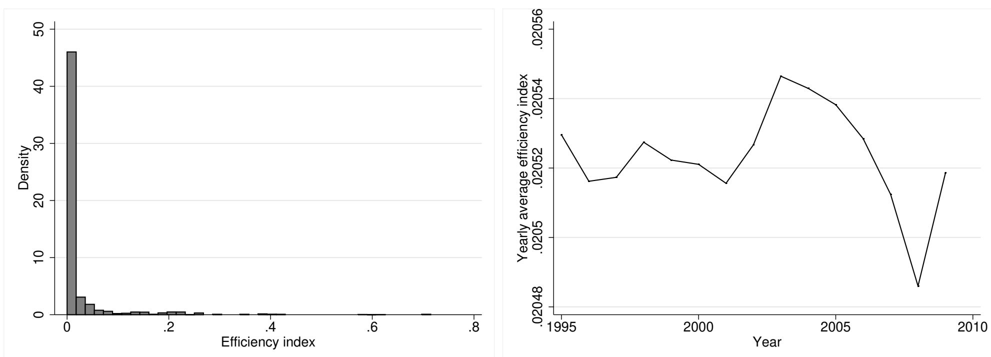


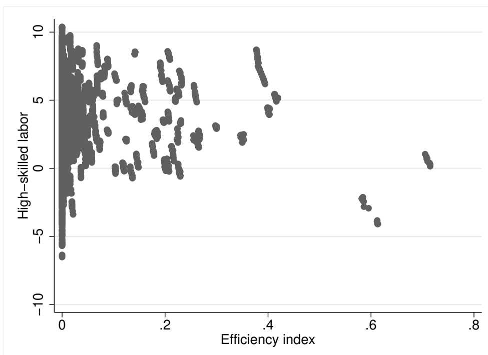
Table 3—: Correlation of labor changes and efficiency change

Variable	$Diff_{HS}$	$Diff_{MS}$	$Diff_{LS}$	$Diff_{efficiency}$
$Diff_{HS}$	1.0000			
$Diff_{MS}$	0.3378	1.0000		
	(0.0000)			
$Diff_{LS}$	0.2969	0.8292	1.0000	
	(0.0000)	(0.0000)		
$Diff_{efficiency}$	-0.0415	-0.1042	-0.1001	1.0000
	(0.0000)	(0.0000)	(0.0000)	

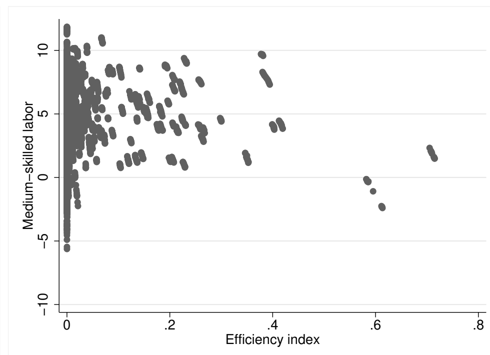
Note: This table shows the correlation matrix of growth rates of labor and efficiency change. $Diff_x$ stands for the change rate of the variable x. The standard errors are in the parentheses. All the correlations are significant at the 1% level.

Figure 4. : Plot of technical efficiency versus high-, medium-, and low-skilled labor

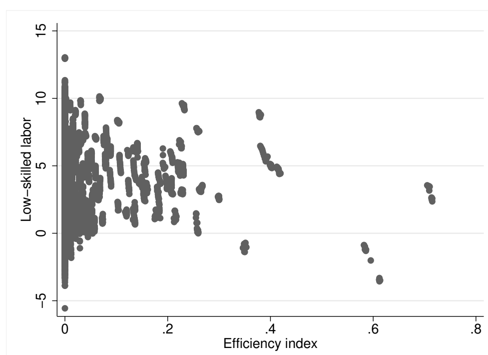
(a) High-skilled labor



(b) Medium-skilled labor



(c) Low-skilled labor

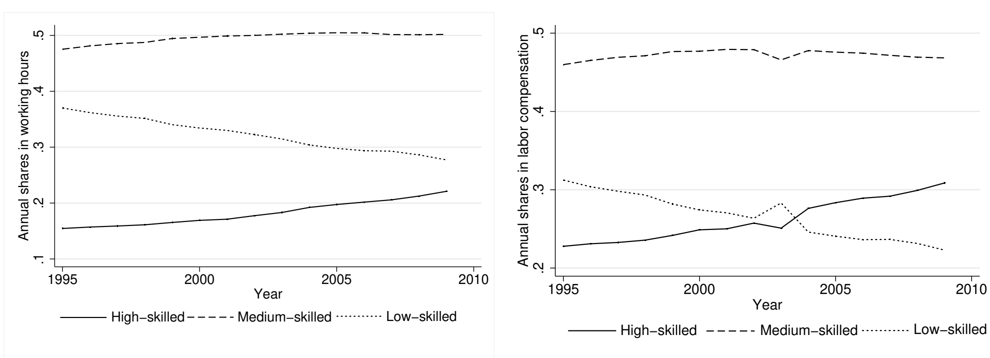


V. Wage Inequality

How does SBTC influence wage differential? After adjusting the measurement of SBTC, in this section, we try to answer this question. During the period from 1995 to 2009, the shares of high-skilled labor in both total working hours and total labor compensation have experienced an increasing trend and on the contrary, those of low-skilled labor have declined (Figure 5). The share of medium-skilled labor remained stable and higher than the other two categories. It can be seen in Figure 5b that high-skilled workers had larger shares in compensation than those of low-skilled workers after 2004, however, in Figure 5a, high-skilled workers had smallest shares in working hours. The wage ratios of different skill groups have been rising across countries and industries, and one of the drivers could be SBTC. On the one hand, SBTC can lead to an increasing demand of high-skilled labor and therefore boost the wage inequality. On the other hand, the relative wage ratio can be used as an additional source of evidence of SBTC (Hornstein, Krusell and Violante, 2005). We now turn to an analysis of the relation between SBTC and wage inequality.

Figure 5. : skill composition in working hours and labor compensation

(a) Yearly average shares in working hours (b) Yearly average shares in labor compensation



A. SBTC and Wage Inequality

Due to that SBTC can have an impact on the ratio of marginal products of different types of labor (MRTS), a MRTS can be used as evidence of SBTC. We calculated MRTSs based on the translog production model. The MRTS of high-skilled to medium-skilled labor ($MRTS_{hm}$) can be obtained by

$$MRTS_{hm} = \frac{MP_h}{MP_m} = \frac{\frac{\partial Y}{\partial HS}}{\frac{\partial Y}{\partial MS}} = \left(\frac{\frac{\partial \ln Y}{\partial \ln HS}}{\frac{\partial \ln Y}{\partial \ln MS}} \right) \frac{MS}{HS}. \tag{35}$$

In the same way, we can also obtain the MRTS of high-skilled to low-skilled labor ($MRTS_{hl}$) and the MRTS of medium-skilled to low-skilled labor ($MRTS_{ml}$). The analysis of $MRTS_{ml}$ and the wage ratio between medium- and low-skilled workers is omitted, because we target on the wage gap between higher- and relatively lower-skilled workers.

