Intensity of environmental regulation and environmentally biased technology in the employment market

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Intensity of Environmental Regulation and Environmentally Biased Technology in the Employment Market

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Abstract: Due to the lack of an appropriate method to measure biased technological progress, the theory of how environmental regulations affect employment demand through biased technological progress in Porter's hypothesis has not been effectively verified. To fill this gap, this study extends Acemoglu's (2012) biased technological progress theory, and reasonably measures environmentally biased technological progress using data envelopment analysis. The effect of environmental regulation on labor supply and demand is analyzed through environmentally biased technological progress. The results show that progress in environmentally biased technology can promote the supply and demand of regional labor force. However, if the development of energy saving and emission reduction technology is inconsistent with economic growth, then progress in environmentally biased technology has a negative impact on the demand for regional labor. Environmental regulation has a significant negative impact on labor demand, but its self-adjusting mechanism reignites labor demand.

Keywords: environmental regulation; environmentally biased technology; employment; non-radial slack based measurement

1. Introduction

Environmental regulation is an important way to control environmental problems in the world [1]. The Chinese government unveiled a series of environmental policies to develop a recycling, resource-saving, and environmentally friendly society. However, these policies have implementation costs for heavy-polluting companies,

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which may result in significant unemployment and worsen China's wealth gap. If these enterprises cannot meet emission requirements after paying implementation costs, they may go bankrupt, which would further increase unemployment. According to the *China Statistical Abstract*, since 2002, China's total unemployed population exceeded 7.7 million. It is particularly important for China, as a developing country with a large population, to manage its sustainable economic development by coordinating and handling the contradiction between environmental regulation and labor supply and demand.

However, there is still debate whether environmental regulation can affect employment. On the one hand, Sun et al. [2] show that environmental regulation leads to the movement of labor from big cities to small ones, which improves the employment rate of the first and third industries of small cities. Porter's hypothesis highlights that appropriate environmental regulations may improve international competitiveness, stimulate technological progress, and improve resource allocation efficiency [3][4]. Thus, there would be an innovative "compensatory effect" and employment would also increase. On the other hand, some studies show that strict environmental regulation adversely affects the employment level and wage level of the labor force by reducing productivity and increasing compliance costs [5]. Greenstone [6] finds that the implementation of the revised Clean Air Act would make substandard counties lose about 590 thousand job opportunities. Some theoretical research shows that environmental regulation can affect the demand for employment through improving innovation and technological progress [7][8][9]. The early economic analysis of environmental regulation is carried out mainly under the condition of exogenous technology, ignoring the endogenous response of technological progress to environmental policy, which will exaggerate the cost of environmental regulation. In recent years, the increasingly mature theory of biased technological progress provided a new idea for research on environmental regulation and regional employment effect.

However, due to the lack of a proper biased method of measuring technological progress, no study empirically analyzes the mechanism linking environmental regulation and employment through biased technology. Therefore, the present study attempts to establish a universal measurement method of environmentally biased technological progress, and studies environmental regulation, environmentally biased technological progress, and regional employment effect based on empirical data in

China.

Our main contributions are as follows. First, scholars provide methods based on total factor productivity (TFP) but they cannot reflect the real meaning of environmentally biased technology. Using the data envelopment analysis (DEA) method, we measure technology bias and divide it into two types—production and environmental bias—which elucidates the conditions of changes in each decision-making unit (DMU) during the evaluation period. Second, the mechanism analysis contributes to an extensive theoretical and empirical debate on the relationship between regulation and employment through environmentally biased technology as a mediating variable. Furthermore, prior studies mostly use data of developed countries for analyses, while our research provides a theoretical basis and practical support for developing countries to accurately formulate environmental regulation policies and measure the progress level of green technology.

The rest of the paper is organized as follows. The second section presents the literature review. The third section outlines the DEA model of environmentally biased technology. The fourth section provides the empirical analysis. The fifth section concludes and provides policy suggestions.

2. Literature Review

Can environmental regulation affect employment? Some studies conclude that it can [10]. The implementation of environmental regulation inevitably impacts many industries, which causes fluctuations in employment demand. Expensive equipment increases both production and operation costs, thereby affecting manufacturing employment. On the contrary, environmental regulation reduces production scale, which leads enterprises to reconfigure their resources. The introduction of advanced equipment can directly improve the efficiency of enterprises, replacing labor and reducing employment [7].

Nevertheless, if appropriate environmental regulations could stimulate technological changes in enterprises and improve their resource allocation efficiencies [11] to compensate for increased pollution costs, they might improve enterprises' international competitiveness, as well as affect demand for employment [12]. Moreover, the upgrading of environmental standards could increase the employment of unskilled workers, as environmental regulations would influence production efficiency [13].

Another group of studies concludes that there is a non-significant relationship between the impact of environmental regulations on employment [14]. Goodstein et al. [15] showed that environmental regulations increase the demand for employment of environmental products manufacturers (EPMs) in a very limited way. Shadbegian and Gray [16] prove this thesis, finding that EPMs had nearly no differences from their counterpart enterprises.

Consequently, the influence of environmental regulation and employment remains unclear [17]. Hong and Guo [18] found that environmental regulation is often biased and ineffective in China, and cannot be ignored in reality [19][20]. China compromised on the two targets of environment and economy, and finds it difficult to protect the environment while maintaining economic growth [21][22]. Thus, the Chinese government preferred to ignore environmental protection, as enterprises can create many job opportunities. Currently, owing to domestic and international pressure, China is paying more attention to both targets. Hijzen et al. [23] proved that technological change resulting from environmental regulation increases demand for labor. Song and Wang [24] showed that only environmentally biased technology could solve the two-target paradox. Therefore, we consider that environmental regulations have stimulative effects on labor force employment. However, Acemoglu [25] considered that fiscally minded biased technological change would reduce employment of low-skilled labor force, finally resulting in unbalanced wages and income gaps among different countries [26].

Biased technological change can explain employment problems well, the concept of which derives from Solow's production function model. Based on the growth accounting method, Kennedy and Thirlwall [27] measured technological progress by calculating residual error of the value added of output and factor input. The shortcoming of this parameter estimation method is that it needs to assume concrete forms of production functions. If the production condition changes, the production function can change significantly. Thousands of production functions exist; thus, it is difficult to set up the most suitable one to fit the production condition. If we set the production function incorrectly, then the calculated rate of technological progress would be incorrect.

Some studies used non-parametric estimation, like the DEA method, which has a *camera obscura*-style production function, and must therefore consider only the camera obscura inputs and outputs, not the type of production function and parameters. Some studies combine DEA with TFP to measure input and output by constructing a DEA–Malmquist evaluation model to calculate the technological level of DMUs. Similarly, Caves et al. [28] constructed the DEA–Malmquist evaluation method by combining DEA and TFP and categorized technological progress into two types: frontier technological progress and technological progress relative to a frontier. Considering input–output conditions at different time periods and technology levels, efficiencies corresponding to input and output in the base period and those in the end period are taken as scale efficiencies. Similarly, under the conditions of fixed input and output, efficiency values calculated while accounting for changes in the production frontier are taken as technological efficiencies. Fukuyama and Weber [29] further divided DEA–Malmquist indexes based on knowledge progress, scale economy, and resource allocation, among other aspects.

According to the new classical growth theory, only technological progress can lead the sustainable growth of per capita output, and the substitution elasticity of capital and labor is assumed to be 1. In this case, technological progress is neutral. However, in many cases, technological progress is biased to the evolution of a certain factor of production rather than neutral. Acemoglu [30] proposed the concept of biased technological progress, comprising labor- and capital-enhanced technological progress. The former implies that technological progress makes the isoquant curve move outwardly in the direction horizontal to the axis denoting capital—and thus, labor can be combined with additional capital for production—while the latter means that technological progress makes the isoquant curve move outwardly in the direction horizontal to the labor axis. Based on Acemoglu's [31] definition, biased technological progress that results from adding varying levels of technological progress to capital and labor in Solow's production function is the quotient for the capital–labor marginal revenue ratio and technological progress ratio. Specifically, if the quotient is greater than 0, technological progress is more capital oriented; otherwise, it is more labor oriented.

