Menggang Li · Qiusheng Zhang
Runtong Zhang · Xianliang Shi
Editors

Proceedings of 2014 1st International Conference on Industrial Economics and Industrial Security

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Preface

This volume contains the proceedings of the 2014 International Conference on Industrial Economics and Industrial Security (IEIS'2014), held in Berkeley, California, USA, and Beijing, China, hosted by the School of Economics and Management, China Center for Industrial Security Research and International Center for Informatics Research of Beijing Jiaotong University (BJTU) in cooperation with University of Reading(UK) and University of California at Berkeley, and supported by FP7 (7th Framework Programme), the National Natural Science Foundation of China (NSFC), and K. C. Wong Education Foundation (Hong Kong).

The conference was held in cooperation with the International Journal of Sustainable Development and Planning (EI Compendex), International Journal of Design and Nature and Ecodynamics (EI Compendex), International Journal of Safety and Security Engineering (EI Compendex), and Pakistan Journal of Statistics (SCI).

With economic globalization, industries in each country have been presenting new phenomena, new situations and new challenges. Thus there is a necessity for academics to conduct in-depth research on industrial organization, industrial structure, industrial development, industrial distribution, industrial policies as well as the theories of industrial security in globalization. The International Conference on Industrial Economics and Industrial Security (IEIS) was initiated under such backgrounds. Focusing on strategic demands of industrial economy and of industrial security in every nation, this conference is to provide a forum for scholars and practitioners in the world to discuss the problems in industrial economics and industrial security theories and practices. It aims to provide insights into solving problems in national economy, social development and economic security.

IEIS 2014 received 168 paper submissions from five countries and regions. Eighty eight papers were accepted and published after strict peer reviews. The total acceptance ratio is 52.3 %. Additionally, a number of invited talks, presented by internationally recognized specialists in different areas, have positively contributed to reinforce the overall quality of the conference and to provide a deep understanding of related areas.

The program for this conference required the dedicated efforts of many people. Firstly, we must thank the authors, whose research and development efforts are recorded here. Secondly, we thank the members of the program committee and the additional reviewers for valuable help with their expert reviewing of all submitted papers. Thirdly, we thank the invited speakers for their invaluable contribution and the time for preparing their talks. Fourthly, we thank the special session chairs whose collaboration with IEIS was much appreciated. Finally many thanks are given to the colleagues from BJTU and Berkeley for their hard work in organizing this event.

Extended and revised versions of the selected papers will be recommended for publication in special issues of the above mentioned four international journals.

We hope you all enjoyed an exciting conference and an unforgettable stay in Berkeley, California, USA, or in Beijing, China. We hope to meet you again next year for the IEIS 2015 at Universitat Politècnica de Catalunya, BarcelonaTech, the details of which will soon be available at http://icir.bjtu.edu.cn/ieis2015.

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Contents

Part V Special Session on Cultural Industry

Part VI Special Session on National Economy

Part I
Industrial Economics

The Financing of Small and Medium-Sized Enterprises' Strategy

Rongdong Zhang and Bing Huang

Abstract The economy in our country get the steady and rapid development, a large number of small and medium enterprises effectively improve the rate of employment, stimulating the development of local economy. However, since twenty-first century, the development of small and medium-sized enterprises has encountered development bottleneck, generally reflected in the financing problem. On this basis, this paper from the financing and enterprise development strategy point of view to analyze the current problems, and puts forward some views on this problem.

Keywords Small and medium sized enterprises • Financing • Development strategy

1 Introduction

Financing, the financing of small and medium-sized enterprises expensive has become an indisputable fact, but the small and medium-sized enterprise has become the most active one subject in modern market economy China, small and medium-sized enterprises to become bigger and stronger cannot do without financial support, short-term funds or financing channel is not smooth is already one of the small and medium sized the core problem of enterprise growth. At present, the most effective method of enterprise financing through the equity financing or the issuance of corporate bonds, but these two methods because of the small and medium-sized enterprise strength is not enough, corporate credit rating is low, can be said to the small and medium-sized enterprise survival in the line, at any time may disappear, so these two kinds of financing ways are not suitable for small and

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medium enterprises. Small and medium-sized enterprises to obtain funds to support the channel is invisible is limited, indirect financing to bank loans as the main way, and the reality that this is almost the only channel of financing development due to small and medium-sized enterprises or banks, the same is not optimistic [1].

According to the survey, found that the small and medium-sized enterprise development speed is slow, difficult is easy to cause the enterprise capital chain rupture or even bankruptcy reason, small and medium-sized enterprises are in the absence of exogenous financing situation, take the endogenous financing way to enterprises will own savings (including retained earnings, depreciation and fixed liabilities) continuously into investment, which causes the enterprise development speed is slow but also great risks. This mode of financing has become the main mode of financing of small and medium-sized enterprises, which led directly to the small and medium-sized enterprise for R&D funds less or even not the only a little money into R&D and market the new product marketing, in the course of time, the development of small and medium-sized enterprises lack of innovation capability, product only imitated or copied or stay in place, market share will not expand or shrink, more and more low profit margins, the development of this vicious spiral will seriously hinder enterprise even may lead to the enterprise product backlog, capital chain rupture initiation of bankruptcy.

2 The Financing Strategy

2.1 Financing Is Not Smooth in Product R&D Blocked

Small and medium-sized enterprises especially private small and medium-sized enterprises, because of its short history, small scale, poor ability to resist risks and other reasons, led to the development of enterprises and win in the market competition and improve core competitiveness, the only way is to rely on R & D. Start early, the traditional mode of development has now has a certain scale enterprises do not adapt to the present small and medium-sized enterprises. To develop the means to invest, also cannot do without financial support, natural financing problem has come up, and become a key link. In other words, the small and medium-sized enterprise to the smooth development, bigger and stronger, and timely product innovation depends on Financing whether can succeed, otherwise it will seriously hinder the development of small and medium sized enterprises [2].

2.2 Poor Financing Led the Market Development

Now the market is already not the era of the planned economy, but from all walks of life become white hot competition in the market economy, small and medium-sized enterprises as a later how to share a cup of a thick soup in the fierce market, cannot do without market development. In addition to good products to foreign market development measures need to open up a market, small and medium-sized enterprises by virtue of its own strength is difficult to compete with the giants on the market tide, only difference. Often the difference of behavior is not consistent with the habits of consumers, which requires the cultivation of user habit that is often said that to develop the product market, this also cannot do without strong financial support, if financing is not successful, will directly lead to the lack of funds led to the market development is slow, good product or idea easily by industry giants imitate and beyond, causes the enterprise cannot be developed or acquired, growth and development of small and medium-sized enterprises seriously hinder [3].

2.3 Poor Financing Leads to Lack of Personnel

We know that the enterprise and talents are closely related, if not outstanding talents, the development of enterprises that is simply Arabian Nights, how to obtain the outstanding, outstanding talent with the development of enterprises and the ability to retain talent? Needless to say, this requires favorable treatment and bright occupation development prospects, which requires the enterprise to pay relatively high human cost, this is on one hand. On the other hand, enterprises need to carry on training to the employees of existing enterprises, upgrade the existing employee occupation skill training and occupation accomplishment, to the small and medium-sized enterprise oneself actual strength is very difficult to do or is difficult to do a good job, often by the decision-makers of enterprises to reduce the cost of enterprise name directly to ignore or cope with the past, so that enterprises lack vitality and dynamic intellectual innovation, make the enterprises lack of stamina, hinders the small and medium-sized enterprises bigger and stronger, dream [4].