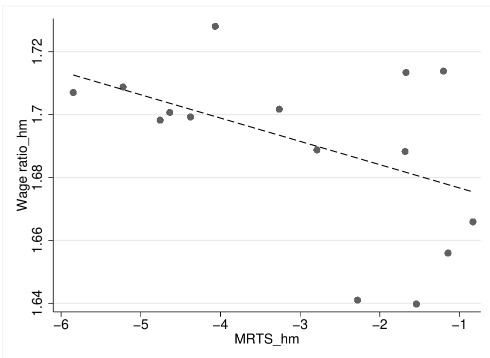
If a labor market is perfectly competitive, a MRTS will be equal to the wage ratio. Figure 6 presents MRTSs and the respective wage ratios, where Figure 6a and 6b show the differences between high and medium skilled labor in alternative models, and Figure 6c and 6d display the differences between high and low skilled labor. As is shown, there is a negative relation between $MRTS_h m$ and the corresponding wage ratio in the fixed-effects model, whereas a positive relation is more obvious and stronger in the frontier model. The negative correlation may be caused by the negative output elasticity for medium-skilled labor. The MRTS between high- and low-skilled labor is positively correlated with the wage ratio in both models, but it presents a flatter fitted line in the frontier model (Figure 6d). This result implies that if a MRTS increases, the relative wage ratio is likely to rise too.

Since SBTC is associated with the asymmetric increases of the marginal productivity of different skill groups (MRTS), SBTC can contribute to the changes in wage ratios. Since $SBTC_{hm}$ was negative and decreased accordingly from 1995 to 2009, it would induce a decline of the respective wage ratio. Meanwhile, positive $SBTC_{hl}$ would give rise to a higher wage differential. Nevertheless, the data of annual average wage ratios did not present many changes. As can be seen in Figure 7, all three wage ratios remained relatively stable, except that in 2003, the wage ratio of high to low skilled labor and the wage ratio of medium to low skilled labor plunged. In order to analyze the association between SBTC and wage ratios, we plotted them and the best fitted lines in Figure 8. It indicates a slightly negative relation between SBTC and the corresponding wage ratio in both the fixed-effects and the frontier models. Even though we did not consider other factors that could affect the correlation between SBTC and wage ratios, the negative relation between the rates of SBTC and the rates of wage ratios can provide some evidence that high-skilled labor is overcompensated. It illustrates that in recent development, technical change does not favor high-skilled workers and SBTC may not be the main driver for wage differentials.

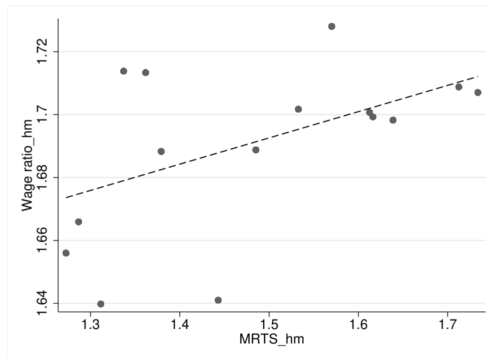
Considering the fact that Figure 6, Figure 7, and Figure 8 only presented

Figure 6. : MRTS and relative wage ratios in alternative models

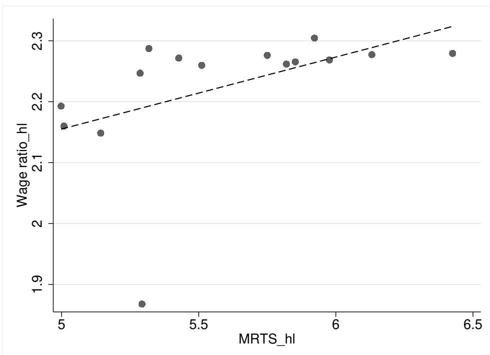
(a) High- vs. medium-skilled in fixed-effects model



(b) High- vs. medium-skilled in frontier model



(c) High- vs. low-skilled in fixed-effects model



(d) High- vs. low-skilled in frontier model

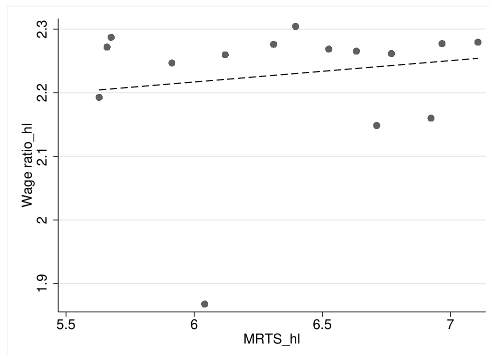


Figure 7. : Annual average wage ratios

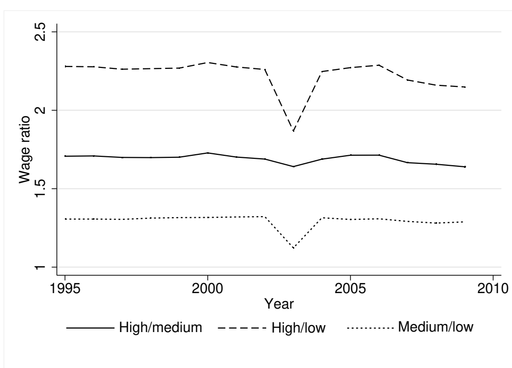
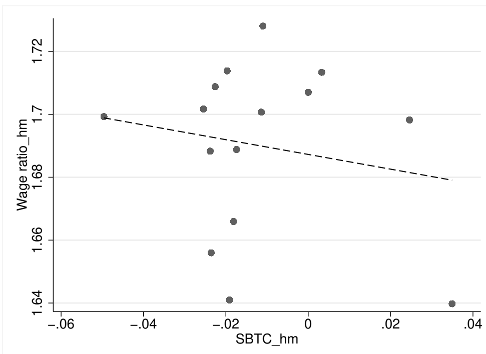
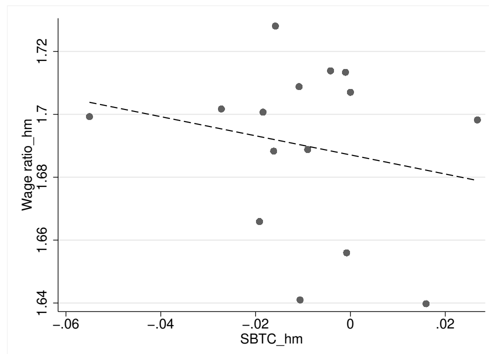


Figure 8. : SBTC and relative wage ratios in alternative models

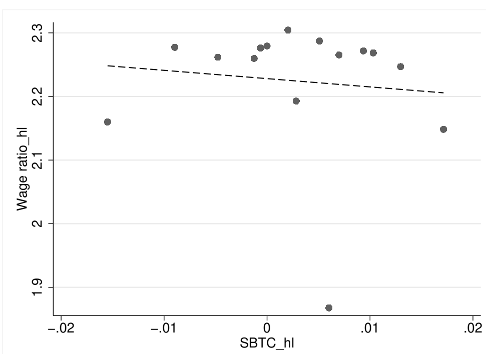
(a) High- vs. medium-skilled in fixed-effects model



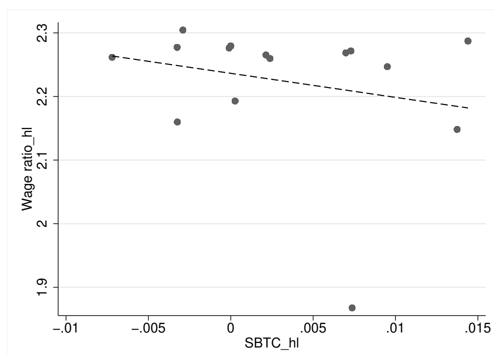
(b) High- vs. medium-skilled in frontier model



