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An empirical study on the endogeneity of directed technical change in China

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ABSTRACT

Research on the endogeneity of directed technical change is very interesting and meaningful. If the direction of technical change is endogenous, policy makers can adjust the technical change value of factors according to specific purpose. We establish a theoretical model of the direction of technical change, relative price of factors and international trade under nested and non-nested CES production functions. We use mature measurement methods such as the unit root test and cointegration analysis to test the theoretical model in practice. We find that the direction of technical change is endogenous in China. The change in the relative price of factors in China causes a technical change in the same direction. Meanwhile, international trade intensifies and accelerates the labour augmenting technical change, but blocks the pace of capital augmenting technical change. Under a substitution elasticity of less than one, technical change is biased toward energy and capital in China, and this bias is brought about by the decrease in their relative price and international trade.

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1. Introduction

In the 1980s, China embarked on the road of market-oriented reforms. The free flow and market pricing of factors continuously improved the factor production efficiency, that is, the factor-augmenting technical change continuously improved. During the 1980s and 1990s, labour, capital, and energy augmenting technical change increased at an average annual rate of 7.7%, 1% and 5.6%, respectively.[1] Among them, labour production efficiency increased at the highest rate. Especially since the 1990s, when China implemented the plan to expand university education, the education level and cultural quality of its workers have generally improved. During this period, the annual growth rate of labour-augmenting technical change has been close to 10%.

However, since this century, the trend of factor-augmenting technical change has been differentiated. Capital production efficiency shows a downward trend on the whole. Labour productivity continued to grow at a high rate until the financial crisis

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of 2008, but after the crisis, growth slowed to single digits. Since 2006, China has incorporated energy intensity as a binding target into its mid-term and long-term plans for national economic and social development. A raft of plans to clean up energy guzzling and polluting industries has been launched. As a result, the energy production efficiency of China has increased year by year since 2006, with an average annual growth rate of 8% in energy-augmenting technical change between 2006 and 2017.

Overall, since the reforms and the opening up of the economy, labour-augmenting technical change in China grew faster than energy-augmenting technical change, which in turn grew faster than capital-augmenting technical change. We attempt to explain the reasons for this phenomenon. Acemoglu put forward the theory of biased technical change in 2002, pointing out that the price effect and the market-size effect determine the direction of technical change. We refer to the theoretical method of Acemoglu (2002) and empirically test the endogeneity of the directed technical change in China. On the one hand, this paper explains the reasons for the different growth trends of the production efficiency of various factors in China, and, on the other hand, it enables Chinese policy makers to realize that the direction of technical change can be designed, providing them with a theoretical reference to design relevant policies. The difference between our paper and Acemoglu (2002) is considering that the factor market in China has not been fully marketized, especially in the field of energy, we take factor price as an exogenous variable and extend the two-factor model of Acemoglu (2002) to the three-factor model.

2. Literature review

The idea of endogenous technical change originally came from Hicks' (1932) 'The Theory of Wages'. He pointed out that the change in the relative price of factors would stimulate the generation of new technologies, and this technology would be used to save on the relatively expensive factors. That is, the manufacturer's choice of the type of technology depends on the relative price of factors and an increase in the relative price of a factor will lead to technology savings. However, Salter (1960) criticised this idea, pointing out that what manufacturers pursue was the total cost rather than the reduction of the cost of a single factor; if a factor can bring about a reduction in the total cost, even if it becomes more expensive, it would be welcomed. Based on Salter's (1960) idea that 'manufacturers only cared about total cost but not single factor cost', Kennedy (1964) proposed the theory of 'induced innovation'. This was the formal initiation of theoretical research on the endogenous nature of technical change. Subsequently, Uzawa (1965), Drandakis and Phelps (1966), Samuelson (1965), and Salter (1966) successively carried out theoretical research on the endogeneity of technical change and put forward some important theoretical concepts such as learning by doing and the innovation possibility frontier.

However, in the following 20 years, theoretical research on endogenous technical change was on hold until the emergence of new economic growth theory in the mid-

1980s and the emergence of biased technical change theory in the 1990s. Economists subsequently picked up this theory and formed two research routes: endogenous research on the intensity and direction of technical change. The first route aims to analyse the factors that influence the total level of technical change and construct the production function of technical change theoretically. The second route aims to analyse the internal reasons for firms to make choices among different types of technology. If the intensity model of technical change determines the total amount of research and development (R&D) investment, then the direction model of technical change determines the allocation of R&D resources.

New economic growth scholars are concerned about the endogeneity of the intensity of technical change. The representative literature mainly includes Romer (1986, 1990), Aghion and Howitt (1992), and Grossman and Helpman (1993). However, scholars of the induced innovation and the biased technical change were concerned about the endogeneity of the direction of technical change. The representative literature mainly includes Arrow et al. (1961), Kennedy (1964), Acemoglu (1998, 2002, 2003, 2007), Acemoglu et al. (2012), and other studies on induced innovation and biased technical change (Dabbous & Tarhini, 2021; Hu et al., 2020; Kijek & Kijek, 2019; Łukasz & Grabowski, 2019; Mushtaq et al., 2020; Philipson, 2020; Shah et al., 2020; Tiberius et al., 2021).

Current research on endogeneity of technical change mainly tends to discuss the endogeneity of the intensity of technical change. There are relatively few studies on the endogeneity of the direction of technical change. Acemoglu (2002), from the micro perspective of profit stimulation, pointed out that the manufacturer's choice of technology type was not only affected by the relative price of factors, but also by the relative scale of factors. Chen and Wang (2015) and Kim (2019) studied the influence of international trade on the bias of technical change,[2] indicating that trade aggravates the bias of technical change. Güven and Turanlı (2014) analyzed the influence of different market structures on biased technical change. In recent years, some scholars have begun to pay attention to indicators such as urbanization, city size, R&D intensity and enterprise scale (Rubinton, 2021; Yang et al., 2019). Among them, the empirical analysis on endogeneity in the direction of technical change is fairly limited. Yang et al. (2019) conducted an empirical study on factors affecting biased technical change in China, which include trade, R&D investment, enterprise size, energy consumption structure, and the proportion of the state-owned economy. Using panel regression analysis, Huang et al. (2021) studied the factors influencing biased technical change and found that improving energy efficiency, promoting urbanization, expanding production scale, and optimizing industrial structures effectively promote biased technical change. Recently, many scholars have begun studying the impact of environmental policies on the direction of technical change (Greaker et al., 2018; Kruse-Andersen, 2016; Wang et al., 2020).