2.4 Poor Financing Increased Production Costs

As everyone knows, enterprises to reduce production costs in addition to technical innovation, optimization of process flow, is a large-scale, integrated production. Due to the small and medium-sized enterprise technical force is relatively weak, rely on technological innovation to reduce the cost of production in a short period of time is difficult to achieve, but also unrealistic. Can only make use of the existing technical conditions for mass production, which is the most reliable and feasible, it must need a lot of money to equipment and recruitment launched large enough production personnel and corresponding supporting staff and management personnel, if the financing channels blocked poor words, no money, no able to form scale production, only small-scale production lead to the production costs are high, the lack of price and quality advantages in the market, seriously affecting the expanded reproduction of the enterprise profit and [5].

3 In View of the Financing Difficulty

3.1 The Use of Advanced Technology Research Efforts

The small and medium-sized enterprise managers when making business decisions, should be aware of the company, the current development trend and market demand and the actual strength of the enterprise, cannot be instant success, blind optimism, the blind pursuit of enterprises temporarily benefit. Look to put in the long run, making a good development of the company's strategy, the author thinks, the small and medium-sized enterprise first to put the limited resources is preferred to the research and development of products, only the truly innovative, made with different products and industry giants, and then actively seek financing, injection for foreign capital. You know, the small and medium-sized enterprise financing difficult why, one point is the small and medium enterprises make the products lack of scientific and technological content, can't let investors have a strong willingness to invest, natural financing difficulties. Only doing good product is the best means of investment.

3.2 Reduce the Financial Pressure

The small and medium-sized enterprise with money from two aspects, one is the endogenous money, another is foreign capital, foreign capital injection in difficult and channel not unobstructed situation, can make more in line with the actual business of advanced marketing strategy, play safe, open up the market expanding share, as far as possible for the enterprise sell more products and timely recovery of funds, develop steadily, not all aggressive, timely sales timely recovery of funds, to ease the pressure on enterprise funds, reduce the financial cost.

3.3 Establish the Alliance of Enterprises

The small and medium-sized enterprise strength is often poor, anti-risk ability is poor, small and medium-sized enterprises in this case can be considered to find and with the cooperation between the enterprises bundled against risk together, common development, division of labor to reduce operating costs. In the selection of enterprises, to give priority to and the enterprise to the common development of enterprises as partners, to exchange information timely seize market opportunities, to resist market risk, through the integration of enterprise alliance of enterprise resources, cooperation, mutual reciprocity and mutual benefit, and formed a new organization system. Let the enterprise alliance in each member enterprise can by force, the high quality resources inside and outside the enterprise integration, improve the overall competitive advantage, to create extraordinary competitive advantage, establish common interests body. The strategic alliance is a partnership of strategic thinking, can let the small and medium enterprises in the same industry to avoid killing each other lead to vicious competition in the way of thinking evolved into mutual cooperation, mutual win-win cooperation, the strategic alliance of small and medium enterprises can realize the small and medium-sized enterprise vision and is the most effective and feasible method.

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Differences of Environmental Policy Timing Among Provinces in Chinese Mainland: A Real Options Methodology

Chengli Zheng and Yan Chen

Abstract According to differences among Chinese provinces, especially economic growth and environmental production technology, real options model is used to analyze implementation timing of environmental policies and its main factors under the uncertainty framework. The closed solution and empirical analysis shows that the most important factor of environmental policy timing is technical parameters of environmental production, followed by economic scale and growth, and the disutility parameters caused by environmental pollution, policy implementation cost, the subjective discount factor. As a controllable parameter, the emission reduction ratio required also play an important role. The differences among Chinese provinces require the flexibility of environmental policy, not rigidly uniform.

Keywords Environmental policy • Execution timing • Real options • Emission trade

1 Introduction

To mitigate the environmental problem, the whole world is doing something, including China. The amount of carbon emission per unit of GDP in China is promised to reduce by 40–45 % of that from the year of 2005–2020. However, it is a very difficult task for the country in the key stage of industrialization and urbanization process. How and when to execute the new environmental policy is very important. And, because of differences among the provinces, especially the difference of economic development level, the optimal timing for new policy must be different for them. This is the theme of our paper here. Most of literatures about

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environmental policy apply the cost-benefit analysis, in which only the present value of cost and benefit are considered (see Cropper and Oates [1]). However, this method fails to capture uncertainties and timing option in adopting a new policy. To solve this problem, real options analysis are used in many environmental literatures such as Pindyck [2], Wirl [3]. It is because that environmental decision-making can be viewed as an American option. Based on Pindyck [4] model, Nishide and Ohyama ([5], NO here after) apply the real options to treat the uncertainty of execution timing of policy. They think that the policy maker must consider the economic size when make a decision about GHG emission for the country, because the stock and flow of pollutants depend strongly on the economic size. Empirical research confirms this, see Azomahou et al. [6]. Empirical evidences show that certain types of environmental pressure exhibit an inverted-U relationship with per capita income, which is called environmental Kuznets curve (de Bruyn et al. [7]). However, it is pointed out that every country does not always trace a similar Kuznets curve, and the relationship between GDP and pollutants are different across different countries. So, how does the economic size and growth give impact on the execution timing of environmental policy? Under the framework of NO, we apply real options method to investigate the optimal execution timing of new environmental policy in Chinese Mainland, considering their differences in economic growth and environmental production technology. We extend the NO model with three aspects. The closed solution and empirical analysis for China are presented.

2 The Model and Its Solution

We consider an environmental policy optimization problem with some modifications based on NO model. Firstly, we assume that policy execution cost is random, which is fixed in NO model. Secondly, in contrast to the assumption of NO that once new policy was executed, pollution emissions declined immediately to the required level, we let emissions decreased with the time on the basis of actual policy requirements. Our assumption is consistent with the real situation. And, we consider the consumer price index (CPI) for all the related variables, such as GDP.

Assume one decision-making for new environmental policy is to reduce pollutant emission, which will impact the level of GDP. At time t, GDP is denoted by Y_{ot}, CPI is denoted by C_t, and GDP deflated by CPI: $Y_t = Y_{ot}/C_t$. Suppose that Y_t follows the process: $dY_t = \mu_Y Y_t dt + \sigma_Y Y_t dz_t^Y$, where z_t^Y is the standard Brownian motion, expected growth rate μ_Y and volatility σ_Y are constants. Here, it means that the GDP is independent of the environmental policy. Then, the stock of pollutant is M_t which evolves according to $\dot{M}_t = \beta_t (Y_t)^{\xi} - \delta M_t$, where $\beta_t(Y_t)^{\xi}$ is the pollutant emission amount at time t, ξ is a constant; δ is the rate of natural decay of pollutants. The equation means that the increment of pollutants for every year is the difference of pollutant emission amount and the natural decay amount. The pollutant emission amount $\beta_t(Y_t)^{\xi}$ is related with the GDP. Assume that new environmental policy is executed at time τ, and at time $t < \tau$ (before execution) $\beta_t = \beta_N$. The new policy requires that the pollutant emission amount for per GDP must decrease by $\alpha\,\%$ of last year from time τ, namely $E\left[\beta_t (Y_t)^{\xi-1} / \left(\beta_{t-1} (Y_{t-1})^{\xi-1}\right) | t-1, t \geq \tau+1\right] = 1-\alpha\%$. So, we have $\beta_t = \beta_{t-1}(1-\alpha\%)\exp\left(-\left[\mu_Y(\xi-1) + \sigma_Y^2(\xi-1)(\xi-2)/2\right]\right)$. With the time elapsing, pollutant emission amount for per GDP will decrease to a stable level but not to zero. We assume it is $\beta_{t\to\infty} = \beta_G$. Apparently, after executing the new policy, the approximate result is $\beta_t = \beta_G + (\beta_N - \beta_G)e^{-\beta(t-\tau)}, \quad t \geq \tau$, where $\beta = -\log(1-\alpha\%) + \mu_Y(\xi-1) + \sigma_Y^2(\xi-1)(\xi-2)/2$. So we have:

$$\dot{M}_t = \begin{cases} \beta_N (Y_t)^{\xi} - \delta M_t, & t < \tau \\ \left[\beta_G + (\beta_N - \beta_G)e^{-\beta(t-\tau)}\right](Y_t)^{\xi} - \delta M_t, & t \geq \tau \end{cases} \tag{1}$$