(c) High- vs. low-skilled in fixed-effects model



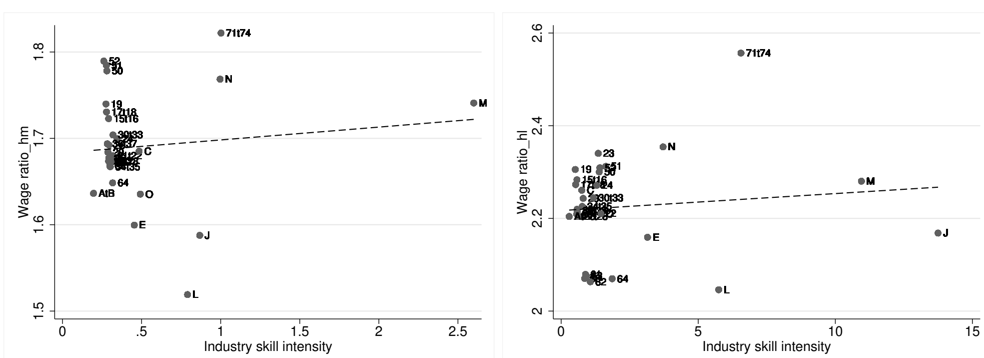
(d) High- vs. low-skilled in frontier model



annual averages, there could be large variations among countries and industries. Goldin and Katz (1998) find that capital-intensive industries rose the demand for skills greatly and increased the wage bill of the nonproduction worker. Haskel and Slaughter (2002) contend that the effects of SBTC on relative wage ratios mainly comes from the sector bias of SBTC, not factor bias. They find that when skill premia were increasing (decreasing), SBTC was concentrated in skill-intensive (unskill-intensive) sectors. Burstein and Vogel (2017) find that the skill premium has been rising in skill-intensive sectors in all countries. As a result, skill-intensity may influence the effects of SBTC on wage deferential. SBTC may concentrate in certain industries, especially high-skilled intensive industries, so we expect higher wage inequality in high-skilled intensive industries. In order to investigate the association between skill intensity and wage ratios, we plotted the relevant wage ratio against the relative industry skill intensity in Figure 9. The relative industry skill intensity is measured as the ratio of the share in total working hours of one skill group to that of the other skill group. The lines of best fit validate a slightly positive relation between skill intensity and the corresponding wage ratio. In high-skilled labor intensive industries, the average wage of high-skilled labor is relatively higher than that of other two types of labor. Especially in industries of renting of m&eq and other business activities, health and social work, and education, the relative wage of high-skilled workers is higher than the relative wage in most industries.

Figure 9. : Industry skill intensity and relative wage ratios

(a) High- versus medium-skilled labor (b) High- versus low-skilled labor



B. The Gap between MRTS and Wage Inequality

So far, we find little evidence that SBTC can affect wage differentials in either models. However, the relations between the estimated MRTSs and the wage ratios do vary across models. Therefore, we assume that efficiency change may play a role in affecting MRTSs, especially when the changes in different categories of labor input influence efficiency change variously. In consequence, accounting for efficiency change may give a better estimation for MRTSs and close the gap between the relative wage ratio and the corresponding MRTS. In order to find out whether this is the case, we compare the gaps between wage ratios and MRTSs between alternative models in Figure 10. It is worth noting that because we take the yearly average of the differences between wage ratios and MRTSs, we take the absolute values of the differences, otherwise the gaps may be cancelled out. As what we expect, in both Figure 10a and 10b, the gaps are much smaller in the frontier model when efficiency is taken into account. In Figure 10a, when we compare high- and medium-skilled labor, the gap is more stable and smaller (close to zero) in the frontier model than that in the fixed-effects model. Comparing high- and low-skilled wage gaps in Figure 10b, we find a smaller gap in the frontier model as well, but it declines over time and rises after 2008.

Furthermore, the ratio of the relative wage ratio to the MRTS may reflect over-compensation or under-compensation of different labor inputs. In order to compare alternative models, we plot the ratio of the relative wage ratio to the MRTS over time. We can observe from Figure 11, different models present distinct results. In Figure 11a, with comparison to medium-skilled labor, high-skilled labor is under-compensated in the fixed-effects model, whereas it is over-compensated in the frontier model. It is more reasonable and realistic that high-skilled labor is over-compensated than under-compensated. In Figure 11b, both models illustrate similar results: compared with low-skilled workers, high-skilled workers are overcompensated and the ratio is increasing over time. However, high-skilled wages are less overcompensated in the SFA model. In sum, it provides some evidence that the gap between wage ratios and MRTSs can be closer after considering efficiency change. It implies that efficiency change can have a impact on the wage gap.

In a perfectly competitive labor market, the wage ratio among different skill groups of labor directly reflect the relative marginal productivity, MRTS. However, in reality, there are frictions in the labor market, for example, labor markets institutions, which include unemployment benefits, a minimum wage, taxes on labor, and a trade union. Those institutions interfere with the exchange of labor power for the wages paid and hence introduce a wedge between the wage of workers and the value of the marginal product of labor (Boeri and van Ours, 2013). We will not discuss how those frictions influence wage inequality and therefore influence the effects of technical change on wages, which is beyond the scope of this paper. Since the labor market is not perfectly competitive and labor markets institutions have played a crucial role, MRTS may not equal to the corresponding wage ratio. Even though technical change can influence wages of different skill levels of labor and thus inequality, we may not observe the direct effects. Based on observations, wage inequality differs across industries and across countries. Therefore, the ratio of the relative wage ratio to the MRTS may be divergent among different industries and country.

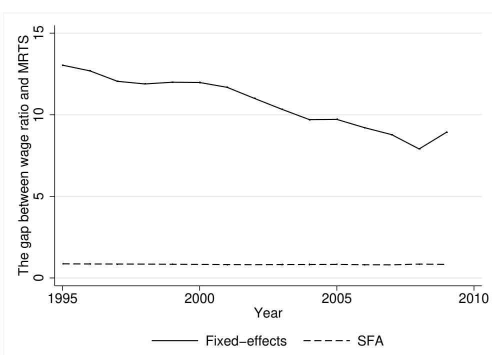
Figure 12 and 13 indicate the variations of the ratio of the relative wage ratio to the MRTS across industries, and across countries respectively. On the basis of preceding discussions, we only present the analysis on the result of the frontier model estimation, which takes efficiency change into account and provides a more reasonable and less biased result. In Figure 12a and 12b, we find high-skilled workers are more likely to be overcompensated in high-skilled intensive industries, such as education, health and social work, financial intermediation, renting of m&eq and other business activities, and public admin and defence and compulsory social security industries. There shows a positive relation between industry skill intensity and the overcompensation of high-skilled labor. Particularly, there is no overcompensation in the agriculture, hunting, forestry and fishing industry, because this industry is mainly focused on low-skilled work and needs more low-skilled workers.

