Technological Forecasting & Social Change xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Can employment structure promote environment-biased technical progress?

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ARTICLE INFO

Article history:
Received 31 October 2015
Received in revised form 12 February 2016
Accepted 29 February 2016
Available online xxxx

Keywords:
Employment structure
Environment-biased technical progress
Data envelopment analysis
Overlapping generations model

ABSTRACT

Environment-biased technical progress can stimulate improvement in environmental quality, leading to coordinated development between the economy and the environment. However, the existing literature scarcely refers to the factors influencing the technical progress bias. We use the overlapping generations model to realize the endogenesis of biased technical progress in the Chinese context. We show that an increase in the aging population will encourage the use of pollution-biased technology and focus the attention of enterprises on improving economic benefits rather than environmental quality. We measure the directions of technical progress during 2003 to 2013 and estimate regressions for the relevant indicators of the labor force employment structure. Under equilibrium, increased ratios of the aging population and state-owned enterprises will stimulate environment-biased technical progress. Further, the effects of research and development and clustering of state-owned enterprises on environmental technology improvement are significant.

1. Introduction

Economic growth is usually accompanied by deterioration of environmental quality. While economic growth improves people's quality of life, the accompanying environmental pollution and resulting degradation simultaneously lowers the same. Besides, the worse the environmental pollution, the greater its influence on economic growth. As per the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2007), the global gross domestic product (GDP) will reduce by 5% for every 4 °C rise in the global temperature. At present, the Chinese government strongly advocates a cyclic economy to construct a resource-saving and environmentally friendly society. Though a series of environmental regulations and policies have been implemented to this end, they are likely to increase the production costs of polluting enterprises, may cause significant unemployment, and aggravate the gap between the rich and the poor in China.

Compared with the short-term effects of environmental regulations and policies, technical progress in energy conservation and emissions reduction is more likely to bring about long-term benefits to the society. Innovation in clean technology has become an effective way to realize a win-win situation between environmental protection and economic growth. However, though the importance of progress in environmental technology is self-evident, hardly any literature identifies the factors influencing this progress. The existing literature mostly focuses on analyzing the relationship between environmental regulations and clean technology; examples include the study of the relationship between environmental regulations and the number of patent applications by Arduini and Cesaroni (2001); Aiken et al.'s (2009) study regarding the influences of environmental regulations on pollution control costs, Popp et al.'s (2009) analysis of the economic incentives of environmental regulations on enterprise innovations, and the construction of the endogenous growth model by Acemoglu et al. (2012b) to analyze the influence of environmental policies on innovation. However, environmental regulation is an exogenous variable. Is there an endogenous variable that can affect environmental technology?

Stricter environmental regulations are likely to increase unemployment, which poses serious problems for any country (Greenstone, 2002). As per the data released by the Ministry of Human Resources and Social Security and the annual China Statistical Yearbook, though the registered urban unemployment rate since 2002 has not increased beyond 4.3%, total unemployment has risen to more than 7.7 million, mainly due to China's enormous population. At the end of 2014, the actual registered urban unemployment rate for China as a whole rose to 4.09%. Increasing unemployment will have tremendous impacts on the physiology and psychology of workers (Roh et al., 2014). Unemployment and the resulting unbalanced employment structure have become serious hindrances to China's economic growth. Peroni and Gomes Ferreira (2011) considered that enterprises with a high level of competition would stimulate investments in research and development (R&D). The increased intensity of competition would stimulate technical progress. If so, can China improve its progress in environment-biased technology by adjusting its employment structure, namely, by adjusting its employment structure in industries with weak environmental regulations or in environmentally friendly industries? One the one hand, environmental regulation raises production costs of enterprises and forces them to retrench labor, leading to considerable

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http://dx.doi.org/10.1016/j.techfore.2016.02.016
0040-1625/© 2016 Published by Elsevier Inc.

unemployment; on the other hand, the increasing stringency witnessed by the environmental protection industry increases the demand for labor, thus promoting employment. If the employment structure of Chinese labor undergoes a reasonable shift from the production industry to the environmental protection industry, will the unemployment rate effectively decline? Furthermore, can the increase in employment in the environmental protection industry promote environment-biased technological progress? Can we achieve sustainable development in both environmental and economic terms by adjusting the employment structure rather than implementing mandatory environmental regulation? This study attempts to answer these questions.

The rest of this paper is structured as follows. Section 2 presents the literature review. Section 3 discusses the theoretical models, and Section 4 refers to indicator selection and model construction. Section 5 presents the results of model estimation and testing, while Section 6 concludes.

2. Literature review

The concept of biased technical progress was first put forward by Hicks (1932), who considered that changes in the relative prices of factors would force entrepreneurs to innovate technologies and use low-cost factors. If the technical progress is beneficial in that it can increase the marginal output of capital, then such progress is referred to as capital-biased technical progress. If it increases the marginal output of labor, then it is defined as labor-biased technical progress. Acemoglu (2003, 2007) further extended the concept of biased technical progress. Technical progress may occur in either direction between any two input factors. Given the increasing attention being paid to environmental issues in recent research on economic theories, the environmental factor, which reflects the quality of life, has been included by most researchers in the production function. However, environment-biased technical progress differs from production-biased technical progress in that the latter requires outputs to increase, while the former requires energy consumption and undesirable outputs to decrease along with technical progress (Wang and Song, 2014). Hence, environment-biased technical progress includes technical progress related to both energy saving and emissions reduction. In this context, Acemoglu et al. (2012b, 2014) took the lead in theoretically defining and analyzing the components of environment-biased technical progress.