It is very different from NO model. There, once the new policy is implemented, the pollutant emission amount decrease to the level required, namely $\beta_t = \beta_G, \quad t \geq \tau$. This is not the real thing. However, our treatment approaches the real situation. The damage by pollutant is called disutility, which translates the damages into monetary cost, and reflects change in preference and technologies. We denote disutility from a unit amount of pollutant at time t by θ_t, and assume that it follows the process $d\theta_t = \mu_\theta \theta_t dt + \sigma_\theta \theta_t dz_t^\theta$, where z_t^θ is the standard Brownian motion. We assume that the decision maker determine the timing to execute the new policy in order to minimize the social costs associated with environmental damage and sunk costs associated with execution of new policy. Specifically, the objective function is as

$$\sup_{\tau \in T} E_0 \left[\int_0^\infty -\theta_t M_t e^{-\phi t} dt - K_\tau e^{-\phi \tau}\right] \tag{2}$$

in which K_τ is the social costs associated with execution of new policy. In NO model, social costs K is fixed. However, K_τ changes with time. In fact, we suppose that $K_\tau = kY_\tau$ with a constant k, which means that it is random. T is the admissible set for implementation times. ϕ is the subjective discount rate reflecting the time preference of policy maker. From Eq. (2), we can see it is just an optimal stopping-time problem. Recently, because of swift growth of emission trade market, its market price p_t can be one alternative for the social costs θ_t associated with environmental damage, see Insley [8] in detail. We apply the same method as NO model: $p_t = E\left[\int_t^\infty e^{-\phi(s-t)}\theta_s\left(e^{-\delta(s-t)}\right)ds|\theta_t\right] = \theta_t/(\phi+\delta-\mu_\theta)$. Assume that the stock of pollutants before and after executing the new policy are M_{Nt}, M_{At} respectively. Then the objective function (2) can be rewritten as

$$V_1 + \sup_{\tau \in T} E_0 \left[\int_\tau^\infty -\theta_t (M_{At} - M_{Nt}) e^{-\phi t} dt - K_\tau e^{-\phi \tau}\right] \tag{3}$$

Where V_1 is constant, and the other part can be viewed as American call option with unlimited term and variable strike price. We denote $\zeta_t = \theta_t (Y_t)^{\xi}$, which is a diffuse process with: $\mu_\zeta = \mu_\theta + \xi\mu_Y + \rho_{\theta Y}\xi\sigma_\theta\sigma_Y + \xi(\xi-1)/2\sigma_Y^2$, $\sigma_\zeta = \sqrt{\sigma_\theta^2 + 2\rho_{\theta Y}\xi\sigma_\theta\sigma_Y + \xi^2\sigma_Y^2}$, $\rho_{\theta Y}$ is the correlation efficient between the growth rate of Y_t and θ_t. The optimal execution of the new policy can be stated as proposition 1.

Proposition 1 Suppose that $\phi > \max(\mu_\theta - \delta, \mu_\zeta)$, then the optimal execution timing (stopping time) takes the form of $\tau = \inf\{t \geq 0, \chi_t \geq \chi_B\}$, and

$$\chi_B = p_B\beta_N Y_B^{\xi-1} = \left[\gamma(\phi - \mu_\zeta)(\phi - \mu_\zeta + \beta)\beta_N k\right]/[(\gamma-1)\beta(\beta_N - \beta_G)] \quad (4)$$

where $\gamma = \left[-\mu_\zeta + \sigma_\zeta^2/2 + \sqrt{\left(\mu_\zeta - \sigma_\zeta^2/2\right)^2 + 2\phi\sigma_\zeta^2}\right]/\sigma_\zeta^2$ and χ_B is the trigger value.

In fact, τ is hitting time. When a stochastic variable obtain the threshold value at the first time (hitting time), it trigger the event of implementation for new policy. The proof is omitted. $\chi_t = p_t\beta_N Y_t^{\xi-1}$ is the social cost associated with pollutant per unit of GDP, which means that every unit of GDP must bear χ_t amount of social cost associated with pollutants; namely, the proportion of one unit GDP must be offset by the social cost associated with pollutants. χ_t is a diffuse process with $\mu_\chi = \mu_\zeta - \mu_K - \rho_{\zeta K}\sigma_\zeta\sigma_K + \sigma_K^2$, $\sigma_\chi = \sqrt{\sigma_\zeta^2 - 2\rho_{\zeta K}\sigma_\zeta\sigma_K + \sigma_K^2}$, $\rho_{\zeta Y}$ is the correlation efficient between the growth rate of Y_t and ζ_t. When $\chi_t < \chi_B$, it means that holding on the old policy can produce more value than executing new policy, so the old policy must be held on. When $\chi_t \geq \chi_B$, it means that the social cost associated with pollutant per unit of GDP is too high, holding on the old policy can produce less value than executing new policy, so the new policy must be executed. The decision-maker observes the real situation of economy and environment system, and evaluates χ_t, then makes a decision about the environmental policy according to proposition 1. Figure 1 displays four kinds of possible situation, which correspond to four kinds of possible paths for $\chi_{it}(i = 1, 2, 3, 4)$.

From proposition 1 and the four situations in Fig. 1, we have following the corollary 1 about the optimal timing of new policy. The proof is easy, so we omitted.

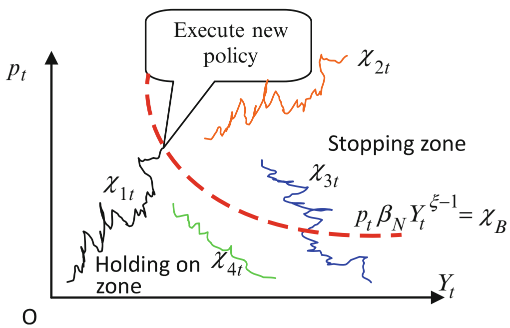

Fig. 1 Threshold value of new policy

Corollary 1 The expected time to the new environmental policy execution is:

$$E[\tau|\chi_0] = \log(\chi_B/\chi_0)/\left(\mu_\chi - \sigma_\chi^2/2\right) \quad \text{if} \quad \chi_B \geq \chi_0, \mu_\chi - \sigma_\chi^2/2 > 0;$$
$$E[\tau|\chi_0] = 0 \quad \text{if} \quad \chi_B < \chi_0; \quad \textit{else} \text{ it is} \quad E[\tau|\chi_0] \to \infty \tag{5}$$

From the proposition and corollary above, we can see that the optimal execution timing is related with many factors, such as the economy (GDP size, growth rate and volatility), environmental technology (amount of pollutant emission during the production), social costs to manage the pollutants, disutility (pollutants emission trade market price as a substitute) and time preference for pollutants. Each decision-maker can determine execute the new policy or not and the optimal timing of execution according to the proposition and corollary and their own parameters.

Moreover, from the formula (5), we know that the relationship between the threshold value and expected hitting time is not monotonous. It can explain environmental Kuznets curve to some extent, combining with the proposition 1. Supposed that some a country has a very high $\xi > 1$ at initial stage, this situation is similar to χ_{1t} in Fig. 2. When GDP increases to a size that can trigger the threshold value and the new policy is executed. The new policy will decrease ξ gradually or lead to $\beta_N \to \beta_G$. With a series of new policies implementation one after another in a long run, the relationship between environmental pressure and per capita income will finally exhibit an inverted-U curve, namely environmental Kuznets curve. Because the factors for different countries are different, it will exhibit different types of environmental Kuznets curve.