Because of different institutional systems and different degrees of flexibility of the labor markets, economies have a great impact either on employment or on wage differentials between skilled and unskilled (Vivarelli, 2014). In empirical studies, an increase in wage differentials between skilled and unskilled has been found in the United States (Autor, Katz and Krueger, 1998; Dinardo and Card, 2002; Goldin and Katz, 2007), and in the United Kingdom (Haskel and Slaughter, 2002). Dustmann, Ludsteck and Schönberg (2009) have found that wage inequality in West Germany has increased from 1975 to 2004, and the wage differential of medium-skilled workers relative to the low-skilled started rising in the late 1980s. They also provide some evidence that technological change asymmetrically affects the bottom and the top of the wage distribution. In spite of that, the increase in wage differentials has been modest in continental European countries, for example, France (Card, Kramarz and Lemieux, 1999; Goux and Maurin, 2000), Belgium (Hertveldt and Michel, 2013), Sweden (Lindquist, 2005), and Italy (Casavola, Gavosto and Sestito, 1996). Distinct labor market institutions, chiefly the wage-setting mechanisms provide persuasive explanation for the differences of wage gaps between the USA and continental European countries (Blau and Kahn, 1996; Guvenen, Kuruscu and Ozkan, 2014; Okazawa, 2013). Countries that features generous nonemployment benefits, strict employment protection legislation, and a strong influence of unions have lower wage inequality. In order to differentiate wage inequality across countries, We plotted the relative wage ratio against the capital intensity of each country. Figure 13 indicates a negative relation between the capital intensity (capital-labor ratio) and wage ratios. Countries with relatively high capital intensity are more developed and they have relatively lower wage inequality among different skill workers, especially Japan, Nordic countries, Ireland, and Australia. We also find that the USA and Germany have higher wage differentials. In less developed countries, Brazil, Hungry, Russia, Turkey, Indonesia, and India have a relatively higher wage differential between high and medium skilled labor and high and low skilled labor, while the wage differentials are lower in China, Cyprus, Estonia, and Lithuania. In countries with higher wage differentials, where the labor market is more flexible, high-skilled labor is more likely overcompensated. As we expected, Figure 13a demonstrates that high-skilled and medium-skilled workers gain relatively higher wages in most developing countries where the wage gap is wider. Spain, Korea, Brazil, Cyprus and some less developed countries compensate high-skilled workers more than medium-skilled workers. Compared with low-skilled workers, high-skilled workers are over compensated in most countries in Figure 13b.

Last but not least, as is analyzed at the beginning of this subsection, inefficiency change may exert an impact on the relative over-compensation or under-compensation of one skill group. In Figure 14, we plotted the ratio of the relative wage ratio to the MRTS against efficiency. Both Figures 14a and 14b illustrate a non-linear and negative relation. This indicates that lower efficiency may lead to the relatively higher over-compensation of high-skilled workers. One explanation is that the recent relative increases of high-skilled workers have decreased efficiency rates, so high-skilled workers are overcompensated. Another explanation could be over-compensation or under-compensation of one skill group might induce inefficiency. The first explanation is consistent with our assumption that newly hired high-skilled workers are less efficient than experienced workers. However, the causality between overcompensation and efficiency change remains an issue for further investigation.

Figure 10. : The gap between wage ratio and MRTS in alternative models

(a) High- versus medium-skilled labor



(b) High- versus low-skilled labor

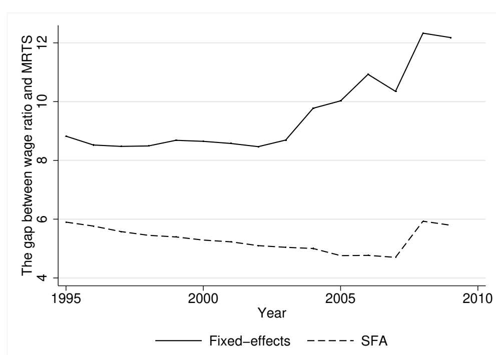


Figure 11. : Ratio of wage ratio to MRTS over the years

(a) High- versus medium-skilled labor

(b) High- versus low-skilled labor

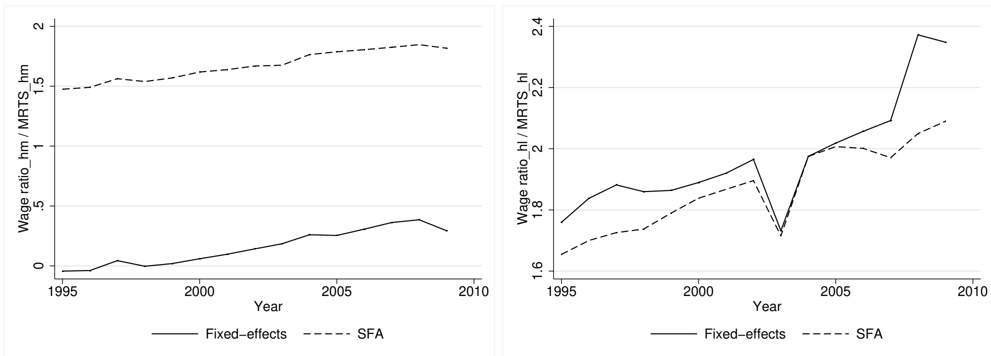


Figure 12. : Industry skill intensity and ratio of wage ratio to MRTS

(a) High- versus medium-skilled labor

(b) High- versus low-skilled labor

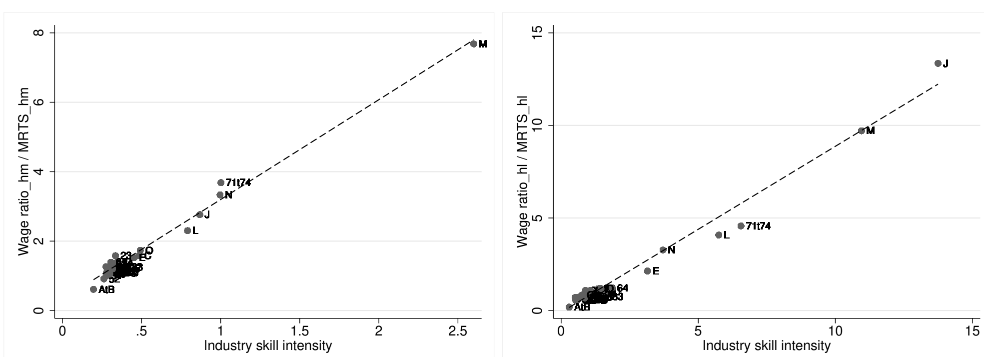


Figure 13. : Ratio of wage ratio to MRTS across countries

(a) High- versus medium-skilled labor

(b) High- versus low-skilled labor

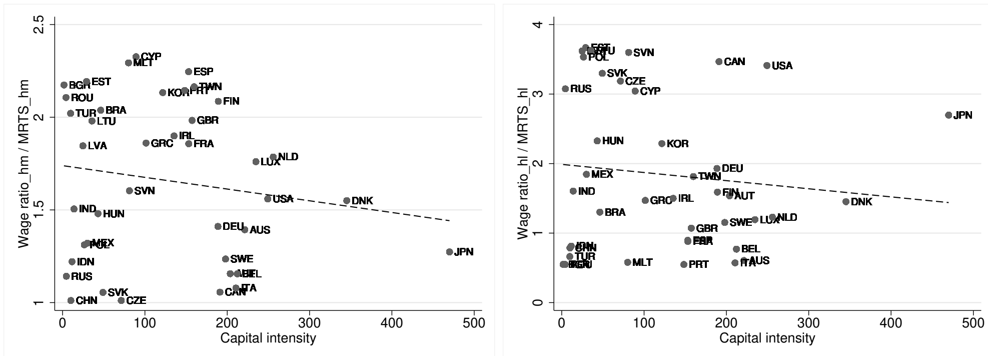
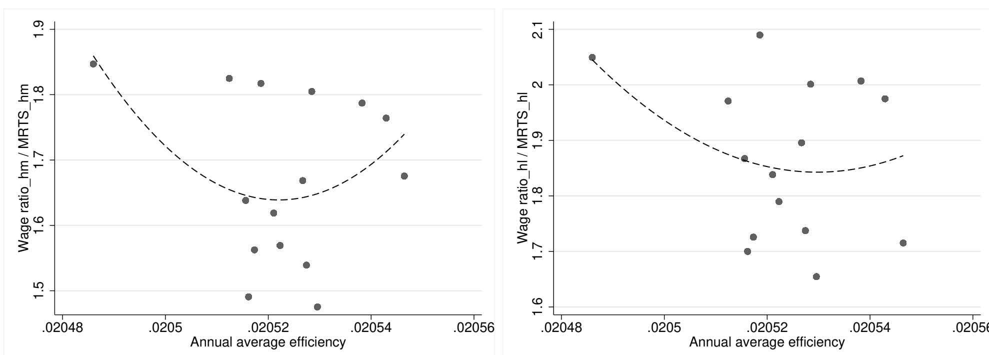