Many researchers have focused on biased technical progress ever since Acemoglu (2003) proposed the concept. However, empirically, there is still no accepted method to measure the same. Most of the literature only adopts a substitution of indicators to express biased technical progress (Harrison, 2002; Welsch and Ochsen, 2005; Arnberg and Bjorner, 2007; Ma et al., 2008, 2009). Although some studies estimated the index of the direction of technical progress through the normalized supply-side system approach (Klump et al., 2007) or the generalized non-linear least square method (Leon-Ledesma et al., 2010), fitting precision was still low. A non-parametric method, however, offers advantages while estimating biased technical progress. Data envelopment analysis (DEA) has become the method of choice in this regard (Bogetoft and Wang, 2005); because there is no need to preset the production function, hidden or ignored relationships in the environment system can be revealed (Liu et al., 2010), and it is easy to compare efficiency across firms and even analyze ineffective decision-making units (Lv et al., 2013). Manne and Richels (2004) introduced the biased technical progress theory into climatic change models and noted the reduction of various technical costs alongside the increase in experience. They observed the effects of biased technical progress on cost and time in the context of CO_2 emission reductions. Popp (2004) introduced biased technical progress in the energy sector into the DICE model of climatic change evaluation and effectively calculated the welfare cost of the optimum carbon tax. In 2012, Acemoglu et al. (2012a) used the biased technical progress in growth models with environmental restrictions and limited resource conditions and analyzed the costs and profits of different environmental policies based on clean technology and pollutive technology. In the same year, Acemoglu et al. (2012b) established an endogenous model from the viewpoint of input, assuming that clean technology and pollutive technology, that is, productive technology, compete with each other. Additional inputs on clean technology would reduce inputs on pollutive technology; the 'extrusion' effect would be observable in scientists' research activities. Greaker and Heggedal (2012) considered that clean technologies are effective in the long run, thus amending Acemoglu et al.'s (2012b) conclusion that research and development pertaining to clean technology was over-subsidized.

As one of the world's largest growing economies, China ranked first globally in terms of carbon emissions in 2006, exceeding those of the U.S. for the first time (Gong et al., 2014). Hence, there is an urgent need for the country to reduce its carbon emissions. Besides, China also faces challenges from the recent slowdown in economic growth. Can reforms of state-owned enterprises via a transformation of the labor force employment structure and innovation help improve environmental quality as well as coordinate development between the environment and the economy? Empirically, biased technical progress can reveal important differences in skill premiums (Van Reenen, 2011), income gaps among countries (Acemoglu et al., 2012a), and changes in environmental technologies (Aghion et al., 2012). Ji (2011) observed the effects of market structure on biased technical progress and found that fixed costs of intermediate products and R&D efficiency are two important factors that affect the degree of bias. Acemoglu et al. (2012b) discussed the factors that influence the direction of technical progress from the perspective of the speed of factor accumulation but did not analyze the factors that affect the relative speed of factor accumulation. According to Hicks (1932) and Acemoglu (2007), the relative prices of input factors decide the degree of biasness of technical progress and the relative factor inputs decide the relative prices of the factors. Therefore, relative factor inputs are decisive to technical progress bias.

Labor force is one of the most important inputs to the production process. Many scholars, for example, Bullock-Yowell et al. (2014); Chillas et al. (2015), and Vayre and Pignault (2014), studied the relationship between the labor force and unemployment. Studying the effects of the labor force employment structure in both state-owned and private enterprises on biased technical progress is vital in the Chinese context. We consider that state-owned enterprises in China exercise the will of the state, while private enterprises reflect changes in the market. Hence, on the issue of environmental protection, state-owned enterprises have more impetus than private enterprises. Further, state-owned enterprises hold more capital and technologies and are better placed to realize the objectives of energy saving and emissions reduction. An increase in the ratio of state-owned enterprises causes the labor force to become scarce and the capital to grow, or an increase in the ratio of state-owned enterprises reduces the labor force and increases capital. Consequently, the relative price of labor-capital will increase, and the direction of technical progress will be inclined toward labor. As state-owned enterprises hold more capital and have the resources to practice clean production, private enterprises may undertake polluting production, thus inclining the direction of technical progress toward pollution. Since wages in state-owned enterprises are lower than those in private enterprises, an increase in the ratio of state-owned enterprises will affect not only the employment structure but also total savings. Hence, it is necessary to analyze the equilibrium effects of the employment structure on the direction of technical progress if we want to clarify the effects of changes in the said structure on the direction of technical progress.

Accordingly, this study analyzes the effects of China's labor force employment structure on environment-biased technical progress from both the theoretical and the empirical aspects. We establish an overlapping generations (OLG) model for our study. In the empirical analysis,

Please cite this article as: Song, M., Wang, S., Can employment structure promote environment-biased technical progress?, Technol. Forecast. Soc. Change (2016), http://dx.doi.org/10.1016/j.techfore.2016.02.016

we use the normalized supply-side system approach proposed by Klump et al. (2007) to estimate the direction of biased technical progress and to analyze the effects of the employment structure on the direction of biased technical progress.