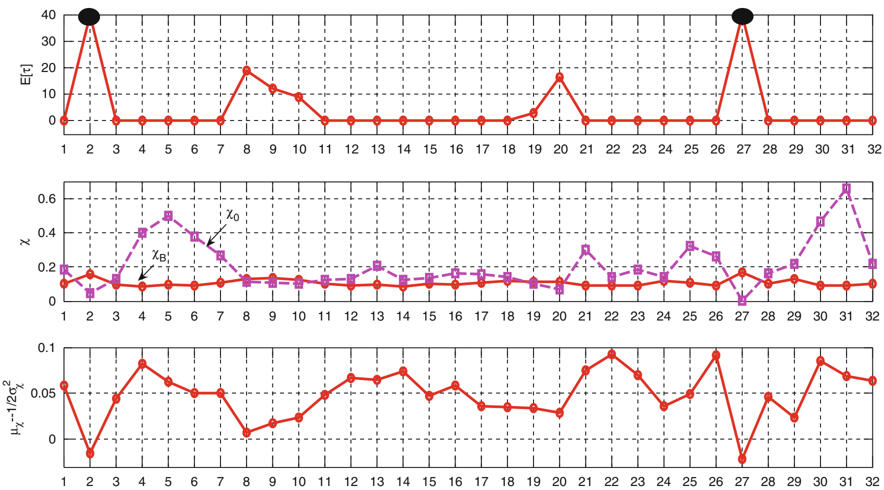

Fig. 2 Threshold value and optimal expected time for provinces in Chinese Mainland. Middle: χ_B*-real line with dot marks*; χ_0*-dashed line with square marks*

3 Empirical Analysis for Provinces in Chinese Mainland

We apply the model and result in above section to analyze the optimal timing of new environmental policy execution for provinces in Chinese Mainland. There are many kinds of pollutants. But we only take carbon emission reduction policy as an example. We have 32 decision-making Units (including 31 provinces and whole China). For convenience, all the units are given a number from 1 to 32, they are: whole China, Beijing, Tianjing, Hebei, Shanxi, Neimeng, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujiang, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Xizang, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang. Data includes annual GDP, CPI, CO2 emission amount from the year of 1992–2010. The data for disutility is substituted by carbon trade market data (CERs price data from ECX, website of Bluenext). Then, the data is pretreated. GDP is deflated by CPI. We estimate the growth rate μ_Y and volatility σ_Y of GDP for all the provinces. Then β_N and ξ are estimated through the relationship that the CO_2 emission amount equals $\beta_N(Y_t)^{\xi}$. The rate of natural decay of pollutants $\delta = 0.0041$. It is the same as NO model. NO select $\beta_G = \beta_N/10$ according to Factor 10 in European Union. We take the same method as them. And according to the promise of our central government, we take $\alpha\% = 20\%$ and will change it for different situations. Then β can be computed. According to Factor 10, NO estimated that the social cost associated with the execution of new policy is 25 % of GDP, so we take $k = 0.25$. And $\mu_\theta = \mu_p$, $\sigma_\theta = \sigma_p$, $p_t = e_t CER_t$, where CER_t is the market spot price of CER and e_t is the exchange rate. p_t is deflated by CPI. Then we compute the parameters such as $\rho_{\theta Y}$,μ_ζ,σ_ζ,$\rho_{\zeta K}$ and μ_χ, σ_χ. According to proposition 1, it must satisfy $\phi > \max(\mu_\theta - \delta, \mu_\zeta)$. Yield of treasury bonds is not suitable, because it is too low (about 4 % annually). The growth rate of Chinese GDP is very high, many provinces exceed 10 % annually. At the meantime, the price of carbon trade increase by 10 % averaged annually, even by 46 % in the year of 2005. This leads to the results that μ_ζ of provinces in China are very high, some of them reach to 23 %. So, we select $\phi = 0.25$ for all provinces. Then, γ can be calculated. After completing calculation for all the parameters for the model, we compute χ_B and $E[\tau|\chi_0]$ according to formulas (4 and 5). The current time is the year of 2011. So the current χ_0 is computed from 2011. Some results are showed in Fig. 2, other results are omitted because of limit of space of the paper. Because the expected time $E[\tau|\chi_0]$ mainly depends on three synthesized factors (namely he threshold value χ_B, current χ_0 and expected growth rate of χ_t), the threshold value χ_B and χ_0 (the current social cost associated with pollutant per unit of GDP), $\mu_\chi - \sigma_\chi^2/2$ and $E[\tau|\chi_0]$ for every decision unit are showed in Fig. 2. The unit of $E[\tau|\chi_0]$ is years. For Beijing and Xizang, 40 years just means the need not to execute.

From Fig. 2, it shows that almost all the provinces in Chinese Mainland need to execute the new environmental policy right now, except a few of them. The situation of the majority is similar to the path χ_{2t} in Fig. 1, where $\chi_0 > \chi_B$, and $\mu_\chi - \sigma_\chi^2/2 > 0$. In the exceptions, Jilin, Heilongjiang, Shanghai, Hunan and Guangdong (no. 8–10, 19–20) can delay some years, which is similar to the path χ_{1t} in Fig. 1, where $\chi_0 < \chi_B$, but $\mu_\chi - \sigma_\chi^2/2 > 0$. However, Beijing and Xizang (no. 2 and 27) need not execute the new policy at all. Beijing as the capital does better than other provinces, and will goes on this way. There are few industries in Xizang, so it emits a small amount of pollutants. And their $\mu_\chi - \sigma_\chi^2/2$ is negative which means their χ_t will decrease with the time. This situation is similar to path χ_{4t} in Fig. 1. There are no provinces similar to the path χ_{3t}.

4 Conclusion and Discussion

The paper analyzes the optimal execution timing of new environmental policy under the framework of real options. It shows that there are many factors that have impacts on the optimal timing, including economic growth rate, volatility, disutility caused by pollutants, policy execution costs, time preference, environmental technology parameter. The last one is most important, it affect the optimal timing directly. The decision-maker observes the real situation of economy and environment system, and evaluates his own social cost associated with pollutant per unit of GDP compared with the trigger value, then makes a decision about the environmental policy. Under the requirements of the new policy, the local government and the micro units (companies) must adjust the environmental technical parameter through adjusting the industrial structure, improving the production techniques to produce less pollutants, and dispose the pollutants before emission.

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A New Production and Inventory Control System Seeking for Inventory Recovery and Operational Cost Trade-off

Bowei Xu, Yongsheng Yang, Guolong Lin, and Bin Yang

Abstract This paper focuses on the triple feed-forward automatic pipeline, inventory and order-based production control system (TFF-APIOBPCS), by introducing a first order differential feedforward to APIOBPCS. The feedforward mechanism help to mitigate the impact of demand fluctuations and enhance supply chain resilience. In this research, analysis of the relationship between parameters of first order differential feedforward and inventory recovery metric (*ITAE*) is conducted. Operational cost model is constructed. Simulations with a unit step signal as the customer demand evaluate the effect of the feedforward mechanism, and reveal the validity of TFF-APIOBPCS.

Keywords Production control system • Inventory recovery • Operational cost

1 Introduction

Supply chain resilience [1, 2] is affected by production strategies. APIOBPCS [3, 4] can reduce the uncertainty of demand, help to reduce production peaks and troughs, and allow the production and inventory with a little cushion. Virginia et al. [5] used the *ITAE* to evaluate an often used benchmark model of make-to-stock supply chain, and found that optimum solutions for resilience do not yield a system that is robust to uncertainties in lead-time.