Regarding the endogeneity of directed technical change in China, most scholars directly examine it from an empirical perspective (Chen & Wang, 2015; Wang et al., 2019, 2020; Yang et al., 2019). However, we will refer to the method of Acemoglu (2002) and examine the endogeneity of the direction of technical change in China from the perspective of theoretical derivation and empirical analysis.

3. Theoretical model

3.1. Theoretical mechanism analysis

By referring to the analysis of Acemoglu (2002) from the micro perspective of profit inducement of manufacturers, we analyzed the influence of relative price changes of factors on the direction of technical change. We divided the production sector into three departments: final goods production, intermediate goods production, and R&D. The intermediate goods production department is further divided into capital-, labour-, and energy-intensive sectors. The input of each intermediate product department consists of corresponding factors and machines, which contain factor-augmenting technology. The change in factor price affects the product price of the intermediate product department. Then, the change in intermediate product price affects the manufacturer's demand for machines. Thus, profits of the R&D department will be changed from the technology demand side, and then the technical direction of the R&D department will be changed.

Acemoglu (2002) further studied the influence of international trade on the direction of technical change. They pointed out that trade between countries would change the relative prices of intermediate goods. This would change the relative expected returns of various technologies and ultimately affect the allocation of R&D resources for new technology production, thereby affecting the direction of technical change. According to Acemoglu (2002), market size and price effects determine the direction of technical change. The author also posited that international trade influences the direction of technical change by influencing the price effect. We also argue that international trade can influence the direction of domestic technical change through the introduction and absorption of different types of foreign technologies.

3.2. Model under non-nested CES

In the study of directed technical change, two concepts are often involved: augmenting technical change and biased technical change. If one technology is used by factor A and increases the efficiency of factor A, we call this technology factor A-augmenting. When the speeds of A- and B-augmenting technical change are not exactly the same, we say that technical change has a direction. If the pace of A-augmenting technical change is faster than that of B-augmenting technical change, or if A-augmenting technical change (relative to B) is increasing, then the direction of technical change is toward factor A. When technical change has a direction, it is inevitable that the efficiency of one factor will be higher than the other. Then, the marginal output and demand of each factor will change accordingly. If technology increases the marginal output (or demand) of factor A more than B, or increases the relative marginal output (or relative demand) of factor A, then this technology is termed as factor A-biased technical change.

We attempt to find out the reasons for the changes in labour (relative to energy) and capital (relative to energy) augmenting technical change in recent years. Based on the CES production function, we deduce an endogenous model of the direction of technical change. Multi-factor CES production functions include non-nested and nested type. Since we do not investigate which structure is more suitable in China's context, we build the model considering both CES structures. Due to space limitation, we only present the theoretical model derivation process under non-nested CES structure.

The production functions of the final goods and the intermediate goods production departments are, respectively:

$$Y = \left(\delta_1 Y_L^{\frac{\varepsilon-1}{\varepsilon}} + \delta_2 Y_K^{\frac{\varepsilon-1}{\varepsilon}} + \delta_3 Y_E^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1}$$

$$Y_L = \frac{1}{1-\beta}\left(\sum\nolimits_{j=0}^{N_L} x_{L,j}^{1-\beta}\right)L^{\beta}\ ,\ \ Y_K = \frac{1}{1-\beta}\left(\sum\nolimits_{j=0}^{N_K} x_{K,j}^{1-\beta}\right)K^{\beta}\ ,$$
$$Y_E = \frac{1}{1-\beta}\left(\sum\nolimits_{j=0}^{N_E} x_{E,j}^{1-\beta}\right)E^{\beta} \tag{2}$$

where Y is the total output, and L, K, and E represent the inputs of labour, capital, and energy, respectively. Y_L is the intermediate input of the economy and the output of the labour-intensive sector. $x_{L,j}$ denotes the number of j^{th} machines using by labour. N_L denotes the number of types of j^{th} machine. $\beta \in (0,1)$ as well as δ_i(i = 1,2,3) are the distribution parameters that can determine how important the input are. $\varepsilon \geq 0$ denotes the elasticity of substitution between intermediate inputs. The production function of the other intermediate was explained in a similar manner. If N_L is larger, we can say that the labour sector has a higher level of technological progress, so the change in N_L/N_E and N_K/N_E can be used to reflect the direction of technical change.

From Equations (1) and (2), as well as the first-order conditions of factors and intermediate goods, we can derive the following equations:[3]

$$\frac{Y_L}{Y_E} = \frac{{\delta_1}^{\varepsilon}}{\delta_3}\left(\frac{p_L}{p_E}\right)^{-\varepsilon}\ ,\ \ \frac{Y_K}{Y_E} = \frac{{\delta_2}^{\varepsilon}}{\delta_3}\left(\frac{p_K}{p_E}\right)^{-\varepsilon} \tag{3}$$

$$\frac{Y_L}{Y_E} = \frac{N_L L}{N_E E}\left(\frac{p_L}{p_E}\right)^{(1-\beta)/\beta}\ ,\ \ \frac{Y_K}{Y_E} = \frac{N_K K}{N_E E}\left(\frac{p_K}{p_E}\right)^{(1-\beta)/\beta} \tag{4}$$

$$\frac{w}{q} = \frac{N_L}{N_E}\left(\frac{p_L}{p_E}\right)^{\frac{1}{\beta}}\ ,\ \ \frac{r}{q} = \frac{N_K}{N_E}\left(\frac{p_K}{p_E}\right)^{\frac{1}{\beta}} \tag{5}$$

$$\frac{V_L}{V_E} = \left(\frac{p_L}{p_E}\right)^{\frac{1}{\beta}}\frac{L}{E}\ ,\ \ \frac{V_K}{V_E} = \left(\frac{p_K}{p_E}\right)^{\frac{1}{\beta}}\frac{K}{E} \tag{6}$$

where w, r and q represent the prices of labour, capital, and energy, respectively, p_L represents the product prices of labour-intensive departments, V_L represents the present discounted value of future profits of the R&D department which produces technology complementing labour. V_K, V_E, p_K, and p_E can be interpreted similarly.