3. Theoretical models

We consider one family sector at time t, which provides the labor force and capital, one final product sector, and two intermediate product sectors in a discrete-time OLG model that runs to infinity. Generally, as state-owned enterprises own large capital stocks, they can better control pollution discharges during the production process. However, private enterprises tend to favor economic benefits over the environment, and their efforts toward energy-saving and emissions reduction are insufficient. In reality, the production efficiencies of state-owned enterprises are lower than those of private enterprises because of redundant organizations in the former. State-owned enterprises reflect the will of the nation. The country subsidizes state-owned enterprises by levying taxes from private enterprises, which is why the risk of bankruptcy of state-owned enterprises is very small. In addition, state-owned enterprises can accumulate wealth quickly because of favorable state policies. The scarcity of the labor force referred to in the article is a reflection of the low efficiency of enterprises and not actual scarcity per se. In many cases, young laborers may also have low efficiencies because of institutional problems and reflect the same status as elderly laborers. Hence, we assume that laborers in state-owned enterprises are mainly elderly people with low productivity but abundant capital accumulation. However, in private enterprises, laborers are mostly young people with high productivity but scarce capital accumulation. The private enterprise is the first intermediate product sector that only takes labor force as the input to produce polluting intermediate products. The state-owned enterprise is the other intermediate product sector that only takes capital as the input to produce clean intermediate products. The family representative only exists for two periods: the youth period and the aging period. That is, the family representative is young at time t and aged at time $t+1$. Young people own the labor force, while aged people own capital, and the family provides the labor force and capital to intermediate product sectors. In such an economic system, there are five trading objects: capital, labor force, clean intermediate product, polluting intermediate product, and final product. The final product can be used for consumption, as capital stock for the future, or as an innovative input to intermediate product sectors. We define technical progress of a clean intermediate product as environment-biased technical progress, and technical progress of the polluting intermediate product as production-intensive technical progress.[1] Then, the environment-biased technical progress and the production-intensive technical progress, respectively, are the results of R&D activities in state-owned enterprises and private enterprises.

3.1. Activity of the decision-making subject

Suppose that the representative enters a private enterprise in his youth and earns a high salary, but being busy, he provides one unit labor of force without elasticity. The salaries will be divided between consumption and savings for senectitude. In his senectitude, the representative will work at a state-owned enterprise, which is a stable working environment. For simplicity, we do not include the salaries from the state-owned enterprise into our model. Population at time t is L_t. Then at time t, there will be L_t young people and L_{t-1} aged people. The growth rate of the labor force λ is exogenous, $\lambda > -$, and $L_t/L_{t-1} = \lambda$ When λ increases, ratio of private enterprises will increase as well. We suppose that consumers are homogeneous; then, the at-sight utility function of each consumer born at time t will be

$$U_t = u(c_{Y,t}) + \beta u(c_{o,t+1}) \tag{1}$$

In Eq. (1), β refers to the utility discount factor, $c_{Y,t}$ refers to consumption in the youthful period, while $c_{o,t+1}$ refers to consumption in senectitude. Marginal utility decreases progressively with the passage of time. To reach the only equilibrium point, suppose that the elasticity of intertemporal substitution of the representative is higher than or equal to 1. Then, the budget constraint the representative faces will be.

$$c_{Y,t} + s_t = w_t; c_{o,t+1} = s_t R_{t+1} \tag{2}$$

In Eq. (2), s_t refers to savings, $w_t, > 0$ is the actual wage, and $R_{t+1}$is the actual level of the interest rate. Using Euler's conditions, we get the optimal plan for the representative: $s_t = s(R_{t+1},\beta)w_t$, in which $s(R_{t+1},\beta)$ refers to the rate of the marginal savings of wage income, and $s_R{}'(R_{t+1},\beta) > 0$ and $s_\beta{}'(R_{t+1},\beta) > 0$.

The production function of the final product sector is $Y_t = F(Y_{c,t},Y_{d,t})$, where Y_t refers to the total output at time t, $Y_{c,t}$ is the clean intermediate product, and $Y_{d,t}$ is the polluting intermediate product. Then, the profit of one unit final product will be $Y_t - p_{c,t}Y_{c,t} - p_{d,t}Y_{d,t}$. The final product sector maximizes the sum of the present value of profit at each time under the given price of the intermediate product. As the final product sector only buys two kinds of intermediate products, its optimization problem is similar to a series of single-period maximization problems. We suppose that production in the intermediate product sector is related not only to the capital and labor force but also to knowledge stock. Then, the production efficiencies of the labor force and capital in the intermediate sector, respectively, will be.

$$\psi_{c,t} = S_{c,t-1}(1-\delta+v_{c,t}); \psi_{d,t} = S_{d,t-1}(1-\delta+v_{d,t}) \tag{3}$$

In Eq. (3), $\psi_{c,t}$and $\psi_{d,t}$, respectively, refer to the production efficiency of the clean product and polluting product in the intermediate product sectors at time t. $S_{c,t}$ and $S_{d,t}$, respectively, refer to the technical knowledge stock in state-owned enterprises and private enterprises. Enterprises that innovate at time t will get free knowledge stock of relevant technology, although there is a certain depreciation $\delta \epsilon (0,1)$ of knowledge. $v_{d,t}$ and $v_{c,t}$, respectively, refer to the polluting and clean enterprises' growth level of productivity at the enterprise level. Suppose that capital is only used for one period. We define function $q(\bullet)$such that it remains unchanged at certain times and is a strictly convex, monotonically increasing function at others:

$$\lim_{v_j \to 0} q(v_j) = \lim_{v_j \to 0} q'(v_j) = 0; \lim_{v_j \to \infty} q(v_j) = \lim_{v_j \to \infty} q'(v_j) = 0 \tag{4}$$