Biased technology, as in Acemoglu's [30] proposition, aroused increasing attention from scholars, as it can identify many important problems, such as labor employment structure, income gap among countries, and change in environmental technology [32][24][33][34]. Although Acemoglu [31] provided a theoretical contribution to biased technology, no study presented a proper method to measure it. Chambers et al. [35] proposed the Luenberger productivity index with additive structure based on the DEA model. In addition, Chung et al. [36] set up the directional distance function (DDF), which considers both the increase in expected output and the decrease in unexpected output and the Malmquist-Luenberger (ML) Index. Miao et al. [37] employ the slack-based measure method and an extended Luenberger productivity indicator to estimate and decompose atmospheric environmental performance [38]. However, we require price information and must set the production functions while calculating the Luenberger productivity index and directional distance function, which limits the application range of this method. Furthermore, the sequential ML productivity index leads to frequent technical regression and increases the measurement error when measuring environmental performance. Moreover, biased technology differs from production factor-oriented change, because the former requires labor and capital, which have different levels of technological progress [39], while the latter can calculate only the same technological progress of productive factors.

3. Models

Enterprises undergo technological change through profit and cost. If environmental regulation is a cost, then it is also a reason for environmentally biased technological progress. However, environmentally biased technological progress inevitably squeezes production-biased technological change and further affects production profits. How does this situation influence local labor demand? Along with the improvement of people's living standards, the requirement for labor to ensure environmental quality is increasingly strict. In this case, how would environmentally biased technological progress influence the employment intentions of laborers, and would it result in workers "voting with their feet?" Can the mode of biased technological change be optimized through rational allocation of capital and labor force? To answer these questions, we introduced biased technological change as a variable into corporate profit functions and laborer utility functions to study the internal mechanism effects of biased technological change on regional employment effects.

3.1 Regional labor demand effect of environmentally biased technological change

We assumed that the output of an enterprise is a function of capital, labor force, and environmental elements, which can be expressed as

$$Q = f(A_1 K, A_2 L, A_3 E) \tag{1}$$

In formula (1), Q refers to the output of the enterprise; K, L, and E are the enterprise's capital, labor force, and environmental elements, respectively; A_1, A_2, and A_3 refer to capital-biased technological change, labor-biased technological change, and environmentally biased technological change, respectively. Based on traditional production theories, element inputs satisfy concave rules, that is, $f_K > 0$, $f_{KK} < 0$, $f_L > 0$, and $f_{LL} < 0$. Because marginal output of the capital stock to labor is positive, $f_{KL} > 0$. Similarly, we considered that moderate environmental regulations and policies trigger environmentally biased technological change so that the marginal output of capital and labor force increase, the product quality improves, and the enterprise competitiveness is enhanced. Thus, we obtain $f_{KA_3} > 0$ and $f_{LA_3} > 0$.

We constructed the following cost function to show the output of the enterprise:

$$C = c(A_1K, A_2L, A_3E) \tag{2}$$

We assumed that the element input cost is linear. The increase in environmentally biased technological change squeezes the partial capital and labor force originally allocated to production, so that unit production cost increases, that is, $c_{KA_3} > 0$ and $c_{LA_3} > 0$. Considering both (1) and (2), we obtain the profit function of the enterprise as

$$\Pi = f(A_1K, A_2L, A_3E) - c(A_1K, A_2L, A_3E) \tag{3}$$

Next, we focused on observing the variations of environmentally biased technological change. Because the increase in environmentally biased technological change is under the exogenous influences of environmental regulations, enterprises adjust inputs of capital, labor force, and environmental elements to maximize profit. Through a complete differential for labor input and environmentally biased technological change, we obtain

$$\frac{\partial L}{\partial A_3} = \frac{f_{LK}f_{KA_3} - f_{KK}f_{LA_3}}{f_{LL}f_{KK} - (f_{LK})^2} - \frac{f_{LK}c_{KA_3} - f_{KK}c_{LA_3}}{f_{LL}f_{KK} - (f_{LK})^2} = A - B \tag{4}$$

For simplicity, we used A and B in (4). A refers to the marginal output of environmentally biased technological change to capital stock and labor force input of enterprise; B refers to the marginal cost of the influences of environmentally biased technological change on capital stock and the labor force input of the enterprise. Both A and B affect the labor force demand. If the profit function satisfies the assumption of decreasing returns to scale, then $f_{LL}f_{KK} - (f_{LK})^2 > 0$, that is, $A > 0$. In this case, an increase in investments in environmentally biased technological change enhances enterprise competitiveness and increases demand for labor force; in addition, $B > 0$ indicates that biased technological change increases enterprise production costs and reduces demand for labor force. Hence, the effects of environmentally biased technological change on the labor force demand of enterprises depend on the respective strength of A and B. If positive effects that stimulate labor force demands are stronger than the negative effects that suppress labor force demand, then biased technological change is favorable to employment in local enterprises. Next we observed the influences of biased technological change on employment from an open angle view. Foreign direct investment (FDI), as capital input, can initially stimulate capital stock in the host country, thereby increasing capital reserves and enhancing employment intentions. Then, FDI also affects biased technological change in the host country. If FDI is used more for production, then because of technological spillover effects, there is production-biased technological change in the host country; if FDI is used more for energy saving and emission reduction, then environmentally biased technological change improves in the host country. Finally, we obtained the labor employment demand function as follows:

$$L_d = l_d(w, A_3, K, FDI) \qquad (5)$$

In (5), w refers to the regional real wage level.

3.2 Regional labor supply effect of environmentally biased technological change

We assumed that laborers are entirely rational and always pursue the maximization of labor utility. However, in reality, utility is decided by the real wage level and the working time of a single laborer. We set up the following equation:

$$U = g(w, L) \qquad (6)$$

As for a single laborer, the longer the working time, the higher the real wages. On the contrary, because of diminishing marginal utility, we know that $g_L > 0$ and $g_{LL} < 0$. Working time and environmental quality have negative effects on laborers. If the working time is too long, laborers feel tired and such negative effects become increasingly significant along with an increase in working time. The harm to laborers from environmental elements is also a key factor affecting their working conditions. In this case, there is a negative function of labor supply:

$$V = \varphi(L, A_3)$$

If environmentally biased technological change increases, negative labor utility decreases. Then, we know that if $\varphi_L > 0, \varphi_{LL} > 0$; and if $\varphi_{A_3} < 0, \varphi_{LA_3} < 0$.

Laborers attempt to maximize their gross effects through the adjustment of labor force supply, and the first-order condition for the maximization of the gross effect is:

$$Z_L = g_L - \varphi_L = 0 \tag{7}$$

Extending the complete differential to formula (6), we could obtain the marginal effect of environmentally biased technological change on the labor force supply as

$$\frac{\partial L}{\partial A_3} = \frac{\varphi_{LA_3}}{g_{LL} - \varphi_{LL}} > 0 \tag{8}$$

Formula (7) indicates that an improvement of environmentally biased technological change can improve regional environmental quality to reduce laborers' negative utility and increase the regional labor force supply.

Similarly, although FDI seeking environmental elements could make the regional economy grow in a short period, the environmental pollution resulting from this economic growth would reduce laborers' utility so as to reduce employment. Based on this, we obtained the labor force supply function as follows:

$$L_s = l_s(w, A_3, welf, FDI) \tag{9}$$

In formula (9), *welf* refers to regional welfare level.