Combining Equations (3) and (4), we get:

$$\frac{p_L}{p_E} = \left(\frac{\delta_1}{\delta_3}\right)^{\frac{\beta\varepsilon}{\varepsilon\beta+1-\beta}} \left(\frac{N_L L}{N_E E}\right)^{\frac{\beta}{\beta-\varepsilon\beta-1}} , \quad \frac{p_K}{p_E} = \left(\frac{\delta_2}{\delta_3}\right)^{\frac{\beta\varepsilon}{\varepsilon\beta+1-\beta}} \left(\frac{N_K K}{N_E E}\right)^{\frac{\beta}{\beta-\varepsilon\beta-1}} \tag{7}$$

Substituting Equation (7) into Equation (5), we obtain the relative demand curve of factors, namely, the demand curve of labour (relative to energy) and capital (relative to energy):

$$\frac{L}{E} = \frac{\delta_1{}^{\varepsilon}}{\delta_3} \left(\frac{N_L}{N_E}\right)^{\varepsilon\beta-\beta} \left(\frac{w}{q}\right)^{\beta-\varepsilon\beta-1} , \quad \frac{K}{E} = \frac{\delta_2{}^{\varepsilon}}{\delta_3} \left(\frac{N_K}{N_E}\right)^{\varepsilon\beta-\beta} \left(\frac{r}{q}\right)^{\beta-\varepsilon\beta-1} \tag{8}$$

Now, we let the elasticity of substitution between factors be σ. The elasticity of substitution reflects the change in relative demand of factors caused by the change in the relative price of factors, with σ defined as, $\sigma = -\frac{\partial \ln(L/E)}{\partial \ln(w/q)} = -\frac{\partial \ln(K/E)}{\partial \ln(r/q)}$. Then, from Equation (8), we can obtain the relationship between ε and σ :

$$\sigma = \varepsilon\beta - \beta + 1 \tag{9}$$

Substitute Equation (8) into Equation (9), we have:

$$\frac{L}{E} = \frac{\delta_1{}^{(\sigma+\beta-1)/\beta}}{\delta_3} \left(\frac{N_L}{N_E}\right)^{\sigma-1} \left(\frac{w}{q}\right)^{-\sigma} , \quad \frac{K}{E} = \frac{\delta_2{}^{(\sigma+\beta-1)/\beta}}{\delta_3} \left(\frac{N_K}{N_E}\right)^{\sigma-1} \left(\frac{r}{q}\right)^{-\sigma} \tag{10}$$

To determine the direction of endogenous technical change, we also need to consider the technology production of R&D departments. Referring to Acemoglu (2002), we adopt the labouratory equipment model as follows:

$$\dot{N}_L = \eta_L R_L \ , \ \dot{N}_K = \eta_K R_K \ , \ \dot{N}_E = \eta_E R_E \tag{11}$$

where $\dot{N}_L$ denotes the number of new types of machines used by labour, R_L denotes the amount of R&D invested by the R&D department which produces technology complementing labour, and η_L is the coefficient associated with the technology production. The other technology production function in Equation (11) is explained similarly. This technology production function indicates that the marginal revenue of R&D input remains unchanged. Thus, the marginal cost (MC) of the R&D department in producing each technology is equal to its average cost (AC):

$$\mathrm{MC}_L = \mathrm{AC}_L = \frac{\mathrm{TC}_L}{\dot{N}_L} = \frac{R_L}{\eta_L R_L} = \frac{1}{\eta_L} \ , \ \mathrm{MC}_K = \frac{1}{\eta_K} \ , \ \mathrm{MC}_E = \frac{1}{\eta_E} \tag{12}$$

When the R&D department is in equilibrium, its marginal revenue is equal to its marginal cost:

$$\mathrm{MC}_L = \frac{1}{\eta_L} = \mathrm{MR}_L = V_L \ , \ \mathrm{MC}_K = \frac{1}{\eta_K} = \mathrm{MR}_K = V_K \ , \ \mathrm{MC}_E = \frac{1}{\eta_E} = \mathrm{MR}_E = V_E \tag{13}$$

Combining the above equation with Equation (6), we get:

$$\frac{\eta_E}{\eta_L} = \left(\frac{p_L}{p_E}\right)^{\frac{1}{\beta}} \frac{L}{E} \ , \ \frac{\eta_K}{\eta_L} = \left(\frac{p_K}{p_E}\right)^{\frac{1}{\beta}} \frac{K}{E} \tag{14}$$

Substitute Equation (5) into Equation (14), we get:

$$\frac{L}{E} = \frac{\eta_E N_L}{\eta_L N_E} \left(\frac{w}{q}\right)^{-1} \ , \ \frac{K}{E} = \frac{\eta_E N_K}{\eta_K N_E} \left(\frac{r}{q}\right)^{-1} \tag{15}$$