Eq. (4) indicates that innovation is the monopolistic knowledge owned by the intermediate sector enterprises. Hence, enterprises must continuously conduct R&D for improving the final product. As to the intermediate product sector, under the given prices and knowledge stock, *each enterprise will choose to maximize the current value of its profit every time*, and the selection of each intermediate product toward production decision-making is independent. If enterprises chose to invest in innovations, then part of the investment cost q, which is independent of the current period's output, would be consumed. If the enterprise chooses to invest in innovation, it will bear an investment cost $q(v_{j,t}) > 0$ related to the productivity growth level $v_{j,t}$. Besides, this investment cost is independent of the yield levels of the two kinds of intermediate products. Hence, only when $p_{c,t} > r_t/\psi_{c,t}$ or $p_{d,t} > w_t/\psi_{d,t}$ will enterprises invest in innovation. r_t and w_t,

[1] As per the model setting employed in this article, production-intensive technical progress is a kind of factor-biased technical progress. By defining factor-biased technical progress, we have actually explained the production-intensive and environment-intensive technical progress as well. Production-intensive technical progress is a type of technical progress that stimulates output, while environment-intensive technical progress stimulates energy saving and emission reduction. These two types of technical progress are consistent with our theoretical mechanism, and thus, our article does not discuss this explicitly.

respectively, refer to income from the capital and *income from labor force participation*. Enterprises will produce on the threshold of productivity, in which case, innovation inputs are the same as the output. Thus, the only solution for the optimal production plan in the intermediate product sector can be expressed as.

$$r_t/S_{c,t-1}(1-\delta+v_{c,t})=q'(v_{c,t});w_t/S_{d,t-1}(1-\delta+v_{d,t})=q'(v_{d,t}) \quad (5)$$

Then, we obtain the equilibrium conditions for the final product sector:

$$w_t/r_t=(S_{d,t-1}/S_{c,t-1})\cdot(1-\delta+v_{d,t})q'(v_{d,t})/(1-\delta+v_{c,t})(v_{c,t})q'(v_{c,t}) \quad (6)$$

If the other conditions remain unchanged, *either the reduction of $v_{d,t}$ in the numerator or the increase of $v_{c,t}$ in the denominator will indicate that technical progress is biased to the environment*. We define $(w_t/S_{d,t-1})/(r_t/S_{c,t-1})$ as the ratio of the relative price, and changes to this ratio govern the transitions in the direction of technical progress.

As the supply of labor force and capital at any time t are always limited, assuming profit maximization, the maximized profit of the intermediate product sector at price equilibrium will be zero. Then, the equilibrium condition for the intermediate product sector will be.

$$p_{d,t}=(1-\delta+v_{d,t})q'(v_{d,t})+q(v_{d,t});p_{c,t}=(1-\delta+v_{c,t})q'(v_{c,t})+q(v_{c,t}) \quad (7)$$

Eq. (7) leads us to draw Proposition 1.

Proposition 1. *The incentives of the intermediate product sector, which are devoted to innovation, originate from the density of the factors in the final product sector, which is decided by the production function of that sector. Under the assumption of constant returns to scale, the inputs of the two kinds of intermediate products are complementary. Hence, if there are more clean intermediate products, the price of polluting intermediate products will increase, and the price of clean products will decrease. These changes in price will increase production-biased technical progress while reducing environment-biased technical progress.*

3.2. Equilibrium system

An economic system comprises of the price system $\{p_{c,t},p_{d,t},w_t,r_t\}$, consumer strategy set $\{c_{Y,t},s_t,c_{o,t+1}\}$, and final product sector strategy set$\{Y_t,Y_{c,t},Y_{d,t}\}$. Under a relative productivity level $\{\psi_{c,t},\psi_{d,t}\}$, total supply of capital K, and labor force L, the system chooses its own optimal labor input and capital input. Under initial capital accumulation and knowledge accumulation, all periods will satisfy the following conditions: young people save up as per the optimal plan, the final product sector is totally cleared, the intermediate product sector is totally cleared, and the labor force and capital are fully utilized. Then, we get

$$Y_{c,t}/Y_{d,t}=\left[S_{c,t-1}(1-\delta+v_{K,t})K_t\right]/\left[S_{d,t-1}(1-\delta+v_{L,t})L_t\right] \quad (8)$$

Eq. (8) leads us to Proposition 2.

Proposition 2. The equilibrium between environment-biased technical progress and production-biased technical progress is decided by $S_{c,t-1}K_t/S_{d,t-1}L_t$. If this ratio increases, production-biased technical progress will improve, while environment-biased technical progress will be hindered. If this ratio decreases, production-biased technical progress will be lowered, while environment-biased technical progress will improve. Any scarcity of factors alone can bring about changes in technical progress.

Proposition 2 *indicates that if the ratio $S_{c,t-1}K_t/S_{d,t-1}L_t$ increases, the profit of intermediate manufacturers of pollutive products will also increase; if $S_{c,t-1}K_t/S_{d,t-1}L_t$ reduces, the profit of the intermediate manufacturers of clean products will reduce as well.*

3.3. Effects of changes in the employment structure

Now, we discuss the restructuring of state-owned enterprises into private enterprises. All other conditions remaining the same, an increase in the ratio of private enterprises will increase the ratio of polluting products, thus hindering environment-biased technical progress. This will result in two kinds of contradictory effects: one, an increase in the labor force will raise the labor–capital ratio, and two, young laborers will increase savings on the premise of rational expectations, so much so that rents for capital will rise. Besides, we consider that the latter effect is stronger than the former, that is, the growth rate of the labor–capital ratio is smaller than that of labor when it is in a stable state. In this case, technical progress will be biased to production. Then, we can prove Theorem 1.

Theorem 1. A change in the labor employment structure modifies the relative scarcity of production factors and significantly influences the direction of technical progress.