4. Environmentally Biased Technology Scheme

We take Werf's [40] definition of neutral technological change as an example to explain our opinions about environmentally biased technological progress in this study. The definitions in other studies are similar to Werf's, that is, a constant elasticity of substitution production function in the form of (*KE*) *L*, as follows:

$$Q = \left[\alpha(A_L L)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)Z^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{10}$$

$$Z = \left[\beta(A_K K)^{\frac{\sigma-1}{\sigma}} + (1-\beta)(A_E E)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{11}$$

In the formula, *Q* refers to final production; *K*, *L*, and *E* refer to capital, labor, and energy input, respectively; Z refers to a capital–energy composite product; α and β represent the share parameter; and A_L, A_K, and A_E refer to labor, capital, and energy-biased technological change, respectively. Based on this, we innovatively add the emission-reducing biased technological change and obtain the following expression using the Solow model:

$$(Y, A_B B) = f(A_K K, A_L L, A_E E)$$

In the formula, B refers to undesirable output and A_B refers to emission-reducing biased technological change. When $A_L = A_K = A_E = A_B$, the technological change in the production function is neutral technological change.

The model for measuring the environmentally biased technological progress based on DEA is constructed according to above definitions. Assume that the input is X (comprised of capital K and labor L, for simplicity expressed as X), energy consumption is E, undesirable output is B, and desirable output is Y to form a multi-dimensional input and output space. For simplicity, we show the space of input X, energy E, and undesirable output B, as shown in Figure 1. Assume that there are eight DMUs, with red points *a* and *a*' and black points all representing DMUs. For simplicity, blue points *C* and *C*', which are Euclidean centers of spatial distribution of DMUs, represent DMUs in period *s* and next period *t*, respectively. Inputs and outputs of all eight DMUs change in these two periods, which causes the production frontier (not shown in the figure) and the Euclidean centers to change as well.

Insert Figure 1 about here

We draw vertical lines from the Euclidean center in period *s* to axis *X*, axis *B*, and axis *E*. The lengths of the vertical lines are *a*, *b*, and *c*, respectively (not shown in the figure). The lengths of the joints of the three vertical lines and the production frontier to the coordinate axis are *d*, *e*, and *f*, respectively (also not shown in the figure). Based on the slack-based measurement (SBM) method, we obtain the efficiency of the input in period *s* as $\rho^s{}_X = d / a$; the efficiency of the undesirable output as $\rho^s{}_B = e / b$; and the efficiency of energy as $\rho^s{}_E = f / c$. Similarly, we obtain the efficiency of the input in period *t* as $\rho^t_X = d' / a'$; the efficiency of the undesirable output as $\rho^t_B = e' / b'$; and the efficiency of energy as $\rho^t{}_E = f' / c'$. As we define technological change as $TP = \rho^t / \rho$, we can obtain the following Theorem 1.

Theorem: If input and output expand in the same proportion within a certain period, there will be neutral technological change, and the following certainly holds:,

$$\rho^t{}_X / \rho^s{}_X = \rho^t{}_B / \rho^s{}_B = \rho^t{}_E / \rho^s{}_E \qquad (12)$$

Proof: If the three ratios in (12) are not all equal, we assume that $\rho^t{}_X / \rho^s{}_X > \rho^t{}_B / \rho^s{}_B$, and then, an increase in efficiency of the input in this period exceeds that of the efficiency of the undesirable output. In other words, input-biased technological change is greater than emission-reducing technological change. Similarly, when $\rho^t{}_X / \rho^s{}_X < \rho^t{}_B / \rho^s{}_B$, an increase in the efficiency of the input in this period is smaller than that of the efficiency of the undesirable output. Both conditions are inconsistent with the assumption of neutral technological change. Then, Theorem 1 is proved.

Theorem 1 also yields the following inference.

Inference: The straight line that connects the two Euclidean centers in two periods certainly passes through the original point, that is, point O is on the same line as the two dark blue points.

From Figure 1, we observe that the position of DMU *a* moves to *X* direction, with angle θ between these two periods, which means that DMU *a* has less energy and emissions under the same production. At this point, DMU *a* has environmentally biased technological progress.

However, it is very difficult to evaluate environmentally biased technological progress empirically, as there is still no suitable measurement method. Based on the definition of Acemoglu (2012), with the effects of biased technological change, the position of DMU *a* changes. We similarly adopt the SBM method to simulate the changing process of DMU *a* and obtain the necessary indexes to evaluate biased technological change. For simplicity, we observe only the *X–B* plane in Figure 1 to express it as a three-dimensional coordinate. The specific thought process is depicted in Figure 2 and described below.

Insert Figure 2 about here

In Figure 2, *X* refers to input; *B* refers to undesirable output; and energy axis *E* passes through point *O* and is vertical to the principal plane. In period *s*, the input of DMU *a* is *x*; and the undesirable output is *b*. In period *t*, the input of *a*' is *x*'; undesirable output is *b*'; and the production envelope surface is *t*. We find that the position of DMU *a* defects in the direction of *X*. If both inputs and outputs increase in period t from period s under the same undesirable output, or if output increases while undesirable output reduces under the same condition of input, the position of DMU a moves in the direction of X. This condition is called emission-reducing biased technological change.

If keeping the original production technology unchanged (i.e., period s does not change), the efficiency of production technology of a in periods s and t is $\rho_x^s(x_s, y_s)$ and $\rho_x^s(x_T, y_T)$, respectively. If period t is invariant, the efficiency of production technology of a in periods s and t is $\rho_x^T(x_s, y_s)$ and $\rho_x^T(x_T, y_T)$, respectively. Considering that the changes of the production frontier mainly result from changes of technology and production efficiencies, by eliminating the factors that influence production efficiency, we can obtain the change in efficiency of pure production technology.

Here, we obtain the rate of change in production technology efficiency as

$$D_x = \frac{\rho_x^s(x_s, y_s) / \rho_x^s(x_T, y_T)}{\rho_x^T(x_s, y_s) / \rho_x^T(x_T, y_T)} \tag{13}$$

Similarly, the rate of change in emission-reducing technology efficiency is

$$D_b = \frac{\rho_b^s(x_s, y_s) / \rho_b^s(x_T, y_T)}{\rho_b^T(x_s, y_s) / \rho_b^T(x_T, y_T)} \tag{14}$$

Thus, the Malmquist index of emission-reducing biased technology progress (*ErBP*) can be expressed as

$$ErBP = \sqrt{D_B / D_X} = \sqrt{\frac{\rho_B^s(x_s, y_s) / \rho_B^s(x_T, y_T)}{\rho_B^T(x_s, y_s) / \rho_B^T(x_T, y_T)} \Bigg/ \frac{\rho_X^s(x_s, y_s) / \rho_X^s(x_T, y_T)}{\rho_X^T(x_s, y_s) / \rho_X^T(x_T, y_T)}} \tag{15}$$

If $ErBP > 1$, there is emission-reducing technological change; the higher the ErBP, the more significant the emission-reducing technological change.

Similarly, the Malmquist index of energy-saving biased technological progress (*EsBP*) is

$$EsBP = \sqrt{D_E / D_X} = \sqrt{\frac{\rho_E^s(x_s, y_s) / \rho_E^s(x_T, y_T)}{\rho_E^T(x_s, y_s) / \rho_E^T(x_T, y_T)} \Bigg/ \frac{\rho_X^s(x_s, y_s) / \rho_X^s(x_T, y_T)}{\rho_X^T(x_s, y_s) / \rho_X^T(x_T, y_T)}} \tag{16}$$

If $EsBP > 1$, there is energy-saving biased technological change; the higher the EsBP, the more significant the energy-saving technological change.

Because improvement of environmental quality requires a combined function of energy-saving and emission reduction, we propose the comprehensive environmentally biased technological progress index (*EBP*) as follows:

$$EBP = ErBP \times EsBP = \sqrt{\left(D_B \times D_E\right) / D_X^2} \tag{17}$$

From this, we obtain Definition 1 as follows.