Then, combining Equations (15) and (10), we obtain the relation between the direction of technical change and the relative price of factors:

$$\frac{N_L}{N_E} = \left(\frac{\eta_L}{\eta_E}\right)^{\frac{1}{2-\sigma}} \left(\frac{\delta_1}{\delta_3}\right)^{\frac{\sigma+\beta-1}{\beta(2-\sigma)}} \left(\frac{w}{q}\right)^{\frac{1-\sigma}{2-\sigma}} \ , \ \frac{N_K}{N_E} = \left(\frac{\eta_K}{\eta_E}\right)^{\frac{1}{2-\sigma}} \left(\frac{\delta_2}{\delta_3}\right)^{\frac{\sigma+\beta-1}{\beta(2-\sigma)}} \left(\frac{r}{q}\right)^{\frac{1-\sigma}{2-\sigma}} \tag{16}$$

The values of N_L/N_E and N_K/N_E cannot be obtained from an empirical perspective. This makes the following empirical analysis difficult. Therefore, we try to find out the relationship between N_L/N_E with labour (relative to energy) augmenting technical change, and N_K/N_E with capital (relative to energy) augmenting technical change. The production function of the final goods production department can also be expressed as:

$$Y = \left[\delta_1 (A_L L)^{\frac{\sigma}{\sigma-1}} + \delta_2 (A_K K)^{\frac{\sigma}{\sigma-1}} + \delta_3 (A_E E)^{\frac{\sigma}{\sigma-1}}\right]^{(\sigma-1)/\sigma} \tag{17}$$

where A_L, A_K, and A_E denote labour, capital, and energy augmenting technical change, respectively. Therefore, from Equations (17) and (1), we have:

$$Y_L^{\frac{\varepsilon-1}{\varepsilon}} = (A_L L)^{\frac{\sigma-1}{\sigma}} \ , \ Y_K^{\frac{\varepsilon-1}{\varepsilon}} = (A_K K)^{\frac{\sigma-1}{\sigma}} \ , \ Y_E^{\frac{\varepsilon-1}{\varepsilon}} = (A_E E)^{\frac{\sigma-1}{\sigma}} \tag{18}$$

Combining the above equation with Equations (4), (5), and (10), we get:

$$\frac{A_L}{A_E} = \left(\frac{\delta_1}{\delta_3}\right)^{(1-\beta)/\beta} \frac{N_L}{N_E} \ , \ \frac{A_K}{A_E} = \left(\frac{\delta_2}{\delta_3}\right)^{(1-\beta)/\beta} \frac{N_K}{N_E} \tag{19}$$

Therefore, we can use A_L/A_E and A_K/A_E to represent the direction of technical change instead. Substituting the above equation into Equation (16), we regain the relation between the direction of technical change and the relative price of factors, which is suitable for empirical analysis:

$$\frac{A_L}{A_E}=\left(\frac{\eta_L}{\eta_E}\right)^{\frac{1}{2-\sigma}}\left(\frac{\delta_1}{\delta_3}\right)^{\frac{1-\beta+\beta\sigma}{\beta(2-\sigma)}}\left(\frac{w}{q}\right)^{\frac{1-\sigma}{2-\sigma}},\quad \frac{A_K}{A_E}=\left(\frac{\eta_K}{\eta_E}\right)^{\frac{1}{2-\sigma}}\left(\frac{\delta_2}{\delta_3}\right)^{\frac{1-\beta+\beta\sigma}{\beta(2-\sigma)}}\left(\frac{r}{q}\right)^{\frac{1-\sigma}{2-\sigma}} \tag{20}$$

Then, we try to add international trade (OPEN) into the above model and provide a theoretical model of the direction of technical change on the relative price of factors and international trade in the form of a logarithmic function:

$$\ln\frac{A_L}{A_E}=\alpha_0+\alpha_1\ln\text{OPEN}+\frac{1-\sigma}{2-\sigma}\ln\frac{w}{q},\quad \ln\frac{A_K}{A_E}=\beta_0+\beta_1\ln\text{OPEN}+\frac{1-\sigma}{2-\sigma}\ln\frac{r}{q} \tag{21}$$

where

$$\alpha_0=\frac{1}{2-\sigma}\ln\frac{\eta_L}{\eta_E}+\frac{1-\beta+\beta\sigma}{(2-\sigma)\beta}\ln\frac{\delta_1}{\delta_3},\quad \beta_0=\frac{1}{2-\sigma}\ln\frac{\eta_K}{\eta_E}+\frac{1-\beta+\beta\sigma}{(2-\sigma)\beta}\ln\frac{\delta_2}{\delta_3} \tag{22}$$

In the non-nested structure, the elasticity of labour (relative to energy), augmenting technical change with respect to labour (relative to energy) price and capital (relative to energy)–augmenting technical change with respect to capital (relative to energy) are both $(1-\sigma)/(2-\sigma)$. Next, we refer to the first equation in Equation (21) related to labour (relative to energy) augmenting technical change to Model I-non-nested, and the second equation related to capital (relative to energy) augmenting technical change to Model II-non-nested.

Equations (23) and (24) provide the theoretical model under the nested CES structure:

$$\ln\frac{A_L}{A_E}=\alpha_0+\alpha_1\ln\text{OPEN}+\frac{1-\sigma_{LE}}{2-\sigma_{LE}}\ln\frac{w}{q},\quad \ln\frac{A_K}{A_E}=\beta_0+\beta_1\ln\text{OPEN}+\frac{1-\sigma_{KE}}{2-\sigma_{KE}}\ln\frac{r}{q} \tag{23}$$

where

$$\alpha_0=\frac{1}{2-\sigma_{LE}}\ln\frac{\eta_L}{\eta_E}+\frac{1-\beta+\beta\sigma_{LE}}{(2-\sigma_{LE})\beta}\ln\frac{\delta_1}{\delta_3},\quad \beta_0=\frac{1}{2-\sigma_{KE}}\ln\frac{\eta_K}{\eta_E}+\frac{1-\beta+\beta\sigma_{KE}}{(2-\sigma_{KE})\beta}\ln\frac{\delta_2}{\delta_3} \tag{24}$$

Under the nested structure, the elasticity of price between different technical levels is no longer equal and is determined by the substitution elasticity between their factors. The elasticity of labour (relative to energy) augmenting technical change with respect to the price of labour (relative to energy) is $(1-\sigma_{\text{LE}})/(2-\sigma_{\text{LE}})$. Meanwhile, the elasticity of capital (relative to energy), augmenting technical change with respect to the price of capital (relative to energy) is $(1-\sigma_{\text{KE}})/(2-\sigma_{\text{KE}})$. As the front part, we call the first equation in Equation (31) Model I-nested and the second equation in Model II-nested.