Certainly, Theorem 1 is only true when other conditions remain unchanged. As China's birth control policy has been in effect for a considerable period of time, its aging problem has become increasingly serious. The sixth nation-wide population census showed that the ratio of population over 60 was 13.26%, 2.93% higher than that in 2000. If the structure of the population's age changes, then as per the assumptions made in this study, the labor force in state-owned enterprises may increase such that the relative price of the labor force and capital may be affected. In that case, the direction of technical progress will be affected as well. However, the model cannot tell us which of the two—the effect of state-owned enterprise reforms or the effect of aging—is stronger. Hence, we need to conduct advanced empirical analysis to find out the extent of the effects of changes to the employment structure on the direction of technical progress.

4. Indicator selection and model construction

We set up following equation for measuring the labor employment structure and environment-biased technical progress.

$$E_{it}=\alpha_0+\alpha_1 age_{it}+\alpha_2 Stat_{it}+\alpha_3 Clu_{it}+\alpha_4 w_{it}+\alpha_5 RD_{it}+\alpha_6 open_{it}+\varepsilon_{it} \quad (9)$$

In Eq. (9), *E* refers to environment-biased technical progress, *age* refers to the ratio of the aged population, *Stat* refers to the ratio of state-owned enterprises, *open* refers to the degree of openness, *RD* denotes the extent of R&D, *w* denotes the wage level, *Clu* refers to the degree of clustering of state-owned enterprises, *i* denotes the area, and *t* refers to time. Next, we explain each indicator in detail.

4.1. Environment-biased technical progress (E)

As per the definition of biased technical progress proposed by Acemoglu et al. (2012b), we use the DEA method to simulate the deflection of the production frontier and to measure the biased technical progress. We assume that production progress contains inputs of both productive production factors and environmentally friendly production factors but provides a single output, which can be expressed, as seen below, as a three-dimensional coordinate.

In Fig. 1, *K* and *L* refer to the input of productive production factors and input of environmentally friendly production factors respectively, and the *Y*-axis is vertical to the principal plane through point O. The input of productive production factors of the decision-making unit (DMU) *A* at time *S* is *k*, the input of environmentally friendly production

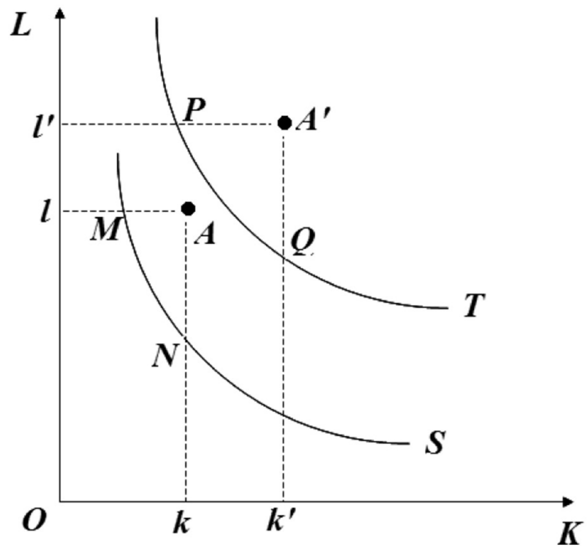

Fig. 1. Deflection of the production frontier.

factors is l, and the production enveloping surface is S. At time T, A's input of productive production factors turns into k', while the input of environmentally friendly production factors becomes l', and the production enveloping surface changes to T. We find that the position of the production-enveloping surface did not move outwards in the radial direction from the original point during the two periods but deflected towards the input of environmentally friendly production factors. Besides, the position of DMU A on the production-enveloping surface deflected as well. Hence, to measure the biased technical progress, we need to consider this deflection of DMU A. We find that, at this time, the DMU can respond to a higher input of environmentally friendly production factors with less input of polluting production factors. Then, as per the definition of Acemoglu et al. (2012b), this DMU shows environment-biased technical progress. Conversely, if the DMU responds to more polluting production factors with less environmentally friendly production factors, then such a DMU shows production-biased technical progress. We first measure the environment-biased technical progress and production-biased technical progress of DMU A at S and T, and then, we compare them to obtain the biased technical progress. Hence, we define the environment-biased technical progress of DMU A as

$$\rho_L = \frac{Nk/Ak}{Qk'/A'k'} \tag{10}$$

The production technical progress is defined as

$$\rho_K = \frac{Ml/Al}{Pl'/A'l'} \tag{11}$$

As per Theorem 1, environment-biased technical progress can be expressed as

$$E = \rho_K/\rho_L \tag{12}$$

If $E > 1$, the technical progress will be environment-biased. If $E < 1$, it will be production-biased, and if $E = 1$, the technical progress will be neutral. With this in mind, we use the singular boundary method (SBM) to measure the rate of environment-biased technical progress. The capital stock and labor force employment at the end of the year (for each year) are selected as input indicators, while the GDP of each area is selected as the output indicator. The data are sourced from the China Statistical Yearbooks and China Industrial Economy Statistical Yearbooks from 2003 to 2014.[2]

4.2. Indicator of the labor employment structure

According to the assumptions made for the model, the enterprises are either private or state-owned. Young people work in private enterprises while the aged work in state-owned ones. Hence, we select the ratio of the aged population and the ratio of state-owned enterprises as indicators to substitute the employment structure. In line with the annual data on population in the China Statistical Yearbooks, the indicator ratio of the aged population is expressed as the ratio of people aged above 65 to those aged between 15 and 64 in each area. If the ratio of the aged population increases, the ratio of social capital will increase as well, and the labor factor will become a scarce input factor. Then, as per Theorem 1, the technical progress will be labor-biased. Hence, the coefficient of the ratio of the aged population is preliminarily judged as negative. *Stat* denotes the nationalization of industrial sectors and is expressed by the ratio of sales revenue of the products of state-owned enterprises to the sum of the corresponding revenues of state-owned enterprises and above-designated-size private enterprises. The relevant data are sourced from the China Industrial Economy Statistical Yearbooks. If the ratio of state-owned enterprise increases, input in R&D may increase as well. As R&D input in state-owned enterprises is more likely to stimulate environment-biased technical progress, we preliminarily consider the coefficient of this indicator to be positive.