Figure 14. : Efficiency and ratio of wage ratio to MRTS

(a) High- versus medium-skilled labor

(b) High- versus low-skilled labor



VI. Conclusion

Recent literature has emphasized the effects of SBTC on labor markets, which causes the shift in the structure of wages and employment towards highs-skilled workers against the low-skilled. This paper considers efficiency change in the production process and measures how the ignorance of efficiency change can bias the estimation of SBTC. First, we theoretically derive the bias in the measurement of technical change, which is attributed to inefficient labor. We start with a simple two-firm setting and then generalize our model to show how this can result in a biased measurement of non-neutral (skill-biased) technical change. Second, we build a simple model to explain how the increase of newly hired workers may influence efficiency change. The underlying reasoning is that newly hired workers are less efficient than experienced workers, and therefore the recent rising supply of high-skilled labor can decrease efficiency rates. Without considering the efficiency loss of new entrants, we may underestimate SBTC.

Third, we conduct an empirical analysis based on the World Input-Output Database, which consists of panel data covering 40 countries and 31 industries during the period from 1995 to 2009. The comparison between the estimation of production function and of production frontier provides evidence of the underestimation of SBTC and shows negative relations between the change of labor inputs and the change of efficiency. Fourth, our Monte Carlo simulation shows that when there is a time trend in efficiency change and high-skilled labor input is negatively correlated with efficiency change, SBTC is underestimated. The t-tests indicate that the TFE model performs better than Fixed effects model, and the estimation of the TVD model is more biased when the efficiency change has no time trend. The TFE model is preferred, because it is more flexible and does not require neutrality of technical change and a function form of efficiency.

Fifth, on the basis of the estimation result of production frontier, we find a positive relation between SBTC and the MRTS and a positive relation between SBTC and the relative wage ratio, which implies that SBTC can increase the wage differential between high and relatively lower skilled labor. However, our empirical findings provide evidence that the skill intensity and institutional effects can also influence wage differentials and thus contribute to the overcompensation or undercompensation of high-skilled labor. Since the level of aggregation is highly macroeconomic, industry-specific analyses might be more appropriate. Besides, the data is highly aggregated, so firm-level data might give more accurate estimation. Lastly, there is a negative relation between the overcompensation of high-skilled workers and efficiency rates, which suggests a topic for future research.

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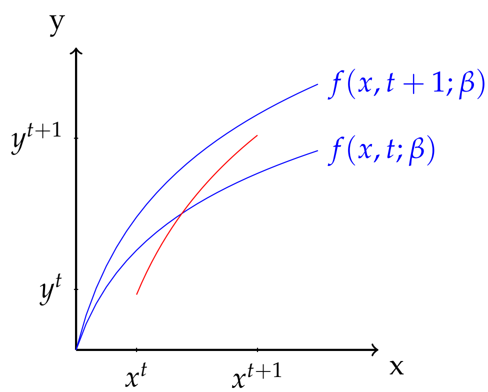
Appendix A: TFP Growth, Technical Change and Efficiency Change revisited

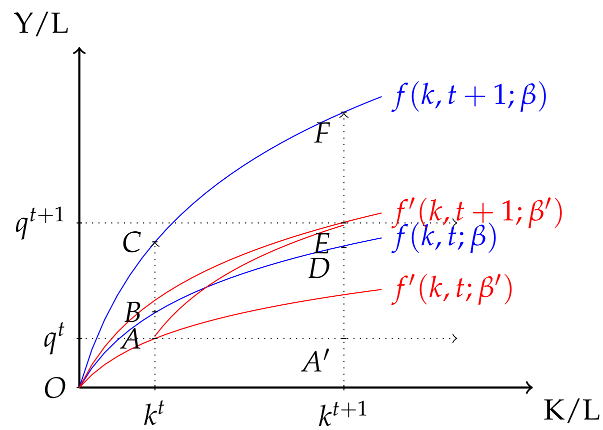
Both technical change and efficiency change are important components of TFP. Nevertheless, they affect production differently. Technical progress can shift the production function to a higher level and rise the maximum feasible output level, while the improvement of efficiency can increase output towards the maximum feasible output based on the current technology. Without separation, Technical change embodies time-varying efficiency change. If all the firms are efficient, efficiency does not matter and it cannot affect TFP growth. If inefficiency is time-invariant, then it can be captured in the individual characteristics. However, if inefficiency exists and it changes over time, it can provide an independent contribution to TFP. If efficiency change is not separated from technical change, it will lead to an erroneous measurement of the latter. To be more specific, if inefficiency is correlated with input factors, which is a reasonable assumption, omitted-variable bias will occur. In other words, the estimation of non-neutral technical change (e.g., SBTC) will be biased by the omission of the efficiency term.

Figure A1. : Technical Change and Efficiency Change



As is demonstrated in Figure A1, a producer utilizes a single input x to produce a single output y, expanding from (x^t, y^t) to (x^{t+1}, y^{t+1}). The blue lines exhibit the production frontiers with decreasing returns of scale, representing the maximum feasible output level given a certain input. Technical progress has occurred during the period between t to $t+1$, as $f(x,t+1;\beta) > f(x,t;\beta)$. Meanwhile, the red line indicates the improvement of efficiency of the producer from time t to $t+1$, because $[y^{t+1}/f(x,t+1;\beta)] < [y^t/f(x,t;\beta)]$, where $[y^t/f(x,t;\beta)]$, inefficiency, shows the discrepancy between the maximum feasible output and the actual output. If we omit the contribution of the growth of technical efficiency, the effect of technical change will be amplified.

Figure A2. : Bias in Labor-augmenting Technical Change



For non-neutral technical change, the bias resulting from efficiency change can be illustrated in Figure A2. Figure A2 shows labor-augmenting technical change by comparing two different production frontiers. Technical change is termed as labor-augmenting, if technical progress raises labor productivity and allows firms to produce more output with the same amount of labor input. As in Figure A2, the output per man q is represented along with the vertical axis and capital-labor ratio k is represented along with the horizontal axis. The function $f(k,t;\beta)$ is the production frontier before technical change and $f(k,t+1;\beta)$ is the production frontier after technical change. When capital-labor ratio stays constant at k^t, labor productivity increases from B to C, so technical change is labor-augmenting. However, when a firm is inefficient, it can not reach the maximum feasible labor productivity on the production frontier, which is depicted by the red lines. If capital-labor ratio rises from k^t to k^{t+1}, but efficiency of labor drops nevertheless, labor productivity only increases from A to E. The gap between the maximum possible labor productivity and the actual labor productivity widens from $B-A$ to $F-E$. If we ignore the change of inefficiency and consider point A and point E as efficient labor productivity, technical change would be the shift from $f'(k,t;\beta')$ to $f'(k,t+1;\beta')$ instead of the shift from $f(k,t;\beta)$ to $f(k,t+1;\beta)$. As a result, the real labor-augmenting technical change is underestimated by the rise of inefficiency. It is worth noting that the direction of the bias of labor-augmenting technical change is dependent on the change of efficiency.