Our theoretical model is summarised in Table 1.

Table 1. Theoretical model of this paper.

Theoretical model	Formula number	Formula
ModelI-non nested	Formula(21)	$\ln\frac{A_L}{A_E} = \alpha_0 + \alpha_1 \ln OPEN + \frac{1-\sigma}{2-\sigma}\ln\frac{w}{q}$
ModelII-non nested	Formula(21)	$ln\frac{A_K}{A_E} = \beta_0 + \beta_1 lnOPEN + \frac{1-\sigma}{2-\sigma} ln\frac{r}{q}$
ModelI-nested	Formula(23)	$ln\frac{A_L}{A_E} = \alpha_0 + \alpha_1 lnOPEN + \frac{1-\sigma_{LE}}{2-\sigma_{LE}} ln\frac{w}{q}$
ModelII-nested	Formula(23)	$ln\frac{A_K}{A_E} = \beta_0 + \beta_1 lnOPEN + \frac{1-\sigma_{KE}}{2-\sigma_{KE}} ln\frac{r}{q}$

Source: formula (21) and (23) of this paper.

4. Empirical analysis

4.1. Measurement of the direction of technical change

We measured the direction of technical change from 1980 to 2017 in China. First, we obtain the value of factor augmenting technical change by nonlinear estimation of Equation (17), which was realised by an article by this author in 2016;[4] then, we calculate the values of the direction of technical change by using factor augmenting technical change. Tables 2 and 3 show our results.

From the values of the direction of technical change, we find the following.

First, whether it is a nested or a non-nested structure, labour (relative to energy) augmenting technical change maintains the growth trend except for individual years. This shows that in the 30 years after the reform and opening up, the growth of labour augmenting technical change in

China is generally faster than that of energy augmenting technical change. Especially since entering the new century, this growth has accelerated significantly. The average annual growth rate of labour (relative to energy) augmenting technical change in 2000–2007 is as high as 13.97% (non-nested) and 20.93% (nested), compared with 2.01% and 2.37% in 1980–1999. However, after the financial crisis of 2008, labour (relative to energy), augmenting technical change in China declined in general. The average annual growth rate of labour (relative to energy) augmenting technical change in 2008–2017 was −1.89% (non-nested) and −2.35% (nested). This is because the growth rate of labour (energy) augmenting technical change has slowed (accelerated) in recent years. This has narrowed the gap between labour and energy augmenting technical change.

Second, capital (relative to energy) augmenting technical change shows a downward trend in both structures, with an average annual decline of −5.09% and −5.58%, respectively. This means that the growth of capital augmenting technical change in China is generally slower than that of energy augmenting technical change. However, the change trend of capital (relative to energy) augmenting technical change is not as smooth as that of labour (relative to energy) augmenting technical change. It shows a wave pattern. In 1988–1993 and 2002–2005, capital augmenting technical change grew faster than energy augmenting technical change. From to 1988–1993, the average annual growth rate of capital (relative to energy) augmenting technical change was 0.47% (non-nested) and 4.69% (nested), compared with 3.36% and 11.73% in 20-02-2005. However, in other periods, including 1980–1987, 1994–2001, and 2006–2017, capital augmenting technical change declined. That is, energy augmenting technical change grew faster than capital augmenting technical change.

Table 2. Values of the direction of technical change under non-nested CES structure.

Year	A_L/A_E	A_K/A_E	year	A_L/A_E	A_K/A_E
1980	1.123	1.351	2000	1.772	0.563
1981	1.016	1.165	2001	1.824	0.530
1982	1.006	1.131	2002	1.981	0.523
1983	1.017	1.092	2003	2.447	0.570
1984	0.997	1.013	2004	3.214	0.569
1985	1.043	0.983	2005	3.959	0.605
1986	1.080	0.962	2006	4.470	0.600
1987	1.139	0.920	2007	4.665	0.545
1988	1.166	0.879	2008	4.524	0.566
1989	1.293	0.939	2009	4.338	0.472
1990	1.285	0.949	2010	4.888	0.446
1991	1.369	0.938	2011	5.214	0.420
1992	1.475	0.889	2012	5.173	0.375
1993	1.649	0.946	2013	5.031	0.326
1994	1.669	0.881	2014	4.846	0.284
1995	1.688	0.837	2015	4.352	0.234
1996	1.719	0.787	2016	4.124	0.217
1997	1.703	0.714	2017	3.854	0.195
1998	1.611	0.625			
1999	1.639	0.573			

Source: calculated from this paper.

Table 3. Values of the direction of technical change under nested CES structure.

Year	A_L/A_E	A_K/A_E	year	A_L/A_E	A_K/A_E
1980	0.864	1.098	2000	2.431	0.548
1981	0.787	0.913	2001	2.518	0.516
1982	0.820	0.911	2002	2.765	0.529
1983	0.871	0.900	2003	3.377	0.648
1984	0.932	0.833	2004	4.110	0.689
1985	1.018	0.828	2005	5.013	0.804
1986	1.068	0.826	2006	5.741	0.827
1987	1.148	0.799	2007	6.164	0.732
1988	1.212	0.771	2008	6.360	0.783
1989	1.323	0.891	2009	5.989	0.593
1990	1.348	0.936	2010	6.490	0.554
1991	1.478	0.962	2011	6.791	0.516
1992	1.664	0.921	2012	6.630	0.438
1993	1.985	1.052	2013	6.337	0.352
1994	2.122	0.976	2014	6.061	0.287
1995	2.244	0.935	2015	5.499	0.214
1996	2.336	0.870	2016	5.179	0.165
1997	2.342	0.755	2017	4.862	0.131
1998	2.234	0.617			
1999	1.348	0.936			

Source: calculated from this paper.