To describe the effect of the regional structure of state-owned enterprises, we also introduce degree of clustering of state-owned enterprises in each area as an indicator and adopt the Hoover coefficient for our calculation. According to the definitions of Naughton (1999) and Young (2000), this indicator can be expressed as the share of one industry in one area to the nationwide total industrial output value. We extend it to the degree of clustering of state-owned enterprises in each area, the formula for which is as below.

$$E_i = s_{ij}/s_i \tag{13}$$

In Eq. (13), i refers to the state-owned enterprise. $s_{ij} = q_{ij}/q_j$ denotes the ratio of the output value of state-owned enterprises in area j to the total industrial output value in the same area. $s_i = q_i/q$ refers to the ratio of the total output value of state-owned enterprises to the nationwide total industrial output value. $E_i > 1$ and $E_i < 1$ denote that the state-owned enterprises in this area are in the clustered state and in the scattered state, respectively. We arrange the regional entropies from small to large and plot the accumulated percentage of state-owned enterprises (s_{ij}) along the Y-axis and the accumulated percentage of each area (s_j) along the X-axis. If the state-owned enterprises are distributed equally among each area, then the curve will coincide with the radial drawn from the original point at the angle of 45°. If there is clustering of state-owned enterprises, the curve will bend towards the X-axis. The higher the degree of clustering, the bigger the radian of the curve. The Hoover coefficient can be obtained by calculating the ratio of the agglomeration degree of state-owned enterprises. As per our model, the higher the ratio of state-owned enterprises, the stronger the effect of knowledge clustering and spillover effect (Dodgson and Rothwell, 1994). In that case, it is easier to stimulate environment-biased technical progress. Hence, we primarily consider the coefficient of this indicator to be positive.

We also adopt the wage level, that is, the ratio of labor remuneration in each area to year-end employment, to measure the labor employment structure. The relevant data are sourced from the China Statistical Yearbook for each year. As we assume that young people get salaries while the aged live on savings, the higher the wage level, the higher the salaries. On the one hand, the consumption habits of the young

[2] http://tongji.cnki.net/overseas/engnavi/NaviDefault.aspx. Accessed October 18, 2015.

will change as they practice high consumption and pursue a better quality of life. This will boost the production of high-end consumer goods, thus stimulating pollution-biased technical progress. On the other hand, the high wage level of the young indicates that this labor force is scarce, and as per Theorem 1, pollution-biased technical progress will also be stimulated. Thus, we consider the coefficient of this indicator to be negative.

4.3. Indicator of research and development strength (RD)

We refer to the ratio of R&D expenditure in each area to the total production value in the same area as R&D strength. These data are sourced from the China Statistical Yearbooks on Science and Technology. However, the selection of this indicator poses some issues, as the source of R&D expenditure is not evident from the statistical data, and thus, the accuracy of the regression results may be directly affected. Therefore, to differentiate between inputs from state-owned enterprises and private enterprises, we introduce the cross term of the R&D indicator and the ratio of state-owned enterprises, to express the effects of R&D in state-owned enterprises on environment-biased technical progress. We also introduce the cross term of the R&D indicator and degree of clustering to express the effects of R&D input on environment-biased technical progress under the influence of clustering of state-owned enterprises. In this case, the conclusions will be more precise. Our theories indicate that the coefficients of the cross terms should be preliminarily judged as positive, while the sign of the coefficient of R&D cannot be decided yet.

4.4. Indicator of openness (open)

Since the 1990s, offshore outsourcing has been favored by developed countries for its absolute cost advantage. The transfer and restructuring of global industries has occurred gradually and has further influenced the direction of technical change in the affected countries (Feenstra and Hanson, 2000; Krugman, 2000; Xu, 2001). Jaffe et al. (2003) considered that the influences of social and economic activities on the environment are deeply affected by the speed of technical change and its direction. Some new technologies may reduce or replace activities that pollute the environment, while others may increase environmental pollution, as evidenced in some developing countries. On the other hand, the trading with developed countries also leads to the overspill effects of technology. Hence, we use dependence on foreign trade to measure the degree of openness for each area. In line with the data presented in the China Statistical Yearbook, dependence on foreign trade is expressed by the ratio of total export–import volume for each area in each year to the GDP in the previous year. As different types of trade stimulate different technologies, we cannot decide whether the coefficient of this indicator is positive.

Table 1
Descriptive statistics of all the variables used in this study.

Variable	Quantity	Mean value	Max. value	Min. value	Standard deviation	Sign of the estimation coefficient
E	330	1.128	1.335	0.484	0.845	/
age	330	0.107	0.118	0.096	0.037	−
Stat	330	0.392	0.997	0.014	0.287	+
Clu	330	0.186	0.314	0.111	0.052	+
w	330	0.014	0.027	0.002	0.024	+
RD	330	0.332	1.071	0.002	0.218	?
RD × *Stat*	330	0.076	0.103	0.024	0.048	+
RD × *Clu*	330	0.059	0.066	0.042	0.036	+
open	330	0.125	0.139	0.030	1.093	?