In this work, to trade off between the optimal inventory recovery and minimal operational cost, we first propose triple feedforward (TFF) APIOBPCS model by introducing a first order differential feedforward to APIOBPCS. We use *ITAE* (integral of time-weighted absolute value of the error) measure to assess inventory recovery in the case of distinct poles under zero steady-state error. When considering

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the supply chain's goal, operational cost involves inventory cost and production regulation cost. Parameter k_2 variations and impact on inventory recovery and operational cost are verified with simulations.

2 Triple Feedforward APIOBPCS

This paper introduces a feedforward control $G_c(s)$ to APIOBPCS (as shown in Fig. 1), in consideration of feedforward control can compensate or counteract the disturbance effect on the general control system. We call it triple feedforward APIOBPCS (TFF-APIOBPCS) because of three feedforward controls in this system. The actual values of signals in Fig. 1 are expressed by the lowercases. And Laplace transform of each signal is named by the uppercases. T_a, T_i, T_q, T_w and T_p are positive.

Let supply chain system response to a unit step input and $G_c(s) = k_1 + k_2 s$, it is easy to deduce that if $1/T_p + 1/T_w > 0$, $1/\left(T_i T_p\right) > 0$ and $1/T_a > 0$, TFF-APIOBPCS would reach steady state.

3 Inventory Recovery Under Zero Steady-State Error

Inventory recovery is one key performance index to assess supply chain resilience. Therefore, we use *ITAE* to evaluate inventory recovery when $cons(t) = 1(t)$, $k_1 = T_i(T_p - T_q)$ (under zero steady-state error).

One of the poles, p_0 is easily identified ($-1/T_a$) and the other two poles (p_1 and p_2) are equal to the roots of the quadratic equation in the denominator. We use the unit step response to evaluate the impact of system dynamics.

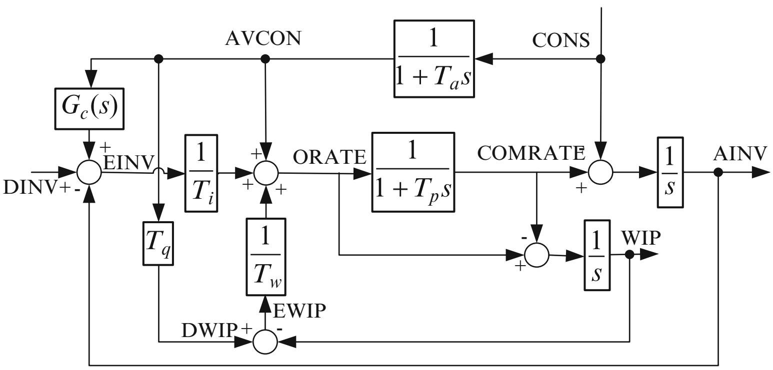

Fig. 1 Block diagram representation of TFF-APIOBPCS

ITAE values are calculated in different pole distributions [5]. In the case of distinct poles: real and/or complex.

$$ITAE = \left| A \cdot T_a^2 + B \frac{\sigma_{p_1}^2 - \omega_{p_1}^2}{\left(\sigma_{p_1}^2 + \omega_{p_1}^2\right)^2} + C \frac{\sigma_{p_2}^2 - \omega_{p_2}^2}{\left(\sigma_{p_2}^2 + \omega_{p_2}^2\right)^2} \right| \quad (1)$$

Where, $A = -\left[T_i T_a \left(T_w + T_p\right) - k_2 T_w\right] / \left[T_i T_p T_a T_w (p_1 + 1/T_a)(p_2 + 1/T_a)\right]$,

$B = -\left[T_p T_a T_i T_w (p_1 + 1/T_a) + T_i T_a \left(T_w + T_p\right) - k_2 T_w\right] / \left[T_i T_p T_a T_w (p_1 - p_2)(p_1 + 1/T_a)\right]$,

$C = -\left[k_2 T_w - T_i T_a \left(T_w + T_p\right) - (p_2 + 1/T_a) T_p T_a T_i T_w\right] / \left[T_i T_p T_a T_w (p_2 + 1/T_a)(p_1 - p_2)\right]$.

For the convenience of analysis, the internal number of the absolute value symbol in Eq. (1) is indicated by $ITAE'$. That is $ITAE = |ITAE'|$.

A, B, C, $ITAE$ and $ITAE'$ are A_0, B_0, C_0, $ITAE_0$ and $ITAE_0'$ when the system is APIOBPCS [3] ($k_2 = 0$). We establish the relation among A, B, C, $ITAE$, $ITAE'$ and A_0, B_0, C_0, $ITAE_0$ in distinct poles. $A = A_0 + k_2 / \left[T_i T_p T_a (p_1 + 1/T_a)(p_2 + 1/T_a)\right]$, $B = B_0 + k_2 / \left[T_i T_p T_a (p_1 - p_2)(p_1 + 1/T_a)\right]$, $C = C_0 - k_2 / \left[T_i T_p T_a (p_2 + 1/T_a) (p_1 - p_2)\right]$, and $ITAE' = ITAE_0' + k_2 \Theta / T_i T_p T_a$. Where $\Theta = \frac{T_a^2}{(p_1 + 1/T_a)(p_2 + 1/T_a)} + \frac{1}{(p_1 - p_2)(p_1 + 1/T_a)\left(\sigma_{p_1}^2 + \omega_{p_1}^2\right)} - \frac{1}{(p_1 - p_2)(p_2 + 1/T_a)\left(\sigma_{p_2}^2 + \omega_{p_2}^2\right)}$ if $\Theta > 0$, $ITAE'$ value increases linearly with increasing k_2. Conversely, $ITAE'$ value decreases linearly with increasing k_2.

Let coefficient of k_2 in Equation $ITAE' = ITAE_0' + k_2 \Theta / T_i T_p T_a$ be λ. T_a, T_i, T_q, T_w, T_p are all sampled in (0,100) using Monte Carlo method according to a Low Discrepancy sequence—Korobov Lattice [6]. Sampling results indicate that $ITAE'$ value changes linearly with k_2 Therefore, *ITAE* value changes linearly or piecewise linearly with k_2.

4 Supply Chain Operational Cost

Suppose that C_h denotes unit stockholding cost, C_p denotes unit stock-out cost, and $IC(n)$ denotes average inventory cost in n cycles

$$IC(n) = \frac{1}{n} \sum_{t=1}^{n} \left\{ C_h [ainv(t)]^+ + C_p [ainv(t)]^- \right\} \quad (2)$$

Where, $x^+ = \begin{cases} x, & x \geq 0 \\ 0, & x \leq 0 \end{cases}$, $x^- = \begin{cases} 0, & x \geq 0 \\ -x, & x \leq 0 \end{cases}$, $C_h [ainv(t)]^+$ denotes stockholding cost in the t^{th} cycle, $C_p [ainv(t)]^-$ denotes stock-out cost in the t^{th} cycle.

We use production regulation cost to describe order rate drifts. $dorate(t)/dt$ denotes the size of the order rate fluctuations per cycle. CO_h denotes unit production regulation cost of a rise in order rate. CO_p denotes unit production regulation cost of a drop in order rate. DC (n) denotes average production regulation cost in n cycles. T_m is the sampling period. For the convenience of implementation, $DC(n)$ is described by difference equation.

$$DC(n) = \frac{1}{n}\sum_{t=1}^{n} \left\{CO_h[orate(t+1) - orate(t)]^+/T_m + CO_p[orate(t+1) - orate(t)]^-/T_m\right\} \tag{3}$$

Operational cost includes production regulation cost and inventory cost. $C(n)$ denotes average operational cost in n cycles. $C(n) = IC(n) + DC(n)$.