A1. Measuring Technical Change

As noted above, there is necessity to disentangle technical change and efficiency change. The next step is to establish a model incorporate both components. Before we illustrate the model, we first need to know how to measure technical change. There are two categorized approaches: parametric and non-parametric methods. It started with a simple time trend embodied in the econometric estimation of the production or cost function (e.g., Tinbergen 1942). Afterward, econometricians advanced and generalized the treatment of technical change by introducing quadratic terms in time and interactions of the time trend with factor input prices and output, allowing technical change to grow at non-constant rates and to be both factor augmenting and scale augmenting (e.g., Gollop and Jorgenson 1980 and Gollop and Roberts 1983). Despite the advances of a more general measure of technical change, the linear and quadratic terms in time have been found to drive the econometric estimation primarily, producing a smooth, slowly changing pattern of technical change. Since the standard time trend has modeled technical change at a constant rate, some research has found that the standard time trend is a poor proxy for the bursts of rapid technical change (innovation), which can not be characterized by simple time trends (e.g., Kopp and Smith 1983).

An alternative methodology, applying index numbers, originated from Solow's general index of technical change $A(t)$. In this case, the production function takes the special form:

$$Q_t = A(t)f(L,K), \tag{A1}$$

and the index factor $A(t)$ measures the accumulated effect of shifts over time. This approach requires three assumptions: constant returns to scale, neutral technical change, and perfect competition, under which technical change ($\dot{T}$) is equivalent to the percentage growth in total factor productivity ($T\dot{F}P$). Precisely, $T\dot{F}P$ is calculated as the difference in the percentage growth in output($\dot{Q}$) less the percentage change in Divisia index of inputs:

$$\dot{T} = T\dot{F}P \equiv \dot{Q} - \sum_i \frac{P_i X_i}{C} \equiv \dot{Q} - \sum_i S_i \dot{x}_i, \tag{A2}$$

where a dot means the percentage change, P_i is the price of the input, x_i is the quantity, C stands for the total cost, and hence S_i represents the cost share. Technical change ($\dot{T}$) is called the Solow residual–the residual change rate of output not explained by the change of inputs.

The index number approach of the Solow residual is non-parametric. There is a parametric production function underlying the method of approximation. Diewert (1976) has showed that the Tornqvist approximation to the Divisia index used by Jorgenson and Griliches (1972) is an exact index number, given the production function has the translog form. In other words, the translog form of the production function serves as a potential function for the discrete Tornqvist index in the same way that the continuous production function serves as a potential function for the continuous Divisia index. However, if the translog function is far from the true production function, if returns to scale are not constant, or if the second-order parameters are different across producers, the Tornqvist index can generate significant biases.

Baltagi and Griffin (1988) developed a general index approach, which utilizes time dummy variables to represent Solow's index of technical change $A(t)$. The translog form of a cost function with a general index of technical change is specified as

$$\begin{aligned} \ln TC = & \alpha_0 + \sum \lambda_n D_n + A(t) + \sum \alpha_k \ln P_k + \gamma \ln Q \\ & + \frac{1}{2} \sum \sum \beta_{kj} \ln P_k \ln P_j + \frac{1}{2} \gamma^* (\ln Q)^2 \\ & + \sum \phi_k A(t) \ln P_k + \sum \psi_k \ln P_k \ln Q + \theta A(t) \ln Q, \end{aligned} \tag{A3}$$

where TC is total cost, D_ns are firm-specific dummies ($n = 2, \cdots, N$), $A(t)$ is the general index of technical change, P_ks are input prices, and Q is output. To estimate the above translog function, the corresponding cost shares (S_k) are derived from Sherphard's lemma,

$$\begin{aligned} S_k = \frac{\partial \ln C}{\partial \ln P_k} = & \alpha_k + \sum_j \beta_{kj} \ln P_j + \phi_k A(t) + \psi_k \ln Q, \\ & k = 1, \cdots, K. \end{aligned} \tag{A4}$$

The index $A(t)$ can be estimated by replacing $A(t)$ with time dummy variables, where

$$A(t) = \sum_{t=1}^{T} \beta_t D_t, \tag{A5}$$

and D_t is the dummy variable for year t. The equivalent equations of the total cost function and the cost shares are indicated as

$$\begin{aligned} \ln TC = & \sum \lambda_n D_n + \sum \beta_t D_t + \frac{1}{2} \sum \sum \beta_{kj} \ln P_k \ln P_j + \frac{1}{2} \gamma^* (\ln Q)^2 \\ & + \sum \sum \alpha^*_{kt} D_t \ln P_k + \sum \psi_k \ln P_k \ln Q + \sum \theta^*_t D_t \ln Q, \end{aligned} \tag{A6}$$

$$S_k = \sum \alpha^*_{kt} D_t + \sum \beta_{kj} \ln P_j + \psi_k \ln Q, \qquad k = 1, \cdots, K, \tag{A7}$$

where

$$\text{(A8)} \qquad \begin{aligned} \beta_t &= \alpha_0 + A(t), \\ \alpha_{kt}^* &= \alpha_k + \phi_k A(t), \\ \theta_t^* &= \gamma + \theta A(t). \end{aligned}$$

When the initial year is taken as the base year for $A(t)$, meaning $A(1) = 0$, the relevant parameters are able to be identified.

Technical change in the general index model is

$$\text{(A9)} \qquad \begin{aligned} \dot{T} =& A(t) - A(t-1) + \sum \phi_k \left[A(t) - A(t-1)\right] \ln P_k \\ &+ \theta \left[A(t) - A(t-1)\right] \ln Q. \end{aligned}$$

As in this model, technical change can be decomposed into three components: $[A(t) - A(t-1)]$ are the effects of pure technical change; $\sum \phi_k \left[A(t) - A(t-1)\right] \ln P_k$ are the effects of non-neutral technical change; and $\theta \left[A(t) - A(t-1)\right] \ln Q$ are the effects of scale augmentation. Note that the non-neutral and the scale augmentation components depend on the neutral component. For instance, if $A(t)$ remains the same, which means $A(t) - A(t-1) = 0$, the non-neutral and the scale augmentation components will have no effect on the rate of technical change.

In sum, one way of measuring technical change is to specify a parametric functional form for production technology, and an alternative is to allocate the growth of output among the growth rates of different factors non-parametrically. By applying either method, we can estimate technical change and incorporate efficiency in the productivity model.

A2. Simulation

In order to further analyze the biases in the estimation of technical change, we use a Monte Carlo method to simulate estimation biases among different models. Based on the results of the preceding production frontier estimation, we utilize estimated coefficients to calibrate the models in the data generating process (DGP), assuming the estimates are the true values of our model. In our simulations, we consider the true model as a stochastic production frontier model with inefficiency term, incorporating the general index of technical change. The model is specified as the same as equation (32).

Since both the effects of technical change and the effects of efficiency change are time-varying, we need a time-varying specification for technical inefficiency to disentangle it from technical change. This specification needs to be estimated separately from the index of technical change. Additionally, different specifications of technical inefficiency will result in different estimation results. Because we aim to explore how the correlation between inefficiency and high-skilled labor input will bias the estimates, we generate inefficiency based on three specifications: (1) random draws from an half-normal distribution, (2) the time-varying decay (TVD) model (Battese and Coelli, 1992), and (3) the TVD model and a correlation with high-skilled labor. The TVD model, considered a suitable model for DGP, has a specific time trend. The temporal pattern of inefficiency is modeled as an exponential function of time:

$$u_{it} = \exp\{-\eta(t - T_i)\}u_i, \quad \text{(A10)}$$

where $u_i \overset{\text{iid}}{\sim} N^+[\mu, \sigma_u^2]$, $v_{it} \overset{\text{iid}}{\sim} N[0, \sigma_v^2]$, T_i is the last period in the ith panel, and η is the decay parameter. When $\eta > 0$, the degree of inefficiency decreases towards the last period; when $\eta < 0$, the degree of inefficiency increases to the last period; and when $\eta = 0$, it reduces to the time-invariant model. When $t = T_i$, $u_{it} = u_i$, which is the base level of inefficiency for panel i. Specifically, we set $\eta = 0.02$ in model (2), presuming that inefficiency has been falling over time. Adversely, we set $\eta = -0.03$ in model (3), which implies that inefficiency has been rising over time, and we correlate inefficiency with high-skilled labor input positively. This accords to our reasoning that the growth of newly hired high-skilled workers can accelerate the rate of inefficiency.