Definition: If DMU *a* in period *t* is more inclined to the direction of input than in period *s*, then environmentally biased technological progress exists for DMU *a*. If DMU *a* in period *t* is more inclined to the direction of environment than in period *s*, then production-biased technological change exists for DMU *a*.

5. Empirical Analysis

Taking Acemoglu et al.'s [41] definition of biased technology as a reference, we put the biased technological progress variables into the profit function of enterprises and the utility function of workers. In this way, we can study the internal mechanism of biased technological progress affecting the regional employment effect (see the Appendix for details). As per our models, environmentally biased technological progress can increase the welfare of labor and raise enterprises' production costs, leading to reduced employment. Thus, the regression coefficient of the index remains uncertain. We set the following measurement equation for labor force employment:

$$\ln L_{it} = \alpha_0 + \alpha_1 A_{3it} + \alpha_2 \ln w_{it} + \alpha_3 \ln K_{it} + \alpha_4 \ln welf_{it} + \alpha_5 \ln FDI_{it} + \varepsilon_{it} \tag{18}$$

where L is the quantity of employment of labor force; A_3 is environmentally biased technological progress; w is wage levels; K is capital; *welf* is regional welfare level; *FDI* is foreign direct investment; i is the region; and t is time. These indexes are explained in the following text. The main data sources in this study are the *Chinese Statistical Yearbook*, *Chinese Statistical Yearbook on Environment*, and *Chinese Statistical Yearbook on Industries*. At the 2009 United Nations Climate Change Conference in Copenhagen, a series of environmental conventions were signed, requiring both developed and developing countries to make visible efforts toward improving environmental quality [15]. We select data for 2002–2017 to allow sufficient time for the policy change.

5.1 Variables and data

Quantity of employment: Industries are the main source of environmental pollution. Hence, we take the year-end quantity of employment in secondary industries as the variable of labor force employment, and the average wage of secondary industries in each region as the nominal wage. Because China's economic situations changed significantly after it became a member of the World Trade

Organization in 2001, we adjusted the price index in 2001, and finally obtained the real wage levels of secondary industries in each region. Some scholars consider that when wage levels are low, the quantity of employment increases along with wage growth. However, when wages reach a turning point, labor chooses voluntary unemployment to ensure the maximization of wages and leisure utility, in which case, employment declines as wages increase. As China is a developing country, we do not know whether it reached the turning point. Hence, we cannot judge the regression coefficient of wages. The data are from each year's *Chinese Statistical Yearbook* and *Chinese Statistical Yearbook on Environment*.

Environmental regulations: The real GDP per capita, the number of administrative penalty cases, and pollution control investment can be regarded as proxy variables of environmental regulation intensity [25]. However, we consider that these indexes can measure only one aspect of environmental regulations and the test results show that the three indexes cannot substitute the effects of the environmental supervision degree index. According to the data, the reinforcement of environmental supervision degree decreases real GDP per capita, increases the number of cases of administrative penalties, and raises investment in pollution treatment. Therefore, we transform the measurement of environmental regulations to a linear programming problem of supervision degrees to evaluate supervision degrees and the effects through supervision efficiency. We obtain the programming equation of supervision degree as

$$\begin{aligned} & \max \rho = 1 - \left(1 - \frac{s_i^-}{inv_{i0}}\right) \Big/ \left(1 + \frac{s_r^+}{gdp_{r0}} + \frac{s_r^+}{n_{r0}}\right) \\ & s.t. \sum_{j=1}^{n} \lambda_j inv_j + s_i^- = inv_0 \\ & \sum_{j=1}^{n} \lambda_j gdp_j - s_r^+ = gdp_0 \\ & \sum_{j=1}^{n} \lambda_j n_j - s_r^+ = n_0 \\ & \lambda \geq 0, \ s_i^-, s_r^+ \geq 0 \end{aligned} \tag{19}$$

where *inv* is the vector of pollution treatment investment; *gdp* is the vector of GNP per capita; n is the vector of case numbers of administrative penalties; s_i^-, s_r^+ are non-radial slack variables; and ρ is the environmental supervision degree. The higher ρ is, the higher is the environmental supervision degree. The data of indexes are from the *Chinese Statistical Yearbook on Environment*. In pollution-intensive industries, the higher is the environmental supervision degree, the more labors are employed by enterprises to reduce pollution emission levels, and the higher is the quantity of employment. Because employment in China is influenced by many factors, the estimation coefficient of environmental supervision degrees cannot be decided.

***Control variables*:** The capital stock index is expressed by the fixed capital sum of state-owned enterprises, private enterprises, and three kinds of foreign investment enterprises in each region. Because the increase in capital stock needs more employment, it is initially estimated that the estimation coefficient of the capital stock index is positive. Regional welfare level, *welf,* is expressed by the number of participants in unemployment insurance. The participation of many people in unemployment insurance indicates that enterprises have enough capital to provide living guarantees to labors. Hence, we initially judge that the coefficient of this index is the DMU position. The *FDI* index is expressed by aggregate investment of foreign enterprises in each year. FDI, on one hand, can increase regional capital stock to stimulate employment; on the other hand, it results in more orders for local enterprises and increased demand for products. However, foreign investment has spillover effects that can influence technology. If production-biased technology is stimulated, then less labor would result in more outputs, and the quantity of employment would reduce. If environmentally biased technological progress is stimulated, then a part of the labor force could be saved to reduce the quantity of employment. Thus, the coefficient of this index cannot be decided for the time being. Data for the variables are from the *Chinese Statistical Yearbook on Industries* of each year. The statistical descriptions of the variables are shown in Table 1.

Insert Table 1 about here

5.2 Empirical test

According to model (18), we verify the impact of environmental regulation and biased technological progress on labor employment. We consider that environmental regulation may affect biased technology and that FDI may have bi-directional causal relationships with biased technology. We do not use the general estimation method for our tests, as they would make model (18) seriously endogenous and result in non-uniform estimation coefficients. For example, spillover effects of FDI would increase biased technology while increasing regional technology would attract foreign investment, so that technology in the region would further improve. If there were such a positive causal effect, then negative influences of the FDI on biased technology would be underestimated using general regression methods. However, it is quite difficult to select the proper instrumental variables to eliminate endogeneity. Hence, we use the differential generalized method of moments (GMM) method. The results are shown in Table 2.

Insert Table 2 about here

In this study, we use differential GMM and systematic GMM methods to estimate equation (18). From Table 2, we can see that the item lagging one period behind the quantity of employment was positive and passed the test under at the 1% significance level, indicating that the quantity of employment has a trend of self-recovery. Though labor force employment at the current phase may decrease under the influence of some factors, it would still return to a proper level at the next period. The effects of environmentally biased technological change are positive and pass the test at the 10% significance level, meaning that although enterprises had to consume certain production factors to stimulate the development of energy saving and emission reduction technology, the improvement in such technology would enhance enterprise competitiveness, and the enterprise would make up for its added inputs by the reduced cost of environmental regulations.

In the long run, enterprises should pay more attention to improving environmental technology rather than focusing only on short-term benefits such as the increase in output. Judging from the estimation coefficient of environmental regulations, under open conditions, the environmental regulations at the current period affect employment negatively, but the estimation coefficient of environmental regulations that lagged one period behind was positive. The coefficient from the use of the instrument variable method passed the test at the 1% significance level, indicating that enterprises would adjust the quantity of the labor force to relieve the negative influence of environmental regulations on production at the current period. However, along with the improvement in technological levels and labor productivity, enterprises would be able to adapt gradually to the influence of environmental regulations and take relevant countermeasures, so the quantity of employment would rise again. The regression coefficient of wages is positive, which indicates that the increase in wages would stimulate an increase in the quantity of employment. However, it also indicates that wages in China are still at a relatively low level and could not go beyond the turning point. The influence of FDI on employment is negative, which indicates that foreign investments did not stimulate employment, though it did provide capital to domestic enterprises for production.