5 Simulation

This section starts comparing the performance of APIOBPCS [3] and the TFF-APIOBPCS proposed in the current work with respect to inventory tracking and operational cost decrease. The comparisons are performed by simulating one echelon supply chain with MATLAB under a unit step in the case of distinct poles.

The simulation time is 100 cycles. $dinv(t) = 1$, $cons(t) = 1(t)$, and $ITAE$ values are calculated. Let $C_h = 2$, $C_p = 10$, $CO_h = 20$ and $CO_p = 10$. Their units are million yuan. Our calculations assume that if the actual order rate response is equal to demand, the production regulation cost would not be affected.

To simulate the dynamics for the case of distinct poles in Sect. 3, let $T_\mathrm{p} = 6$, $T_\mathrm{i} = 5$, $T_\mathrm{a} = 12$, $T_\mathrm{w} = 18$, $T_\mathrm{q} = T_\mathrm{p}$ and $k_1 = T_i(T_p - T_q) = 0$. In this case, TFF-APIOBPCS is stable, steady state error is 0. Figure 2a discloses $ITAE$, $IC(n)$, $DC(n)$ and $C(n)$ changes with parameter k_2 under a unit step input. In order to plot $ITAE$, $IC(n)$, $DC(n)$ and $C(n)$ on a figure for compare and analysis their trends of changes with k_2, $ITAE$ values are divided by 250 in Fig. 2a. We see that $ITAE$ value first decreases linearly, and then increases linearly. $DC(n)$ first decreases slightly, and then increases slowly. $IC(n)$ and $C(n)$ first decreases rapidly, and then increases slowly.

Figure 2b discloses $dinv(t)$ and $ainv(t)$ changes with parameter k_2 under a unit step input. Actual inventory fluctuates dramatically and shortage cost is high in APIOBPCS (when k_2 is 0). With the increase of k_2, system response is improved, and the deviation from the target inventory is minimized firstly. And then the actual inventory fluctuations strengthen, shortage cost decreases and stockholding cost increases gradually. When k_2 is 100, the actual inventory exhibits the least volatility.

Figure 2c discloses $cons(t)$ and $orate(t)$ changes with parameter k_2 under a unit step input. Order rate fluctuates dramatically, which leads production to be more volatile with some compromise in increased production regulation cost

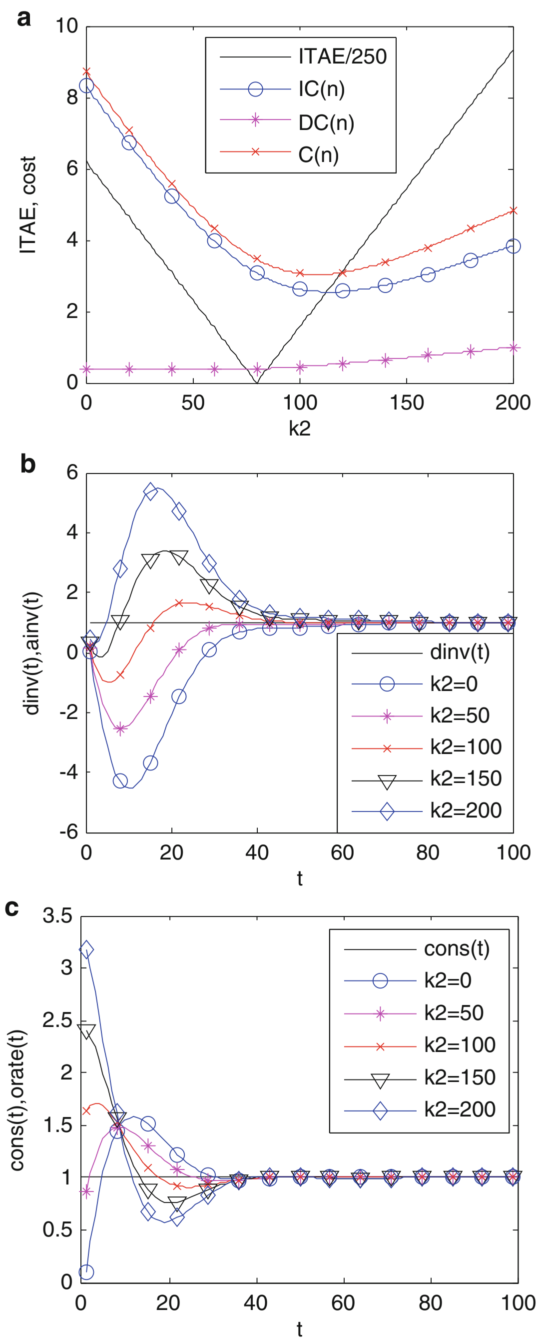

Fig. 2 Dynamic response performance of supply chain system under a unit step input

Table 1 Variations of *ITAE*, *IC*(n), *DC*(n) and *C*(n) under a unit step input

k_2	*ITAE*	*IC(n)*	*DC(n)*	*C(n)*
0	1,550.07	8.33	0.38	8.71
50	581.28(−62.50 %)	4.57(−45.14 %)	0.37(−5.26 %)	4.93(−43.40 %)
100	387.52(−75.00 %)	2.62(−68.55 %)	0.44(15.79 %)	3.06(−64.87 %)
150	1,356.31(−12.50 %)	2.87(−65.55 %)	0.70(84.21 %)	3.57(−59.01 %)
200	2,325.11(50.00 %)	3.83(−54.02 %)	0.99(160.53 %)	4.82(−44.66 %)

when $k_2 = 0$ (APIOBPCS). With the increase of k_2, the order rate drift first weakens, and then strengthens, which verifies production regulation cost first decrease, and then increase in Fig. 2a.

Table 1 discloses values of *ITAE*, *IC*(n), *DC*(n) and *C*(n) under a unit step input when $k_2 = 0$, 50, 100, 150, 200. The percentages of Table 1 in line 3–6 row 2–4 indicate change rates of *ITAE*, *IC*(n), *DC*(n) and *C*(n) values of TFF-APIOBPCS relative to *ITAE*, *IC*(n), *DC*(n) and *C*(n) values of APIOBPCS ($k_2 = 0$). Positive/Negative numbers denote increase/decrease. Table 1 highlights a rather worrying situation that APIOBPCS (when k_2 is 0) has poor inventory recovery (*ITAE* value is 1,550.07) and high cost (*IC*(n) is 8.33, *C*(n) is 8.71). When we take TFF-APIOBPCS and let $k_2 = 100$, the inventory recovery performance improves significantly (*ITAE* value drops by 75 %) and average operational cost decline dramatically by 64.87 %. Therefore, in the process of the actual operation and management, parameter k_2 is suitable for relatively large number (such as 50–100), so as to trade-off between the optimal inventory recovery and minimal operational cost.

6 Conclusions

To sum up, supply chain is a complex system where the customer demand changes with time. In this research, steady state error of TFF-APIOBPCS is analyzed, and inventory recovery under zero steady-state error is assessed. Supply chain operational cost model is constructed. Supply chain system simulations show that TFF-APIOBPCS is more successful than APIOBPCS.

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The Data Envelopment Analysis of Eco-efficiency in Western China from 2000 to 2010

Xuemei Zhang, Xiuping Yang, and Qianhong Li

Abstract In the view of sustainable development, there are some resources and environmental problems increasingly prominent in the economic development of western China due to its fragile ecosystem. This paper evaluates the eco-efficiency and analyzes the changes based on DEA model with the data of Provinces in western China from 2000 to 2010. The results show as follows: the average value of eco-efficiency is less than 1 and fluctuated since the west development, not reaching the most effective production frontier; there are some striking differences among provinces from two respects of efficiency and redundancy rate; such pollutants as waste gas, industrial waste water and solid wastes and such natural resources as energy are major factors influencing the western eco-efficiency.