4.2. Description of other indicators

Using the index of factor share ratio, we can calculate the relative price of factors. The calculation equations are $w/q = (\varsigma^L E)/(\varsigma^E L)$ and $r/q = (\varsigma^K E)/(\varsigma^E K)$, where ς^L, ς^K, and ς^E respectively represent the share of labour, capital, and energy, respectively.[5] The index of international trade is measured by the amount of real imports and exports. This is calculated by the nominal amount of imports and exports in terms of the gross domestic product (GDP) deflator. Table 4 lists the values of the indicators.

Table 4. Data of relative price of factors and international trade.

Year	Relative price of labour	Relative price of capital	International trade	Year	Relative price of labour	Relative price of capital	International trade
1980	11.089	8.071	1903.288	1999	24.314	4.826	30510.091
1981	11.805	7.849	2398.418	2000	22.815	4.264	39273.200
1982	12.500	7.778	2518.944	2001	24.940	4.288	41323.761
1983	13.473	8.100	2777.613	2002	26.840	4.378	50014.299
1984	15.705	8.946	3696.049	2003	27.398	4.238	66848.528
1985	15.860	8.783	5769.501	2004	25.316	4.865	84711.566
1986	16.132	8.281	6879.015	2005	24.335	4.486	99780.817
1987	16.587	8.255	7827.419	2006	24.882	4.234	115739.945
1988	17.814	8.276	8650.083	2007	28.840	4.535	127042.137
1989	15.768	6.902	8660.696	2008	32.918	3.261	127092.777
1990	15.836	6.086	10958.794	2009	40.518	3.508	106557.486
1991	15.720	6.103	13350.321	2010	39.680	3.225	133374.846
1992	15.877	6.352	15570.401	2011	42.371	3.008	144474.685
1993	15.325	5.336	16708.951	2012	47.028	2.857	145788.602
1994	17.687	5.577	25042.672	2013	53.757	2.901	150856.897
1995	20.803	5.692	25412.838	2014	60.324	2.882	153140.281
1996	22.018	5.417	24498.919	2015	74.037	3.112	142147.287
1997	21.994	5.047	26930.621	2016	82.048	3.306	139234.758
1998	23.670	4.889	27045.318	2017	90.619	3.452	134176.385

Source: calculated from this paper, and the original data come from 'China Statistical Yearbook'.

4.3. Unit root and JJ co-integration test

Next, we use the statistical software Eviews for the unit root test, and the co-integration test of variables and model estimation.

The ADF test is used to obtain the single integral order of the variable. The test results[6] show that regardless of whether the structure is non-nested or non-nested, all variables tested are first-order integral sequences. However, note that the test statistic value of variable ln*OPEN* is at the probability of 0.078: if the significance level is relaxed to 0.1, there will be no unit root in *lnOPEN*, that is, no random trend. However, regardless of whether the variable *lnOPEN* is a first-order integral series, there is the possibility of co-integration between variables $\ln(A_L/A_E)$, $\ln(w/q)$, and ln*OPEN*, as well as between the variables $\ln(A_K/A_E)$, $\ln(r/q)$, and ln*OPEN*.

Before the co-integration test, the lag order of the models is determined first. We select the optimal lag stage according to the five test standards provided by Eviews: LR, FPE, AIC, SC, and HQ. The results[7] show that whether the structure is non-nested or nested, the lag order of Model I is 2 and that of Model II is 4.

The lag order of the vector autoregressive (VAR) model in the co-integration test is the original VAR model minus 1. Therefore, the lag order of Model I is selected as 1, while that of Model II is 3. Regarding the selection of intercepts and trend terms in the JJ cointegration equation, most scholars go straight to Eviews default item 3; however, many economic data do not have the nature of default item 3. Option 3 requires that the long-term equilibrium value of each time series does not contain a deterministic trend. If some or all time series contain trend items, option 4 should be selected. The ADF test shows that all variables in our study have a deterministic trend (test equation contains a constant term or a time trend term). Therefore, we conduct a co-integration test according to option 4. The results of the JJ co-integration test[8] show that there is a long-term stable co-integration relationship between labour (relative to energy) augmenting technical change, and relative price of labour and international trade, as well as between capital (relative to energy) augmenting technical change, and relative price of capital and international trade, whether in nested or non-nested structures. Note that under the non-nested structure, the test shows that there are two co-integration relationships between capital (relative to energy) augmenting technical change, and relative price of capital and international trade. However, we only focus on whether there is a co-integration relationship between variables.

4.4. Estimate

Here, we estimate Models I and II under both non-nested and nested structures. Technological progress comes from the enterprise's purposeful R&D activities, or from the digestion and absorption of foreign new equipment. Both the creation and absorption processes need a certain amount of time. Therefore, the change in direction of technological progress has a delayed response to changes in price and international trade. We determine the lag period of the explanatory variables entering the model and the estimation according to the significance of the coefficients, the interpretation degree of the model, and the economic significance of the coefficients.

Table 5. Estimation results of modellin non-nested and nested structures.

Parameter	Variable	Non-nested	Nested
α_0	Constant	-58.802^{**} (24.090)	-73.951^{***}(21.738)
α_1	$\ln(OPEN)_t$	0.125(0.123)	0.131^{**}(0.061)
$(1-\sigma)/(2-\sigma)$	$\ln(w/q)_{t-5}$	0.353^{***}(0.075)	0.314^{***}(0.102)
α_2	t	0.029^{**}(0.012)	0.036^{***}(0.011)
AR(1)	$u_{1,t-1}$	1.669^{***}(0.129)	1.759^{***}(0.121)
AR(2)	$u_{1,t-2}$	-0.884^{***}(0.135)	-0.922^{***}(0.139)
R^2	——	0.992	0.995
DW	——	1.79	2.18

Note: (1) Model I corresponds to the first equation of formula (21) and formula(23). (2) In the nested structure, the parameter of $(1-\sigma)/(2-\sigma)$ refers to $(1-\sigma_{LE})/(2-\sigma_{LE})$.
Source: estimate model I by Eviews.