4.3 Verification and robustness tests

To ensure that the conclusions are stable and convincing, we divide China into three regions: eastern, central, and western. The level of economic development, environmental regulation, and technology are different in these three regions. In this subsection, we undertake further analysis.

According to the *Statistical Bulletin on the Development of Human Resources and Social Security 2018*, there were 158.08 million migrant workers in eastern China in 2018, a decrease of 1.85 million from the previous year. The central and western regions actively accepted the transfer of domestic and foreign industries, so that the labor force that previously migrated to the eastern provinces returned to the central and western regions, aggravating the contradiction between environmental concerns and employment in the eastern region. Therefore, we select the eastern region as our key point of analysis. We also divide the employment effect into two kinds—labor demand and labor supply effects—to enhance the stability of the estimation results.

Here, we introduce two new variables. One is regional industrial structure, which can explain the change in labor demand; it is the ratio between added value of secondary industries and added value of GDP. The second variable is regional education degree. The higher its level, the higher is the quality of labor, and the higher the possibility that this labor is skilled. As per the conclusions of Hijzen et al. [23], technology increases demand for skilled labor. Educational degree is an index of skilled labor supply measured by the number of college students per 10000 people.

Table 3 presents the estimation results.

Insert Table 3 about here

As Table 3 shows, environmental regulation in eastern China has a significant negative impact on labor demand, and the impact is more significant than the national average level is. This may be due to the high degree of skills concentration in the eastern region, where enterprises are more inclined to reduce costs by increasing the layoff rate in the short term to mitigate the impact of environmental regulations. Biased technology in the eastern region has positive effects on both labor supply and labor demand. This may be because the economic level and living standard in the eastern region are relatively high.

Next, we focus on the effects of the structure of secondary industries in the eastern region on educational degrees. First, we carry out a cross-term operation on industrial structure with biased technology and FDI indexes to reveal the effects of environmentally biased technological progress and FDI on labor demand under changing conditions of industry structure. From the estimation coefficients, we know that environmentally biased technology has negative effects on labor demand, and we surmise that this index significantly stimulates both labor supply and demand in the eastern region. Combining these results, we find that if the added inputs are used only to improve environmental and pollution treatment levels under current industrial production conditions, there is no benefit to labor employment demand. The employment of labor can only improve when the input of environmental treatment and input for increasing output are properly proportional to economic growth. The estimation coefficient of the cross-term of industrial structure and FDI is positive and passes the 1% significance test, indicating that secondary industries and FDI mutually promote one another, while better industrial structure absorbs FDI to stimulate greater efficiency of labor employment demand.

The estimation coefficient of educational levels in the equation are negative, which indicates that the higher the proportion of college students is, the lower the employment supply level would be. This may be because China is at the low-end of the global production chain, and the primary demand is for low-skilled labor. When compared to other markets, China has a low demand for skilled laborers. Therefore, the labor supply is at a very low level. In this case, laborers in China are likely to seek employment within the foreign labor force market, further aggravating the losses to the Chinese labor supply.

5. Conclusions and Policy Implications

Based on DEA, we propose a reasonable method to measure biased technological progress, which we divide into production-biased technological progress and environmentally biased technological progress. Then, we study the functional mechanism between environmental regulation and employment. The empirical analysis shows that environmental regulation can promote the progress of environmentally biased technology, and the resulting positive effect of enterprise competitiveness is stronger than the negative effect caused by the reduction of production scale, thereby increasing the amount of labor demand of enterprises. The effect of labor demand brought by environmentally biased technological progress in eastern China is stronger than those in other regions, while the effect of labor supply is weaker than those in other regions. Therefore, the employment effect in the eastern region is higher than the average level. This indicates that environmentally biased technological progress in the eastern region brings more demographic dividend.

China's industrial structure must change to accommodate the high proportion of secondary industries. If China needs to increase labor demand, then it is necessary to enhance industries' ability to restructure, especially those in eastern China, to ensure harmony between the economy and environment. Generally, environmental regulations and employment have a U-shaped relationship that can be made to move toward the upper-left direction through industrial restructuring, that is, realization of coordinated development under weak environmental regulations. Hence, it would be helpful to realize the double dividends of employment and the environment as early as possible by following a new industrialization path to transfer resources to low-input, low-emission, and high-output enterprises.

The central and western regions should set environmental thresholds to guarantee that their FDI or industrial transfer benefits local comprehensive strengths. The eastern region has superior conditions, such as capital, technological change, and skills reserves, to carry out economic reform and undertake advanced FDI. However, in recent years, its disadvantages with respect to labor cost and environmental regulations have become increasingly pronounced, and there is a notable phenomenon of industrial gradient transfers. Industries with this phenomenon are mostly pollution intensive that are situated in areas with low environmental regulation levels and labor costs. Low economic levels and environmental damage further reduce labor productivity in the central and western regions and cause increasingly serious income gaps. In conclusion, it is of great importance to set up rational environmental regulations and continuously enhance the force of environmental protection in the central and western regions to ensure the balanced development of both economy and environment in each region.

Future research should consider environmentally biased technology change as a multi-agent and multi-factor system, and should conduct in-depth analysis of system interactions. In addition, future studies should combine the concepts of resource conservation and eco-friendly and green technology to construct a policy system that can stimulate environmentally biased technology and yield the perfect set of tools to realize low-carbon development, resource circulation, and society's green development. This would include accounting for such factors as ecology, resources, and environment; analyzing the interaction mechanism of the system; measuring interaction efficiency from multiple dimensions; and conducting empirical analyses and analogue simulation.

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References

[1] Li G, Lim M, Wang Z. Stakeholders, green manufacturing, and practice performance: Empirical evidence from Chinese fashion businesses. Ann Oper Res 2019; https://doi.org/10.1007/s10479-019-03157-7

[2] Sun W, Yang Q, Ni Q, Kim Y. The impact of environmental regulation on employment: an empirical study of China's two control zone policy. Environ Sci Pollut Res 2019; 26: 26472–87.
[3] Ferreira J, Fernandes C, Ratten V. Entrepreneurship, innovation and competitiveness: what is the connection? Int J Bus Glob 2017; 18(1): 73–95.
[4] Munir K, Ameer A. Effect of economic growth, trade openness, urbanization, and technology on environment of Asian emerging economies. Manag Environ Qual Intern J 2018; 29(6): 1123–1134.
[5] Walker W. The transitional costs of sectoral reallocation: evidence from the Clean Air Act and the workforce. Q J Econ 2013; 128(4): 1787–835.
[6] Greenstone M. The impacts of environmental regulations on industrial activity: evidence from the 1970 and 1977 Clean Air Act Amendments and the census of manufactures. J Political Econ 2002; 110(6): 1175–219.
[7] Orlitzky M, Schmidt F, Rynes S. Corporate social and financial performance: a meta-analysis. Organ Stud 2003; 24(3): 403–41.
[8] Ramanathan R, Ramanathan U, Bentley Y. The debate on flexibility of environmental regulations, innovation capabilities and financial performance—a novel use of DEA. Omega 2018; 75: 131–8.
[9] Chen Z, Kahn M, Liu Y, Wang Z. The consequences of spatially differentiated water pollution regulation in China. J Environ Econ Manag 2018; 88: 468–85.
[10] Sun W, Yang Q, Ni Q, Kim Y. The impact of environmental regulation on employment: an empirical study of China's two control zone policy. Environ Sci Pollut Res 2019; https://doi.org/10.1007/s11356-019-05840-5.
[11] Yang C, Huang R, Ke W. Applying QFD to build green manufacturing system. Prod Plan Control 2012; 23(2-3): 145–59.
[12] Kondoh K, Yabuuchi S. Unemployment, environmental policy, and international migration. J Int Trade Econ Dev 2012; 21(5): 677–90.
[13] Sen A, Acharyya R. Environmental standard and employment: impact of productivity effect. Environ Dev Econ 2012; 17(2): 207–25.
[14] Walker W. Environmental regulation and labor real location: evidence from the Clean Air Act. Am Econ Rev 2011; 101(3): 442–7.
[15] Goodstein J, Gautam K, Boeker W. The effects of board size and diversity on strategic change. Strat Manag J 1994; 15: 241–50.
[16] Shadbegian R, Gray W. Pollution abatement expenditures and plant-level