Keywords Western China • Eco-efficiency • DEA model

1 Introduction

How to reach a win-win situation for economic development and environment resources protection has always been concerned by environment experts and economists. Scholars (Schaltegger, Sturm) propose the concept of eco-efficiency, and constantly enrich, improve and develop it [1]. According to World Business Council of Sustainable Development [2–3], the concept of eco-efficiency combines two dimensions of economics and ecology to establish a relationship between the product or service value and its environmental impact, seeking to achieve a greater aggregate value to the product or service with reduced environmental impacts [2]. The Organization of World Economic Cooperation and Development (OECD) expands the concept into government, industries, enterprises and other organizations and thinks that eco-efficiency is “the efficiency of ecological resources to meet human needs”, as a ratio of the output and input [4]. Although there are different expressions, a

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common point is that the economic value is maximized while resource consumption and environmental load is minimized.

Eco-efficiency has become a significant tool of assessing sustainable development at different levels. It mainly develops in the products, companies, industries and is measured in different ways. But two typical methods are popular in the calculation: one is the ratio of the value to impact, and another is data envelopment analysis (DEA) based on the relative efficient concept. In recent years, Chinese scholars not only introduce foreign advanced ideas and theoretical methods, but also focus on quantitative study of regional eco-efficiency in China more and more. As a whole, most studies concentrate on the nationwide evaluation of eco-efficiency by utilizing the data envelopment analysis [5–8]. However, there are almost few researches about the eco-efficiency of specific area, such as western China, where the contradiction is obvious and serious between the economic development, resources and environment.

In view of this, the article attempts to take western region as the research object, measures the eco-efficiency of West region since the west development, with modifying the CCR of DEA model and regarding the resources and environment indicators, and explicates the improving directions of western economy to realize eco-efficient in the future.

2 Methodology and Data

2.1 The DEA Model for Assessing

DEA is a non-parametric assessment method that was created in 1978 by Charles, Cooper etc. mainly using mathematical programming model to estimate the relative effectiveness and the production frontier about multi-input, multi-output sectors or decision-making units (DMU) [9]. The regional eco-efficiency measurement is a process of the relative efficiency assessment according to inputs and outputs in a complex system. So the approach of DEA is consistent with the relative and procedural characteristics of regional eco-efficiency. The research is based on the hypothesis that there are n areas, of which one is called as a decision making unit (DMU) during the same period, and each DMU has m kinds of input X, r kinds of output Y. If x_{ij} represents the total volume of i input in j area ($i = 1, 2, \ldots, m$) and y_{lj} represents the total volume of l output in j area ($l = 1, 2, \ldots, r$), the input and output in j area can be expressed as $X_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$ and $Y_j = (y_{1j}, y_{2j}, \ldots, y_{rj})^T$ respectively. Then (X_j, Y_j) reflects the entire production activities of DMU_j. Taken the eco-efficiency of DMU_{j0} as the objective function and the efficiency indexes of all decision making units as constraint conditions, the linear programming model of optimal CCR is shown as follows:

$$
\begin{aligned}
& \min\theta \\
s.\mathrm{t.}\quad & \sum_{j=1}^{n}\lambda_j X_j + s^- = \theta X_j \\
& \sum_{j=1}^{n}\lambda_j Y_j - s^+ = Y_j \\
& \lambda, \mathrm{s}^-, s^+ \geq 0, j = 1, 2 \ldots, n
\end{aligned} \tag{1}
$$

In Eq. (1), s^-, s^+ remark the slack variables of input/output respectively. The ratio of slack variables s_{ij}^- to corresponding index x_{ij} can be defined as the input redundancy rate that indicates the proportion of input component reduced. If the optimal value $\theta^* = 1$, $s^{-*} = 0$, and $s^{+*} = 0$, the eco-efficiency of DMU_{j0} is effective. It means that the output relying on the original input has reached the optimum. If the optimal solution $\theta^* = 1$, $s^{-*} \neq 0$, or $s^{+*} \neq 0$, the eco-efficiency of DMU_{j0} is weakly efficient. That is to maintain the output by decreasing s^{-*} of input or increase s^{+*} of output by remaining the input. If $\theta^* < 1$, the eco-efficiency of DMU_{j0} is inefficient.

However, besides the desired inputs/ outputs, the undesirable inputs/outputs are often accompanied just like environmental pollutants. It is generally known that the smaller pollutants produced are the better. Therefore, from a standpoint of outputs (fix the output and minimize the inputs), environmental impacts are treated as inputs and added into the DEA model to form Eq. (2).

$$
\begin{aligned}
& \min\left[\theta - \varepsilon E^T\left(s^u + s^+ + s^-\right)\right] \\
& s.t.\sum_{j=1}^{N}\lambda_j X_j + s^- = \theta X_j \\
& \quad \sum_{j=1}^{N}\lambda_j Y_j - s^+ = Y_j \\
& \quad \sum_{j=1}^{N}\lambda_j U_j + s^u = \theta U_j \\
& \lambda, s^u, s^+, s^- \geq 0, \varepsilon > 0, j = 1, 2 \ldots, n
\end{aligned} \tag{2}
$$

Where u_{pj} represents the undesirable output p in j area (p = 1, 2, ..., k), the total volume of undesirable outputs can be expressed as $U_j = (u_{1j}, u_{2j}, \ldots, u_{kj})^T$. The slack variable of desired output is denoted by s^u.So the redundancy rate of undesirable output refers to the proportion of the slack variable s_{pj}^u to the corresponding index u_{pj}, which means how many pollutants should be cut down. Thus, under the condition of the output is constant, when the optimal value $\theta^* = 1$, $s^{-*} = 0$, $s^{+*} = 0$, and $s^{u*} = 0$, the eco-efficiency of DMU_{j0} is effective. When $\theta^* = 1$, $s^{-*} \neq 0$, $s^{+*} \neq 0$, or $s^{u*} \neq 0$, the eco-efficiency of DMU_{j0} is weakly efficient. If $\theta^* < 1$, the eco-efficiency of DMU_{j0} is non-effective.

Table 1 Index system for measuring of ecological efficiency

	Aspects	Attributes	Indicators
Input index	Resource consumption	Energy	Total energy consumption
		Water	Total water use
		Land	Construction land area
Undesired output index	Environmental pollution	Waste water	Volume of industrial waste water discharge; chemical oxygen demand (COD) discharge
		Waste gas	Volume of SO_2 emission by industry; volume of industrial soot emission; volume of industrial dust emission
		Solid wastes	Volume of industrial solid wastes discharge
Expected output index	Economic value	Total economic development	Regional GDP

2.2 Index System and Data Source

Considering the above DEA model, we establish the index system of inputs, undesired outputs and desired outputs that covers three aspects of resources consumption, environmental pollution and economic value. As seen in Table 1, each aspect is a set of attributes, which in turn is composed of indicators that can be used to construct regional eco-efficiency measures.

Under the index system, in order to evaluate the western eco-efficiency objectively and correctly, the sample data are mainly available in "*Statistical Yearbook of China*", "*Chinese environmental Statistical Yearbook*", "*Chinese energy statistics yearbook*", "*Chinese land resources Yearbook*", "*Chinese water resources bulletin*". Due to the lack of Tibet's data in several years, Tibet cannot be selected in this study. Through dealing with some data, we get the final panel data of 11 western provinces, autonomous regions and municipalities from 2000 to 2010 since the west development.