Because the time trend option in the co-integration equation is selected in the JJ co-integration test here, the time term is also added to the estimation. Tables 5 and 6 present the estimation results.

4.5. Analysis

First, there is a positive influence relation between the relative price of factors and relative augmenting technical change of factors, that is, the rise in the relative price of factors will promote the relative augmenting technical change of this factor, or it will make the pace of technological progress of this factor faster than that of other factors. For every 1% increase in the relative price of labour, labour (relative to energy) augmenting technical change increases by 0.353% or 0.314% (see Table 5). This can be understood as an increase of 0.353 or 0.314 percentage points in labour augmenting technical change over energy augmenting technical change when labour price increases by one percentage point over energy price. For every 1% increase in the relative price of capital, capital (relative to energy) augmenting technical change increases by 0.344% or 0.543% (see Table 6). According to Acemoglu's (2002) theory of directed technical change, this is because when the elasticity of substitution between labour and energy, and capital and energy are less than one, the increase in the relative price of factors will lead to an increase in the relative price of intermediate products. This will dominate the relative technical profit of R&D enterprises, thus determining the choice type of technological progress of enterprises. Consequently, it will bring about a change in the technological progress direction. However, this effect does not occur immediately; it has a certain lag: the change in the relative price of labour takes five years to have an impact on labour (relative to energy) augmenting technology, and the change in the relative price of capital takes two years to have an impact on capital (relative to energy) augmenting technology. Therefore, we empirically verify the price effect of the directed technical change in China.

We can further analyse bias in technical change. Since labour augmenting technical change in China grows faster than the energy augmenting technical change (see Table 2), the efficiency of labour increases faster than that of energy. However, when the elasticity of substitution between labour and energy is less than one, this trend increases the marginal productivity of energy more than labour, which will increase the relative demand for energy by enterprises. Note that technology is biased toward

Table 6. Estimation results of modelII in non-nested and nested structures.

Parameter	Variable	Non-nested	Nested
β_0	Constant	54.959(54.655)	118.921(300.045)
β_1	$ln(OPEN)_{t-7}$	−0.177**(0.076)	−0.266**(0.119)
$(1-\sigma)/(2-\sigma)$	$ln(r/q)_{t-1}$	0.344***(0.077)	0.543***(0.121)
β_2	t	0.027(0.027)	−0.059(0.149)
AR(1)	$u_{2,t-1}$	1.591***(0.182)	1.753***(0.169)
AR(2)	$u_{2,t-2}$	−0.696***(0.197)	−0.805***(0.195)
R^2	——	0.989	0.975
DW	——	2.27	2.18

Note: (1) Model II corresponds to the second equation of formula (21) and formula(23). (2) In the nested structure, the parameter of $(1-\sigma)/(2-\sigma)$ refers to $(1-\sigma_{KE})/(2-\sigma_{KE})$.
Source: estimate model II by Eviews.

energy in terms of labour and energy in China. This bias is caused by the increase in the relative price of labour, according to the above analysis. Similarly, since capital augmenting technical change in China grows slower than the energy augmenting technical change (see Table 2) and the elasticity of substitution between capital and energy is less than one, technology is biased toward capital in terms of capital and energy in China, and the decline in the relative price of capital leads to that bias; in general, technology is biased toward capital and energy because of the increase in the relative price of labour and the decrease in the relative price of capital.

Second, the elasticity coefficient of labour (relative to energy) augmenting technical change with respect to international trade is 0.125 or 0.131 (see Table 5). That is, for every 1% increase in the amount of imports and exports, labour (relative to energy) augmenting technology will increase by 0.125% or 0.131%, or that labour augmenting technology will add 0.125 or 0.131 percentage points more than energy augmenting technology. Similarly, the elasticity coefficient of capital (relative to energy) augmenting technical change with respect to international trade is −0.177 or −0.266 (see Table 6). This indicates that for every 1% increase in the amount of imports and exports, the relative capital augmenting technology will decrease by 0.177% or 0.266%, or that energy augmenting technology will increase by 0.177 or 0.266 percentage points more than capital augmenting technology. The reasons why international trade increases labour (relative to energy) augmenting technology while decreasing capital (relative to energy) augmenting technology are as follows.

On the one hand, China is a country with a large labour force. Meanwhile, the labour resources of other countries are still scarce compared with China. Therefore, labour-intensive products manufactured in China have a price advantage over labour-intensive products of the average level of the world. When the world's door opens to China, the demand for labour-intensive products in China will increase greatly, and the price will also increase accordingly. However, the opposite is true for capital-intensive products in China. Capital-intensive products are relatively scarce compared to the average level of the world. Therefore, opening to the outside world will reduce the price of capital-intensive products in China. For energy-intensive products, energy resources (especially coal resources) are more abundant than the world's average level and environmental costs are not considered in the price of energy-intensive products in China. Therefore, the price of energy-intensive products in China is low compared with the world average. Hence, opening up to the outside world will raise the price of energy-intensive products in China. According to some studies on the structure of China's export products, labour-intensive products account for the largest proportion, followed by resource-intensive products. Therefore, we think that international trade will increase the price of labour-intensive products more than the price of energy-intensive products. Overall, international trade raises the relative price of labour (to energy) and lowers the relative price of capital (to energy). This increases (decreases) the relative profit of labour (capital) augmenting technology. Therefore, enterprises are more willing to allocate research and development resources to labour augmenting technology. Meanwhile, regarding capital and energy augmenting technology, enterprises are more willing to carry out the innovation of energy augmenting technology. Thus, international trade intensifies (blocks) the pace of labour (capital) augmenting technical change.