productivity: a production function approach. Ecol Econ 2005; 54: 196–208.
[17] Liu M, Shadbegian R, Zhang B. Does environmental regulation affect labor demand in China? Evidence from the textile printing and dyeing industry. J Environ Econ Manag 2017; 86: 277–94.
[18] Hong Z, Guo X. Green product supply chain contracts considering environmental responsibilities. Omega 2019; 83: 155–66.
[19] Wu H, Lv K, Liang L, Hu H. Measuring performance of sustainable manufacturing with recyclable wastes: a case from China's iron and steel industry. Omega 2017; 66: 38–47.
[20] Wang K, Wei Y, Huang Z. Potential gains from carbon emissions trading in China: a DEA based estimation on abatement cost savings. Omega 2016; 63: 48–59.
[21] Li Z, Zhang Q, Liao H. Efficient-equitable-ecological evaluation of regional water resource coordination considering both visible and virtual water. Omega 2019; 83: 223–35.
[22] Ramanathan R, Ramanathan, U, Bentley Y. The debate on flexibility of environmental regulations, innovation capabilities and financial performance—a novel use of DEA. Omega 2018; 75: 131–8.
[23] Hijzen A, Gorg H, Hine R. International outsourcing and the skill structure of labor demand in the United Kingdom. Econ J 2005; 115: 860–78.
[24] Song M, Wang S. Can employment structure promote environment-biased technical progress? Technol Forecast Soc Change 2016; 112: 285–92.
[25] Acemoglu, D. Equilibrium bias of technology. Econometrica, 2007; 75(5): 1371–410.
[26] Acemoglu D, Gancia G, Zilibotti F. Offshoring and directed technical change. 2012b, NBER Working Paper 18595.
[27] Kennedy C, Thirlwall A. Surveys in applied economics: technical progress. Econ J 1972; 82: 11–72.
[28] Caves D, Christensen L, Diewert W. The economic theory of index numbers and the measurement of input, output, and productivity. J Econom Soc 1982; 6: 1393–414.
[29] Fukuyama H, Weber W. A directional slacks-based measure of technical inefficiency. Socio-Econ Plan Sci 2009; 43: 274–87.
[30] Acemoglu D. Directed technical change. Rev Econ Stud 2002; 69(4): 781.

[31] Acemoglu D. Labor and capital-augmenting technical change. J Eur Econ Assoc 2003; 1(1): 1–37.
[32] Song M, Wang S. Measuring environment-biased technological progress considering energy saving and emission reduction. Process Safety Environ Prot 2018; 116: 745–53.
[33] Baležentis T, Oude Lansink, A. Measuring dynamic biased technical change in Lithuanian cereal farms. Agribusiness 2019; 74: 211–42.
[34] Li T, Baležentis T, Cao L, Zhu J, Streimikiene D, Melnikienė R. Technical change directions of China's grain production: application of the bias-corrected Malmquist indices. Technol Econ Dev Econ 2018; 24(5): 2065–82.
[35] Chambers R, Färe R, Grosskopf S. Productivity growth in APEC countries. Pac Econ Rev 1996; 1: 181–90.
[36] Chung, Y. H., R. Färe, S. Grosskopf. Productivity and undesirable outputs: a directional distance function approach. J Environ Manag 1997; 51(3): 229–40.
[37] Miao Z, Baležentis T, Tian Z, Shao S, Geng Y, Wu R. Environmental performance and regulation effect of China's atmospheric pollutant emissions: evidence from "three regions and ten urban agglomerations." Environ Resour Econ 2019; 74: 211–42.
[38] Hou L, Keske C, Hoag D, Balezentis T, Wang X. Abatement costs of emissions from burning maize straw in major maize regions of China: balancing food security with the environment. J Clean Prod 2019; 208: 178–87.
[39] Wang S, Song M. Review of hidden carbon emissions, trade, and labor income share in China, 2001–2011. Energy Policy 2014; 74: 395–405.
[40] Werf EVD.. Production function for climate policy modeling: an empirical analysis. Energy Econ 2008; 30(6): 2964–79.
[41] Acemoglu D, Aghion P, Bursztyn L, Hemous D. The environment and directed technical change. Am Econ Rev 2012; 102: 131–66.
[42] Tone K, Sahoo B-K. Scale, indivisibilities and production function in data envelopment analysis. Int J Prod Econ 2003; 84(2): 165–92.

Appendix

SBM models are widely used in many business environments. However, the environmental protection perspective is different from that of enterprises, as the SBM approach is used with a foothold of environmental efficiency maximization. According to the SBM model of Tone and Sahoo [42] and the weak disposability assumption, the production possibility set (PPS) under constant returns to scale is defined as

$$PPS = \{(x, y^g, y^b) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b = Y^b\lambda, \lambda \geq 0\}$$

Then, the improved SBM model for measuring the efficiency of DMU0 based on the PPS is shown as follows:

$$Min\ \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{X_{i0}}}{1 + \frac{1}{s}\sum_{r=1}^{s}\frac{t_r^+}{Y_{i0}}}$$

$$s.t.\ \sum_{j=1}^{n}\lambda_j X_{ij} + s_i^- = X_{i0} \qquad \text{(A-1)}$$

$$\sum_{j=1}^{n}\lambda_j Y_{rj} - t_r^+ = Y_{r0}$$

$$\lambda_j \geq 0, s_i^- \geq 0, t_r^+ \geq 0$$

Then, we assume that each DMU has four types of input and output vectors: a desirable input vector, an undesirable input vector, a desirable output vector, and an undesirable output vector. Then, the PPS under constant returns to scale can be redefined as

$$PPS = \{(x, y^g, y^b) \mid x^g \geq X^g\lambda, x^b \leq X^b\lambda, y^g \leq Y^g\lambda, y^b = Y^b\lambda, \lambda \geq 0\}$$

The improved model is as follows:

$$\min\ \rho_2 = \frac{1 - \frac{1}{m}\left(\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}\right)}{1 + \frac{1}{s+t}\left(\sum_{r=1}^{s}\frac{s_r^+}{y_{r0}} + \sum_{p=1}^{t}\frac{s_p^+}{b_{p0}}\right)}$$

$$s.t.\ \begin{cases} \sum_{j=1}^{n}\lambda_j x_{mj} + s_i^- = x_{i0},\ m = 1,2,\ldots,m \\ \sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = y_{r0},\ r = 1,2,\ldots,s \\ \sum_{j=1}^{n}\lambda_j b_{pj} + s_p^+ = b_{p0},\ p = 1,2,\ldots,t \\ s_i^-, s_r^+, s_p^+ \geq 0;\ \lambda \geq 0 \end{cases} \qquad \text{(A-2)}$$

According to formula (A-2), we adopt energy factor to formula A-3, as follows:

$$\min \rho = \frac{1 - \frac{1}{m+t}\left(\sum_{i=1}^{m}\frac{s_{xi}^{-}}{x_{i0}} + \sum_{i=1}^{t}\frac{s_{ei}^{-}}{e_{i0}}\right)}{1 + \frac{1}{p+q}\left(\sum_{i=1}^{p}\frac{s_{yi}^{+}}{y_{i0}} + \sum_{i=1}^{q}\frac{s_{bi}^{-}}{b_{i0}}\right)}$$

$$s.t. \begin{cases} \sum_{j=1}^{n}\lambda_j x_{ij} + s_{xi}^{-} = x_{i0}, i = 1,2....,m \\ \sum_{j=1}^{n}\lambda_j e_{ij} + s_{ei}^{-} = e_{i0}, i = 1,2,...,t \\ \sum_{j=1}^{n}\lambda_j y_{ij} - s_{yi}^{+} = y_{i0}, i = 1,2,...,p \\ \sum_{j=1}^{n}\lambda_j b_{ij} + s_{bi}^{-} = b_{p0}, \ i = 1,2,...,q \\ s_{xi}^{-}, s_{ei}^{-}, s_{yi}^{+}, s_{bi}^{-} \geq 0; \lambda \geq 0 \end{cases} \qquad \text{(A-3)}$$

x refers to the factor input; *m* is the quantity of input indexes; *e* represents the energy index; *t* refers to the quantity of energy indexes; *y* is desirable output; *p* stands for quantity of desirable output; *q* refers to quantity of undesirable output; and ρ is the evaluated value of environmental efficiency.