On the basis of the preceding application on the WIOD data and the analysis, we generate data for independent variables and fit the formerly proposed model to generate the true outputs. The generated data consists of 18600 observations over the period 1995-2009. In order to obtain a realistic configuration of the right hand side of the estimation equation, we generate capital input and different labor inputs based on the statistics of the actual input data from the WIOD (in logs). Depending on the specifications of inefficiency, three true models are built and corresponding outputs are generated. For each model, we use three estimation methods: a linear fixed-effect regression (FE), the TFE frontier method, and the TVD method. We can prove our assumptions by measuring the differences among the estimates of distinct models. The data generation processes and the estimations are replicated 1000 times. It is worth mentioning that because the generated data may not applicable for the estimation, there are fewer than 1000 results of the iterations.

In addition, we conduct one-sample t-tests to identify the differences between the estimated parameters and the true values. The results of t-tests are summarized in Table 5, and they differ among models and estimation methods as we would expect. It can be seen that there is no significant biases in the FE and TFE estimations in model (1), when the inefficiency rates do not have a time trend and a correlation with high-skill labor. However, the coefficients for time dummies (α_t) are biased in the TVD estimation. When we introduce a time trend into the inefficiency term in model (2), the estimations of α_t have biases in all three methods, although the estimates of the cumulative effects of high-skilled labor augmenting technical change (α_{ht}) are not significantly biased. The FE estimator and the TFE estimator of the parameter α_t are both overestimated, whereas the TVD estimator is underestimated. Since inefficiency declines over time in this model, the overestimations confirm our conclusion that the effect of technical change will be exaggerated, if we ignore the contribution of the growth of technical efficiency. Moreover, when the inefficiency rates are positively correlated with the high-skilled labor input in model (3), the estimator of the parameter α_{ht} is underestimated in all three models. In contrast to model (2), the FE estimator and the TFE estimator of the parameter α_t are both underestimated, while the TVD estimator is overestimated. As a result, an upward trend in inefficiency can generate the underestimation of neutral technical change, and a positive correlation between inefficiency and the high-skilled input can induce the underestimation of SBTC.

Table A1—: T-Tests for Differences between Estimated Parameters and True Values

True Model	Parameter	FE	TFE	TVD
Model (1)	$\hat{\alpha}_t^1 - \alpha_t^1$	$= 0$	$= 0$	$> 0^{***}$
	$\hat{\alpha}_{ht}^1 - \alpha_{ht}^1$	$= 0$	$= 0$	$= 0$
Model (2)	$\hat{\alpha}_t^2 - \alpha_t^2$	$> 0^{***}$	$> 0^{***}$	$< 0^{**}$
	$\hat{\alpha}_{ht}^2 - \alpha_{ht}^2$	$= 0$	$= 0$	$= 0$
Model (3)	$\hat{\alpha}_t^3 - \alpha_t^3$	$< 0^{***}$	$< 0^{***}$	$> 0^{***}$
	$\hat{\alpha}_{ht}^3 - \alpha_{ht}^3$	$< 0^{***}$	$< 0^{***}$	$< 0^{***}$

Note: The difference $=$ 0 means that the estimator is not significantly different from the true value. The difference > 0 (< 0) means that the estimator is significantly larger (smaller) than the true value. *** Indicates significant at the 1% level. ** Indicates significant at the 5% level.

Subsequently, we perform two-sample t-tests in order to compare the estimators of different methods. Our main focus is to make comparisons of the differences between the FE estimators and the TFE estimators. Despite the results of the FE and the TFE estimations are similar in Table 5, the t-tests indicate that there are statistically significant differences between two estimators. In both model (2) and model (3), the estimators of the coefficients α_t and α_{ht} based on the FE regressions are more biased than that based on the TFE regressions. Furthermore, the t-tests illustrate that the TFE estimator and the TVD estimator of the coefficient α_{ht} are not significantly different from each other in model (2) and (3), which implies that the TFE estimation can capture the cumulative effects of high-skilled labor augmenting technical change, even though the true model is the TVD model. In conclusion, the TFE model performs better than fixed effects model when efficiency changes over time, and the estimation of the TVD model is more biased when efficiency change has no time trend.

APPENDIX B: TABLES AND GRAPHS

Table B1—: Industry Description

Industry	Code	Number
Agriculture,hunting, forestry and fishing	AtB	24
Mining and quarrying	C	25
Food, beverages and tobacco	15t16	1
Textiles and textile	17t18	2
Leather and footwear	19	3
Wood and of wood and cork	20	4
Pulp, paper, printing and publishing	21t22	5
Coke, refined petroleum and nuclear fuel	23	6
Chemicals and chemical	24	7
Rubber and plastics	25	8
Other non-metallic mineral	26	9
Basic metals and fabricated metal	27t28	10
Machinery, Nec	29	11
Electrical and optical equipment	30t33	12
Transport equipment	34t35	13
Manufacturing nec and recycling	36t37	14
Electricity, gas and water supply	E	26
Sales, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	50	15
Whole sale trade and commission trade, except of motor vehicles and motorcycles	51	16
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52	17
Hotels and restaurants	H	29
Other inland transport	60	18
Other water transport	61	19
Other air transport	62	20
Other supporting and auxiliary transport activities; activities of travel agencies	63	21
Post and telecommunications	64	22
Financial intermediation	J	27
Renting of m&eq and other business activities	71t74	23
Public admin and defence; compulsory social security	L	28
Education	M	29
Health and social work	N	30
Other community, social and personal services	O	31

Table B2—: Country Description

Country	Acronym	Number
Australia	AUS	1
Austria	AUT	2
Belgium	BEL	3
Brazil	BRA	4
Bulgaria	BGR	5
Canada	CAN	6
China	CHN	7
Cyprus	CYP	8
Czech Republic	CZE	9
Denmark	DNK	10
Estonia	EST	11
Finland	FIN	12
France	FRA	13
Germany	DEU	14
Greece	GRC	15
Hungary	HUN	16
India	IND	17
Indonesia	IDN	18
Ireland	IRL	19
Italy	ITA	20
Japan	JPN	21
Korea	KOR	22
Latvia	LVA	23
Lithuania	LTU	24
Luxembourg	LUX	25
Malta	MLT	26
Mexico	MEX	27
Netherlands	NLD	28
Poland	POL	29
Portugal	PRT	30
Romania	ROU	31
Russia	RUS	32
Slovak Republic	SVK	33
Slovenia	SVN	34
Spain	ESP	35
Sweden	SWE	36
Taiwan	TWN	37
Turkey	TUR	38
United Kingdom	GBR	39
United States	USA	40

Table B3—: Data Description

VA	Gross value added at current basic prices (in millions of national currency)
VA_P	Price levels of gross value added, 1995=100
K_GFCF	Real fixed capital stock, 1995 prices
H_EMP	Total hours worked by persons engaged (millions)
H_HS	Hours worked by high-skilled persons engaged (share in total hours)
H_MS	Hours worked by medium-skilled persons engaged (share in total hours)
H_LS	Hours worked by low-skilled persons engaged (share in total hours)
LAB	labor compensation (in millions of national currency)
LABHS	High-skilled labor compensation (share in total labor compensation)
LABMS	Medium-skilled labor compensation (share in total labor compensation)
LABLS	Low-skilled labor compensation (share in total labor compensation)

This table shows the variables we adopt from the World Input-Output Database (WIOD). We convert all the national currency into US dollar. Output is calculated as the gross value added (VA) devided by its price indice (VA_P). We use real fixed capital stock (K_GFCF) as capital input. Multiplying total hours worked by persons engaged (H_EMP) by respective shares in total hours, we obtain high-, medium-, and low-skilled labor inputs. By the same measure, we can obtain the respective labor compensation.