On the other hand, under the opening up to the outside world, enterprises can introduce corresponding machines and equipment according to the direction of technological progress determined by themselves, and improve the factor augmenting technical change by learning and absorbing the new technology contained in this equipment. If a country does not engage in international trade, enterprises can only create new technologies through their own R&D efforts to save the use of certain elements. Such R&D efforts may succeed or fail, and the process may be short or long. Import activities can reduce this process. For example, if an enterprise wants to invent a labour augmenting technology, it can directly import labour augmenting technology, rather than relying on independent R&D activities with a probability of success. Thus, import activities under international trade accelerate the factor augmenting technical change of a country.

Further, we analysed the influence of international trade on factor bias. International trade makes labour augmenting technical change grow faster than energy augmenting technical change, which in turn grows faster than capital augmenting technical change. Therefore, similar to the previous analysis, when the elasticity of substitution between factors is less than one, there is technology bias to energy (capital) for factor labour (capital) and energy. Notably, international trade has strengthened the bias of technology toward capital and energy.

5. Conclusions

By referring to Acemoglu's (2002) endogenous model, we deduce the theoretical model between the direction of technological progress, and the relative prices of factors and international trade. Then, we conduct an empirical test on the theoretical model with mature measurement methods, such as the unit root test and co-integration analysis. The results provide reference on the endogeneity of directed technical change in China. There is a long-term stable co-integration relationship between the direction of technical change, and the relative prices of factors and international trade. For every 1% increase in the relative price of labour, the labour (relative to energy) augmenting technical change will increase by 0.353% (or 0.314%). For every 1% increase in the relative price of capital, capital (relative to energy), augmenting technical change will increase by 0.344% (or 0.543%). Lastly, for every 1% increase in the amount of imports and exports, the labour (relative to energy) augmenting technical change will increase by 0.125% (or 0.131%), while the capital (relative to energy) augmenting technical change will decrease by 0.177% (or 0.266%).

Thus, we find that the relative factor prices and international trade influence factor augmenting technical change in China. On the one hand, factor augmenting technical change is driven by price. Acemoglu (2002) pointed out that this change is determined by the price effect and the market scale effect of the factor. However, our empirical research shows that the price effect plays a decisive role in factor augmenting technical change in China. This is also consistent with Acemoglu's (2002) theoretical analysis, who pointed out that when the factor substitution elasticity is less than 1, the price effect dominates and the technical change is directed towards the factors with higher prices. On the other hand, international trade promotes labour augmenting technical change but blocks capital augmenting technical change.

From these findings, we can explain the phenomenon that labour (energy) augmenting technical change grows faster than energy (capital) augmenting technical change in China. The rise in the relative price of labour and the decline in the relative price of capital in recent years have made labour augmenting technical change grow faster than energy augmenting technical change, which in turn grows faster than capital augmenting technical change in China. The accelerated pace of China's opening up in recent years has exacerbated this phenomenon. Furthermore, we can explain why China's technological progress in recent years is biased towards energy and capital, that is, why the relative demand for energy and capital is increasing. The energy augmenting technical change grows faster than the capital augmenting technical change. However, when the factor substitution elasticity is less than one, this increases the demand for capital. Therefore, it can be said that the growth of capital relative to energy demand is caused by a decline in its relative price and international trade. The same analysis applies to labour and energy.

Our findings can also provide reference values for relevant policymakers. We show that the factor augmenting technical change in China is determined by the price of the factor itself rather than its scale. Therefore, if policymakers want to improve the technical change of a factor, they should focus on its price rather than its size. For example, if the government wants to improve energy augmenting technical change or improve energy efficiency, it should raise the price of energy relative to other factors. However, implementing this policy will increase the demand for factors with relatively low prices. This is not only caused by the substitution effect among factors, but also by the biased technical effect. That is, when the government increases the price of a certain factor, on the one hand, it will increase the technical change or efficiency of the factor; on the other hand, it will bring a large increase in the demand for other factors. This large increase means that the increase in demand is brought about by the technical effect besides the substitution effect.

Notes

1. The data are calculated from our paper, the same as below.
2. Biased technical change is a concept often involved in the research of directed change, which will be explained below.

3. The derivation process can be referred to Acemoglu (2002), which will not be repeated in this paper.
4. Liu, H., & Lei, Q. (2016). Measurement of the Rate of Energy-augmenting Technical Change and Substitution Elasticity of Factors in China. *Statistical Research*, 33(002), 18–25.
5. The indicators of capital stock, total labour, energy consumption in the production field and share of various factors can be referred to Liu and Lei (2016). The original data are from 'China Statistical Yearbook' and 'China Energy Statistical Yearbook'.
6. In the non-nested structure, the t-values of the horizontal and the difference values of variable are −2.277 and −2.432, respectively, and those of variable are 2.698 and −4.928, respectively. In the nested structure, the values are −2.153, −2.098, −1.156, and −3.981, respectively. The t-values of the horizontal value of variable , , and are 1.772, −3.053, and −2.737, respectively, and the t-values of the difference value are −4.152, −7.160, and −4.471, respectively.
7. In the non-nested structure, the second-order lag test values of Model I of the five test methods are 31.006, 0, −7.566, −6.614, and −7.246, respectively. The four-order lag test values of Model II of LR, FPE, AIC, and HQ are 20, 0, −7.846, and −7.251, respectively. In the nested structure, the second-order lag test values of Model I of LR, FPE, AIC, and HQ are 21.65, 0, −7.411, and −7.09, respectively. The four-order lag test values of Model II of LR, FPE, AIC, and HQ are 22.953, 0, −6.97, and −6.375, respectively.
8. In the non-nested structure, the statistical value of Model I without the co-integration assumption is 45.64, Model II without the co-integration assumption is 78.81, and the statistical value of at most one co-integration assumption is 25.959. In the nested structure, the statistical value of Model I without the co-integration assumption is 27.483, and that of Model II without the co-integration assumption is 76.893.

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