Theorem 1: When $\rho < 1$, DMU $(x_0, e_{0,} y_0, b_0)$ is ineffective.

Proof: $\because$ Value of $(x_0, e_{0,} y_0, b_0)$ is positive and $\rho < 1$,

$\therefore$ There is input redundancy that makes $s_i^{-} > 0 \ (1 < i < m)$.

To prove the universality of the model, in linear programming, making any $s_v^{-} > 0 \ (1 < v < m)$, $s_v^{-} > 0$. Then, by setting $\bar{x} = (x_{10}, x_{20}, ..., x_{v-1,0}, x_{v0} - s_v^{-}, x_{v+10}, ..., x_{m0})$, $\bar{e} = e_0, \bar{y} = y_0$, and $\bar{b} = b_0$, we can easily know that $(\bar{x}, \bar{e}, \bar{y}, \bar{b})$ is in the PPS and production decision $(\bar{x}, \bar{e}, \bar{y}, \bar{b})$ is not inferior to $(x_0, e_{0,} y_0, b_0)$. As $(\bar{x}, \bar{e}, \bar{y}, \bar{b})$ and $(x_0, e_{0,} y_0, b_0)$ are different production possibility sets, according to the definition of effectiveness, we can say that $(x_0, e_{0,} y_0, b_0)$ is ineffective.

Theorem 1 is proved as true.

Theorem 2: When $\rho \geq 1$, $(x_0, e_{0,} y_0, b_0)$ is weakly Pareto effective.

Proof: Assume that $(x_0, e_{0,} y_0, b_0)$ is ineffective. DMU *d* yields $(\bar{x}, \bar{e}, \bar{y}, \bar{b}) \in T$ and $\bar{x} \leq x_0$, $\bar{e} \leq e_0$, $\bar{y} \geq y_0$, $\bar{b} \leq b_0$. There is at least one inequality that is strictly unequal among these four. In other words, when maintaining other indexes as equal, there is at least one input that is smaller than x_0 in $(\bar{x}, \bar{e}, \bar{y}, \bar{b})$, at least one energy unit that is smaller than e_0, at least one desirable output that is larger than y_0, or at least one undesirable output that is smaller than b_0.

We may as well set $\bar{y} > y_0$, then DMU *d* yields $\bar{y}_d > y_{d0}$.

Because $(\bar{x}, \bar{e}, \bar{y}, \bar{b})$ satisfies the required conditions of programming, $\lambda = (\lambda_1^*, \lambda_2^*, ..., \lambda_N^*)$, which yields:

$$\begin{cases} \bar{x}_i - \sum_j \lambda_j^* x_{ij} \geq 0 \quad i = 1,2,...,m \\ \bar{e}_i - \sum_j \lambda_j^* e_{ij} \geq 0 \quad i = 1,2,...,t \\ \sum_j \lambda_j^* y_{ij} - \bar{y}_i \geq 0 \quad i = 1,2,...,p \\ \bar{b}_i - \sum_j \lambda_j^* b_{ij} \geq 0 \quad i = 1,2,...,q \end{cases} \tag{A-4}$$

Because the production decision of $(\bar{x}, \bar{y}, \bar{b})$ is not inferior to that of $(x_0, e_{0,} y_0, b_0)$, we obtain

$$\begin{aligned} & x_{i0} - \sum_j \lambda_j^* x_{ij} \geq \bar{x}_i - \sum_j \lambda_j^* x_{ij} \geq 0, \ i = 1,2,...,m \\ & e_{i0} - \sum_j \lambda_j^* e_{ij} \geq \bar{e}_i - \sum_j \lambda_j^* e_{ij} \geq 0, \ i = 1,2,...,t \\ & \sum_j \lambda_j^* y_{ij} - y_{io} \geq \sum_j \lambda_j^* y_{ij} - \bar{y}_i \geq 0 \ \ i = 1,2,...,p \\ & b_{i0} - \sum_j \lambda_j^* b_{ij} \geq \bar{b}_i - \sum_j \lambda_j^* b_{ij} \geq 0 \ \ i = 1,2,...,q \end{aligned}$$

This is contradictory to the condition $\rho \geq 1$.

In conclusion, when $\rho \geq 1$, corresponding $(x_0, e_{0,} y_0, b_0)$ is weakly Pareto effective. Theorem 2 is proved.

From Theorems 1 and 2, we know that $\rho \geq 1$ is fully equivalent to being weakly Pareto effective. If the DMU is advanced-SBM effective when defining $\rho \geq 1$, then it is fully equivalent to the previous definition of effectiveness. We also know that DMU $(x_0, e_{0,} y_0, b_0)$ is definitely weakly Pareto effective in *T*, and hence, there are definitely DMUs that are weakly advanced-SBM effective in *T* as well. This completes the proof.

According to formula (17), we obtain the input efficiency in period *s* as $\rho_X^s = 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{s,xi}^-}{x_{s,i0}}$, energy efficiency as $\rho_E^s = 1 - \frac{1}{t}\sum_{i=1}^{t}\frac{s_{s,ei}^-}{e_{s,i0}}$, and undesirable output efficiency as $\rho_B^s = 1 - \frac{1}{q}\sum_{i=1}^{q}\frac{s_{s,bi}^-}{b_{s,i0}}$. Similarly, in period *t*, input efficiency is $\rho_X^t = 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{t,xi}^-}{x_{t,i0}}$, energy efficiency is $\rho_E^t = 1 - \frac{1}{t}\sum_{i=1}^{t}\frac{s_{t,ei}^-}{e_{t,i0}}$, and undesirable output efficiency is $\rho_B^t = 1 - \frac{1}{q}\sum_{i=1}^{q}\frac{s_{t,bi}^-}{b_{t,i0}}$.

When there is neutral technological change, according to Theorem 1, $\rho^t{}_X / \rho^s{}_X = \rho^t{}_B / \rho^s{}_B = \rho^t{}_E / \rho^s{}_E$ definitely holds.