As the data for Tibet are missing, we use the data of 30 provinces and cities from 2003 to 2013. The descriptive statistics of all the variables used in this study appear in Table 1.

5. Model estimation and testing

5.1. Preliminary testing of employment and technical progress

Using Eq. (8), we confirm the relationship between the labor employment structure and environment-biased technical progress. In this study, indicator of openness is an exogenous variable, and there is bidirectional causality between the ratio of the aged population and employers in state-owned enterprises. If we use the general estimation approach, there will be strong endogeneity in our models, which may result in inconsistencies and deviations in the estimated coefficients. For example, an increase in the ratio of the aged population will reduce environment-biased technical progress while simultaneously affecting the number of employers in state-owned enterprises and further stimulating environment-biased technical progress. In the presence of such contradictory functions, the general regression equations will underestimate the negative effects of the ratio of the aged population on biased technical progress, returning us to the problem of endogeneity. To resolve this issue, one may think of applying the instrumental variable method. However, in doing so, we would need to select appropriate instrumental variables outside the model, which is difficult in the context of this study. If we use only lagged variables as instrumental variables, then there will be a significant degree of information loss (Arellano and Bover, 1995). Therefore, we adopt the differential generalized method of moments (GMM) and the systematic GMM to ensure the stability and reliability of the estimation results of our model (see Table 2 for details).

The estimation results indicate that the overall fitting precision of the model is relatively high, and most variables pass the test at the 10% significance level. The estimation coefficient of the ratio of the aged population is negative as expected. This indicates that aged people pay more attention to health preservation and environmental protection, and an increase in the ratio of the aged population will enhance

Table 2
Estimation results of our model (variable explained: environment-biased technical progress).

Indicator	Differential GMM	Differential GMM	Systematic GMM	Systematic GMM
C	0.2847***	0.3741***	0.1394***	0.3518***
	(0.0746)	(0.0820)	(0.0247)	(0.1073)
Age	−0.0032***	−0.0014***	−0.0017***	−0.0014***
	(0.0218)	(0.0034)	(0.0030)	(0.0026)
Stat	−0.0427*	−0.0415*	−0.0444*	−0.0381*
	(0.0012)	(0.0020)	(0.0027)	(0.0016)
Clu	0.0204*	0.0322*	0.0279**	0.0217***
	(0.0097)	(0.0151)	(0.0121)	(0.0058)
w	−0.0178**	−0.0124**	−0.0754**	−0.0289**
	(0.0049)	(0.0095)	(0.0031)	(0.0024)
RD	−0.0375**	−0.0512**	−0.0419**	−0.0365**
	(0.0014)	(0.0045)	(0.0120)	(0.0094)
RD ×•*Stat*	0.0022	0.0031*	0.0023	0.0044**
	(0.0017)	(0.0012)	(0.0018)	(0.0015)
RD•×•*Clu*	0.0123	0.0512*	0.0439	0.0304*
	(0.0081)	(0.0142)	(0.0138)	(0.0102)
open	−0.0124**		−0.0381**	
	(0.0067)		(0.0099)	
AR(2) test value	0.37	0.29	0.26	0.34
P value	0.87	0.83	0.78	0.76
Area fixed	Yes	Yes	Yes	Yes
Hansen test value	9.2185	8.3949	9.3284	10.2698
P value	1	1	1	1
Observations	330	330	330	330

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

overall awareness regarding environmental protection in the labor force. In the model, the aged population holds both capital and power. They stipulate environmental protection policies to ensure that the production process is low-carbon and environmentally friendly, which incentivizes environmental technology improvements. However, the estimation coefficient of the ratio of state-owned enterprises is negative, which indicates that this indicator will hinder environment-biased technical progress. This is contradictory to our expectations. This may be because the ratio of state-owned enterprises is calculated through the profits of state-owned enterprises. In China, state-owned enterprises reflect the will of the state. In some highly polluting industries, such as petroleum, steel, and coal, although the ratio of state-owned enterprises is high, they do not invest a part of their profits in environmental protection technology. On the contrary, the clustering of state-owned enterprises apparently promotes environment-biased technical progress. Generally, the Hoover coefficient is only used for measuring clustering effects among industries because governments in developed countries do not participate in the production and operation processes at enterprises, and communications among enterprises are only limited to the industrial level. However, in China, the government has absolute control on state-owned enterprises, so much so that their general managers can be transferred by the government. This results in cross-industry cooperation. Hence, we innovatively adopt the Hoover coefficient to measure the degree of clustering of state-owned enterprises. The results of the model indicate that a higher degree of clustering of state-owned enterprises further stimulates environment-biased technical progress. This indicates that resource allocation among state-owned enterprises by the national government through macro-control boosts technical progress and optimizes the development of enterprises.

The estimation coefficient of the R&D indicator is negative and significant at the 5% level. Although state-owned enterprises generally reflect pollution-biased technical progress, there is some quantity of environment-biased technical progress too. Polluting products can bring more benefits to enterprises. Thus, enterprises will have more impetus to stimulate pollution-biased technical progress, as per Theorem 1. Thus, the estimation result of R&D indicator just matches the estimation results of the state-owned enterprises. The estimation coefficient of the cross term of the indicators for R&D and state-owned enterprises is positive, which means that R&D in state-owned enterprises stimulates environment-biased technical progress. Similarly, under the influence of industrial clustering, optimized allocation of resources in state-owned enterprises will also stimulate environment-biased technical progress. The estimation coefficient indicates that the effect of clustering of state-owned enterprises is stronger than that of R&D. However, the estimation coefficient of this cross term is significant at 10% only and becomes insignificant when the variable of openness is introduced. We consider that this may be attributed to the improper selection of the ratio of state-owned enterprises as an indicator. Hence, further research is necessary in this regard.