Table B4—: Descriptive Statistics of Variables

Label	Variable	Obs	Mean	Std. Dev.	Min	Max
$\ln Y_{ijt}$	Output	18,529	7.683	2.457	-2.383	14.123
$\ln K_{ijt}$	Capital Stock	17,608	8.417	2.488	-1.747	16.464
$\ln HS_{ijt}$	High-Skilled Labor	18,526	3.387	2.375	-8.374	10.386
$\ln MS_{ijt}$	Medium-Skilled Labor	18,531	4.590	2.343	-7.411	11.853
$\ln LS_{ijt}$	Low-Skilled Labor	18,530	3.925	2.430	-5.578	13.159

This table shows summary statistics for the main variables used in the analysis. All the variables are shown in natural logarithms. The data is the industry data of WIOD. It consists of 18600 observations covering 40 countries and 31 industries for the period from 1995 to 2009.The obervations are specific to ith country and jth industry at time t. The standard deviations of all the variables are fairly large, which means there is heterogeneity across countries and industries.

Table B5—: Parameter Estimates in Different Models

	Fixed-Effects		True Fixed-Effects		Wang& Ho	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
α_k	0.9833	(0.0777)	1.0388	(0.0154)	0.9053	(0.0154)
α_h	0.1232	(0.0191)	0.0138	(0.0178)	0.3277	(0.0242)
α_m	0.1395	(0.0322)	0.1160	(0.0266)	0.9856	(0.0444)
α_l	0.1958	(0.0305)	0.0597	(0.0180)	0.3595	(0.0245)
α_{kk}	-0.0349	(0.0098)	-0.0431	(0.0019)	-0.0222	(0.0021)
α_{hh}	0.0164	(0.0043)	0.0470	(0.0044)	0.0266	(0.00334)
α_{mm}	-0.0480	(0.0066)	-0.0458	(0.0051)	-0.0008	(0.0076)
α_{ll}	-0.0147	(0.0066)	0.0120	(0.0036)	-0.0124	(0.0044)
α_{kh}	-0.0004	(0.0001)	-0.0002	(0.0001)	-0.0005	(0.0001)
α_{km}	0.0003	(0.0001)	0.0001	(0.0001)	0.0004	(0.0001)
α_{kl}	0.0005	(0.0001)	0.0006	(4e-05)	0.0006	(0.0001)
α_{hm}	0.0023	(0.0003)	0.0022	(0.0002)	0.0021	(0.0003)
α_{hl}	-0.0006	(0.0002)	-0.0008	(0.0001)	-0.0003	(0.0002)
α_{ml}	0.0003	(0.0003)	0.0003	(0.0002)	-0.0007	(0.0002)

Table B6—: Technical Change in Different Models

Period	Production Function				Stochastic Frontier			
	Neutral	High	Medium	Low	Neutral	High	Medium	Low
1996	-0.1400	-0.0156	0.0070	-0.0066	-0.1358	-0.0096	0.0013	-0.0063
	(0.0644)	(0.0165)	(0.0175)	(0.0103)	(0.0327)	(0.0084)	(0.0094)	(0.0055)
1997	-0.1212	-0.0244	0.0252	-0.0196	-0.1458	-0.0286	0.0264	-0.0214
	(0.0590)	(0.0139)	(0.0146)	(0.0088)	(0.0319)	(0.0085)	(0.0095)	(0.0055)
1998	-0.0499	0.0076	-0.0170	0.0006	-0.0509	0.0063	-0.0205	0.0042
	(0.0482)	(0.0116)	(0.0120)	(0.0072)	(0.0301)	(0.0085)	(0.0096)	(0.0054)
1999	-0.0385	-0.0000	0.0113	-0.0103	-0.0458	-0.0034	0.0151	-0.0103
	(0.0428)	(0.0100)	(0.0110)	(0.0066)	(0.0300)	(0.0086)	(0.0097)	(0.0054)
2000	-0.0171	0.0008	0.0118	-0.0013	-0.0193	-0.0025	0.0133	0.0004
	(0.0369)	(0.0086)	(0.0100)	(0.0059)	(0.0294)	(0.0086)	(0.0096)	(0.0054)
2001	-0.0312	-0.0088	0.0167	-0.0081	-0.0307	-0.0090	0.0182	-0.0089
	(0.0301)	(0.0075)	(0.0092)	(0.0053)	(0.0292)	(0.0087)	(0.0097)	(0.0054)
2002	-0.0204	-0.0073	0.0101	-0.0060	-0.0010	-0.0031	0.0059	-0.0055
	(0.0285)	(0.0071)	(0.0090)	(0.0052)	(0.0293)	(0.0087)	(0.0097)	(0.0054)
2003	0.0036	-0.0082	0.0109	-0.0142	0.0360	-0.0048	0.0058	-0.0122
	(0.0313)	(0.0067)	(0.0081)	(0.0048)	(0.0294)	(0.0087)	(0.0097)	(0.0054)
2004	-0.0006	-0.0024	0.0214	-0.0153	0.0193	-0.0031	0.0131	-0.0126
	(0.0572)	(0.0083)	(0.0132)	(0.0073)	(0.0295)	(0.0088)	(0.0098)	(0.0054)
2005	-0.0361	0.0027	-0.0006	-0.0067	-0.0292	0.0003	0.0013	-0.0070
	(0.0469)	(0.0095)	(0.0135)	(0.0070)	(0.0300)	(0.0090)	(0.0100)	(0.0054)
2006	-0.0222	-0.0049	0.0148	-0.0100	-0.0105	0.0030	0.0072	-0.0114
	(0.0391)	(0.0106)	(0.0116)	(0.0060)	(0.0303)	(0.0091)	(0.0101)	(0.0055)
2007	-0.0098	-0.0056	0.0126	-0.0084	-0.0249	-0.0082	0.0109	-0.0085
	(0.0518)	(0.0136)	(0.0154)	(0.0085)	(0.0308)	(0.0090)	(0.0101)	(0.0055)
2008	-0.0611	-0.0104	0.0132	0.0051	-0.0472	-0.0003	0.0005	0.0029
	(0.0620)	(0.0181)	(0.0209)	(0.0104)	(0.0334)	(0.0103)	(0.0117)	(0.0059)
2009	-0.1607	0.0172	-0.0177	0.0001	-0.1400	0.0079	0.0080	-0.0058
	(0.0700)	(0.0219)	(0.0261)	(0.0114)	(0.0351)	(0.0141)	(0.0131)	(0.0063)
average	-0.0504	-0.0042	0.0085	-0.0072	-0.0447	-0.0039	0.0065	-0.0073
	(0.0056)	(0.0016)	(0.0018)	(0.0011)	(0.0028)	(0.0009)	(0.0010)	(0.0006)