Because the production frontier of period *s* is adopted to measure the efficiencies of the DMUs of period *t*, such as $\rho_x^s(x_T, y_T)$, or the production frontier of period *t* is used to measure the efficiencies of DMUs of period *s*, such as $\rho_x^t(x_S, y_S)$, in the absolute environmentally biased technological progress, there may be a condition that the production frontier cannot envelop the DMUs of the next period under the current production frontier. In this case, if we were to use formula (17), then the measurement would not be possible. Considering that the necessary value can be obtained by adding DMUs that are beyond the production frontier in the next period one by one to the technological level in period *s*, we construct the super-efficiency advanced-SBM model with reference to Tone's (2000) method. The form of the model can be expressed as

$$\min \rho = \frac{1 - \frac{1}{m+t}\left(\sum_{i=1}^{m}\frac{\bar{x}}{x_{i0}} + \sum_{i=1}^{t}\frac{\bar{e}}{e_{i0}}\right)}{1 + \frac{1}{p+q}\left(\sum_{i=1}^{p}\frac{\bar{y}}{y_{i0}} + \sum_{i=1}^{q}\frac{\bar{b}}{b_{i0}}\right)}$$

$$s.t. \begin{cases} \sum_{j=1}^{n+1}\lambda_j x_{ij} \le \bar{x}, i = 1,2....,m \\ \sum_{j=1}^{n+1}\lambda_j e_{ij} \bar{}_{ei} \le \bar{e}, i = 1,2,...,t \\ \sum_{j=1}^{n+1}\lambda_j y_{ij} \ge \bar{y}, i = 1,2,...,p \\ \sum_{j=1}^{n+1}\lambda_j b_{ij} \le \bar{b},\ i = 1,2,...,q \\ \bar{x} \ge x_{i0}; \bar{e} \ge e_{i0}; \bar{y} \le y_{i0}; \bar{b} \ge b_{i0};\ \lambda \ge 0 \end{cases} \tag{A-5}$$

In formula (A-5), $(\bar{x}, \bar{e}, \bar{y}, \bar{b})$ refers to the distance between the production frontier and the newly added DMU vector beyond the previous production frontier.

$$\rho_X^s(x_T, y_T) = 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{i0}} \tag{A-6}$$

The super-efficiency advanced-SBM formulae of energy and undesirable output are similar to the above. Then, according to formulae (7), (8), and (9), we can obtain the absolute environmentally biased technological progress and the relative environmentally biased technological progress.

Table 1. Statistical description of the variables

Variable	Number	Mean value	Maximum value	Minimum value	Standard deviation	Estimation coefficient
L	480	1359	5998	91	912	/
EBP	480	1.12	2.49	0.06	0.68	?
REG	480	0.66	1	0.11	0.59	?
w	480	16581	61281	4346	9190	?
K	480	20994	205201	379	25868	+
welf	480	428	2197	40	299	+
FDI	480	21014	144724	69	22773	?

Note: *EBP* refers to environmentally biased technological progress.

Table 2. Estimation results for model (employment demand)

Index	Differential GMM (1)	Differential GMM (2)	Systematic GMM (1)	Systematic GMM (2)
C	2.3472*** (11.1969)	2.7124*** (29.0170)	3.0405*** (12.3618)	3.2419*** (11.5208)
$logL_{-1}$	0.9088*** (15.5727)	0.8973*** (16.7814)	0.8352*** (13.7147)	0.8197*** (13.9538)
EBP	3.8130* (1.8441)	3.9311* (1.9610)	3.6876* (1.9648)	3.0419* (1.8227)
REG	-0.0414* (-1.8124)	-0.0672* (-1.9130)	-0.0108* (-1.8593)	-0.0206* (-1.7968)
REG_{-1}	0.0122 (1.1021)	0.0179 (1.3951)	0.0137 (1.0596)	0.0054 (1.3954)
logw	0.0324** (3.0303)	0.0354** (2.6392)	0.0259** (3.0248)	0.0228** (3.0083)
logK	0.0134*** (4.3548)	0.0149*** (7.2515)	0.0414*** (6.2181)	0.0384* (0.8891)
welf	0.0025*** (-5.7741)	0.0026*** (-5.0258)	0.0045*** (-5.2647)	0.0048*** (-5.6674)
logFDI		-0.0741** (-2.1190)		-0.0750** (-2.6091)
AR(2) test value	0.34	0.33	0.28	0.24
P-value	0.91	0.92	0.88	0.85
Region fixed	Yes	Yes	Yes	Yes
Hansen test value	13.491	12.133	12.706	11.437
P value	1	1	1	1
Obs	480	480	480	480

Notes: *, **, and *** denote 10%, 5%, and 1% significance, respectively. The null hypothesis of the Hansen test is that excessive identification is effective. The data in parentheses are standard errors.

Table 3. Employment effects in eastern region

$logL_d$	Differential GMM	Systematic GMM	$logL_s$	Differential GMM	Systematic GMM
C	-0.0963*** (-17.31)	-0.1278*** (-39.87)	C	-0.1634*** (-11.22)	-0.1554*** (-20.63)
$logw$	0.0480*** (4.25)	0.0081*** (2.90)	$logw$	0.0138* (1.84)	0.0005 (0.04)
EBP	0.0701*** (62.76)	0.0635*** (79.26)	EBP	0.0927*** (32.97)	0.0579*** (32.74)
REG	-0.012*** (-2.96)	-0.016*** (-7.43)	edu	-0.0034*** (-3.97)	-0.0016* (-1.85)
$logK$	0.0035*** (8.34)	0.0020*** (8.10)	$welf$	0.0043*** (4.28)	0.0043*** (7.75)
$is \times EBP$	-0.0003 (-0.19)	-0.0024** (-2.25)			
$is \times logFDI$	0.0223*** (2.68)	0.0040 (0.62)			
Regional fixed	Yes	Yes	Regional fixed	Yes	Yes
Hansen test value	10.1183	6.8184	Hansen test value	13.4989	15.0673
P-value	1	1	P-value	1	1
Obs	480	480	Obs	480	480

Notes: *, **, and *** indicate that the test passes at the 10%, 5%, and 1% significance levels, respectively. The null hypothesis of the Hansen test is that excessive identification is effective. The data in parentheses are standard errors.

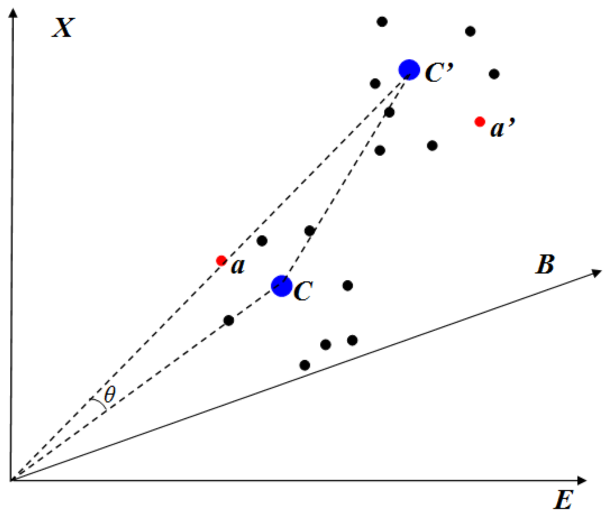

Figure 1. Three-dimensional view of biased technological change

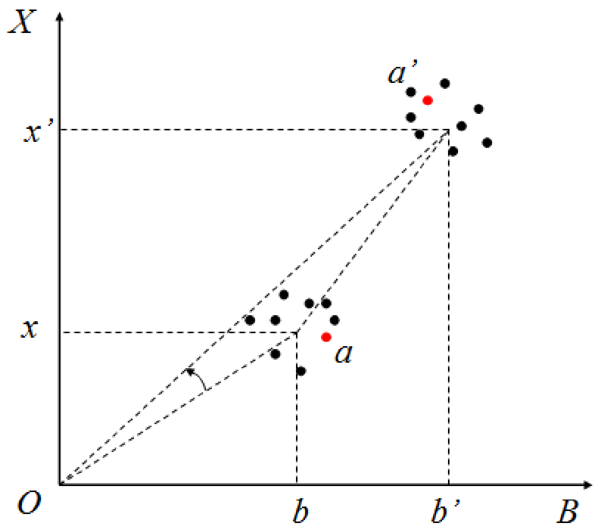

Figure 2. Change in DMU *a* of biased technological change

Author Statement

Malin Song: Conceptualization, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

Qianjiao Xie: Formal analysis, Investigation, Writing - Review & Editing.

Shuhong Wang: Methodology, Software, Validation, Resources, Writing - Original Draft.

Li Zhou: Methodology, Writing - Review & Editing.