5.2. Retesting employment and technical progress

We use the ratio of profits of state-owned enterprises to the profits of all enterprises to calculate the ratio of state-owned enterprises. The estimation coefficient is negative contrary to our expectation. We consider that our selection of this indicator may not be incorrect. Therefore, we replace the original indicator with the ratio of annual average employment in all state-owned industrial enterprises in each area to the annual average employment in all state-owned and above-designated-size private enterprises and conduct the estimation again using model (8). Table 3 provides the results of the estimation using the new indicator.

Table 3 shows that the estimation coefficient of the ratio of state-owned enterprises is positive, which indicates that an increase in the number of employers at state-owned enterprises can bring about environment-biased technical progress. However, the first and third equations are not significant and the second and fourth equations are significant at the 10% level only. These results raise similar concerns as before. Theoretically, the ratio of the aged population and the ratio of state-owned enterprises are strongly correlated. To avoid this problem, we selected the profits of state-owned enterprises in our preliminary test, but the estimation result was negative. We selected an indicator for retesting, but the estimation coefficient is not significant. However, it is gratifying that the regression coefficient of cross term of the ratio of state-owned enterprises and R&D is significant at 5%, as is the cross term of R&D and the clustering level of state-owned enterprises.

Table 3
Estimation results of our model using the new indicator (variable explained: environment-biased technical progress).

Indicator	Differential GMM	Differential GMM	Systematic GMM	Systematic GMM
C	0.3107*** (0.0814)	0.4083*** (0.0895)	0.1521*** (0.0270)	0.3840*** (0.1171)
Age	−0.0035*** (0.0238)	−0.0015*** (0.0037)	−0.0019*** (0.0033)	−0.0015*** (0.0028)
Stat	0.0466 (0.0013)	0.0453* (0.0022)	0.0485 (0.0029)	0.0416* (0.0017)
Clu	0.0223* (0.0106)	0.0351* (0.0165)	0.0305** (0.0132)	0.0237* (0.0063)
w	−0.0194** (0.0053)	−0.0135** (0.0104)	−0.0823** (0.0034)	−0.0315** (0.0026)
RD	−0.0409** (0.0015)	−0.0559** (0.0049)	−0.0457** (0.0131)	−0.0398** (0.0103)
RD × Stat	0.0024** (0.0019)	0.0034** (0.0013)	0.0025** (0.0020)	0.0048** (0.0016)
RD × Clu	0.0134** (0.0088)	0.0559** (0.0155)	0.0479** (0.0151)	0.0332** (0.0111)
open	−0.0135** (0.0073)		−0.0416** (0.0108)	
AR(2) test value	0.38	0.36	0.46	0.44
P value	0.89	0.91	0.86	0.88
Area fixed	Yes	Yes	Yes	Yes
Hansen test value	9.5148	9.6584	9.6442	10.2774
P value	1	1	1	1
Observations	330	330	330	330

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

6. Conclusions

Environment-biased technical progress is an important factor influencing environmental quality. Then, which factors influence technical progress bias? The previous literature has not studied this question. Using the OLG model, we discussed the effects of the labor force employment structure on the direction of technical progress. Our results provide new insights into the causes of technical progress and contribute to the theoretical literature on the direction of technical progress. We also proposed a new perspective for researching the relationship between employment structure and environmental quality. Environmental technical progress influences environmental quality, and the labor employment structure can affect technical progress through its influence on industrial structure. Our study provided a unique perspective in that the labor employment structure can affect environmental quality through the direction of technical progress.

As per the model in this study, the scarcity of factors decides the direction of technical progress. However, our results show that an increase in the ratio of the aged population will reduce the labor force input as well as stimulate pollution-biased technical progress, and conversely, also reduce total savings. The results of our empirical analysis indicate that the former exerts a stronger influence.

The empirical analysis shows that China's degraded environment in recent years can be attributed to the production biasness of technical progress; that is, technical progress favors improvements in production efficiency. Increasing global economic integration exerts stricter environment-related requirements on Chinese exports, which points to the need for paying heed to environment-biased technical progress alongside improvements in production-biased technical progress. China's current employment structure is characterized by the majority stake of the state in the country's enterprises. Hence, environmental quality improvements can only come about by speeding up reforms at state-owned enterprises and by stipulating rigid environmental regulations and policies that force these enterprises to improve environment-biased technical progress. Improvement in environmental technologies by these enterprises will affect certain production factors, and the enterprises will need to increase their capital stock and labor force to maintain their original production levels. Doing so will lead to a virtuous cycle of economic benefits and environmental protection.

Acknowledgement

This work was supported by Major Projects in Philosophy and Social Science Research of the Ministry of Education of China under Grant No. 14JZD031, the Program for New Century Excellent Talents in University under Grant No. NCET-12-0595, the National Natural Science Foundation of China under Grant Nos. 71171001 and 71471001, China Postdoctoral Science Foundation under Grant No. 2015 M570613, Special Project of Postdoctoral Innovation Projects of Shandong under Grant No. 201503013, and Natural Science Foundation of Shandong, China, under Grant No. ZR2015PG003.

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