2.3 Measure Results

Eco-efficiency Analysis The results calculated by the DEAP2.1 software supply values in the interval (0, 1], closer the 1 more efficient will be the DMU. The average value of western eco-efficiency changes not greatly between 0.935 and 0.974. But the eco-efficiency of each province exist obvious difference. For Guangxi, Chongqing, Sichuan, Yunnan and Shaanxi, their eco-efficiencies are higher than other provinces, and equal 1 annually during the whole evaluation period. That means they comprise the efficiency frontiers and they do not need improvement in relation to their indicators. The eco-efficiencies of Guizhou and Inner Mongolia progressively grow from about 0.8 to 1, so that the annual values reach 0.968 and 0.975 separately. Otherwise, the eco-efficiencies of Qinghai and Xinjiang show a downward trend, falling to 0.690 and 0.956 in 2010 respectively from 1 in 2000. The eco-efficiency of Gansu is fluctuating at the range [0.811, 1]. Ningxia has always been in a non-efficiency frontier where its eco-efficiency is lowest and undulating between 0.591 and 0.760.

Redundancy Rate Analysis For the areas on non-efficiency or weakly-efficiency frontier, whose inputs or outputs fail to achieve the optimizations, we can adjust their inputs or outputs to improve their eco-efficiencies in the light of the redundancy rates. As illustrated in Table 2, there are four areas not eco-efficient including Inner Mongolia, Guizhou, Gansu and Ningxia in 2000. Ningxia has the highest redundancy rate of input and undesirable output which is up to more than 39 %, whereas Gansu has the lowest one that is less than 5 %. From the aspect of average redundancy rate, the inputs and undesired outputs with higher redundancy rate are COD, industrial soot, SO_2, industrial waste water, industrial solid wastes and energy in proper order, which are all above 18 %. In 2010, there are only three areas of Qinghai, Xinjiang and Ningxia as demonstrated in Table 3. All of inputs and undesired outputs redundancy rates are over 23 % and higher than those of 2000. Thus it indicates that the discharge of industrial waste gas, industrial wastewater, industrial solid waste and energy consumption are the key factors impacting on the eco-efficiencies of non-efficiency production frontier areas, as well as it is necessary to progress their the eco-efficiencies by means of energy conservation and emission reduction in these factors.

3 Conclusions

From adopting the approach of DEA to assess western eco-efficiency, we can draw the following fundamental conclusions:

On the whole, the west has not yet realized the production eco-efficient and its economy has grown rapidly still at the cost of the abundant resources consumption and the heavy environment pollution since the west development.

The differences among provinces are remarkable at two respects of eco-efficiency value and redundancy rate within western region. On the one hand, some provinces are relatively eco-efficient, such as Guangxi, Chongqing, Sichuan, Yunnan and Shaanxi, but other provinces eco-efficiencies are fluctuating during the evaluation period. On the other hand, the non-efficiency frontiers and redundancy rates also present the changes in different years. It indicates there are the huge potential improvements for inefficient provinces to become eco-efficient.

In addition, energy consumption and industrial "three wastes" pollution are the main factors influencing the western eco-efficiency. Hence it is emphasized to control and reduce these inputs and undesired outputs for the improvement of western eco-efficiency.

Table 2 Redundancy rate of nonproduction frontier area in 2000

Area	Efficiency	Input redundancy rate/%			Redundancy rate of undesired output/%					
		Energy	Water	Land	Wastewater	COD	SO_2	Soot	Dust	Solid wastes
Inner Mongolia	0.868	13.18	13.23	13.19	13.18	13.38	13.10	13.03	13.50	13.18
Gui zhou	0.858	14.24	14.26	14.24	14.24	14.37	14.24	14.14	14.37	14.24
Gan su	0.952	4.77	4.75	4.78	4.77	4.83	4.78	4.58	4.89	4.77
Ning xia	0.602	39.83	39.09	39.45	39.83	40.97	40.60	41.25	39.00	39.83
Average	0.82	18.01	17.83	17.92	18.01	18.39	18.18	18.25	17.94	18.01

Table 3 Redundancy rate of nonproduction frontier area in 2010

Area	Efficiency	Input redundancy rate/%			Redundancy rate of undesired output/%					
		Energy	Water	Land	Wastewater	COD	SO_2	Soot	Dust	Solid wastes
Qing hai	0.69	30.97	31.17	31.26	30.97	29.84	30.31	29.77	31.6	30.97
Ning xia	0.64	36.03	35.83	35.31	36.03	35.44	35.92	37.1	35.44	36.03
Xin jiang	0.956	4.4	4.4	4.4	4.4	4.46	4.41	4.44	4.52	4.4
Average	0.57	23.8	23.8	23.66	23.8	23.25	23.55	23.77	23.85	23.8

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Comprehensive Evaluation of Environmental TFP Index in China: Based on the DEA Model of Directional Distance Function

Juan Gao, Dawei Zhang, Hui Liu, Ning Xu, and Wenji Sun

Abstract In the process of Chinese industrialization, industrialization has significantly effects on economic growth, but also poses a serious environmental problem. Under the DEA way of Directional Distance Function to make up for the deficiency of the traditional DEA model, using the directional distance function of VRS linear programming model, China's Environmental TFP Index is evaluated. The results showed that: for the time trend, China's industrial environmental TFP presents a dynamic process, which affected by a number of major events or policy changes; for different regions, there are some differences in unbalanced regional development, and industry TFP changes. Overall, levels of Environmental TFP Index in china are on the decline, technological advance is a key factor to improve industrial environmental TFP, technical efficiency is secondary cause.

Keywords Industrialization • Environmental total factor productivity • Directional distance function • DEA

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1 Introduction

As we all known, industrial has a significant contribution to the economic growth. It is an important symbol of human society and progress of technology. However, the path of China's economic growth (Especially before 1999, China's industrialization is taking the road of extensive development, which is a high investment and high pollution output.) has brought serious environmental problems. It is necessary to study the China's industrial TFP, especially under the background of the domestic environmental problems have become increasingly prominent and the people become more and more anxious about the environmental problem.

2 Empirical Methodology

In the study of measuring the environmental TFP index method, the most popular approach is Stochastic Frontier Analysis method (SFA) which proposed by Aigner et al. [1], Meeusen et al. [2], and Data Envelopment Analysis method (DEA) proposed by Fare [3], which gives great enlightenment to the scholars. SFA method has the advantages of taking into account the environmental changes and the influence of random factors on the productive behavior, but the overdependence on the production function and the stochastic error term which are set in advance is prone to having problems. So, this paper makes use of DEA model without incurring into model or estimation errors.

2.1 The Data Envelopment Analysis (DEA) Method

DEA method and Malmquist index method are wildly applied to measure TFP problem by scholars. The basic idea is to define the distance function firstly, using DEA method from the perspective of inputs or outputs; then construct Malmquist index; finally, to measure the TFP.

The Directional Distance Function (DDF) is used to measure the environmental TFP, in order to make up for the deficiency of traditional DEA model. We use DEA method of the DDF to measure the process of industrialization in China Environmental TFP Index, and combined with the data of China's province level. There are several advantages: first is the method can be used to more clearly observed that the effect of the difference of industrialization on the environment, because of the great differences are exist in the provincial cross section data; second, the pollution emission price data are unnecessary to the DDF model, when it is used to measure the environment TFP; finally, in the given input conditions, the method encourage “good” output increased to the production frontier directions at the same time, reward “bad” output (e.g. pollution) to reduce pollution minimization direction [4]. This article attempts to measure the TFP index based on the industrial environment by using DDF model with the provinces’ industrial data.

2.2 Model

This model assumes that each decision making unit (DMU) using n inputs, m outputs in each period, the provincial industrial input-output is an closed convex set, combined with weak disposability and input-output free processing conditions, the production technology can be expressed as:

$$p^t(x^t) = \left\{ y^t_{j,m} \leq \sum_{j=1}^{J} z_j y^t_{j,m}, x^t_{j,n} \geq \sum_{j=i}^{J} z_j x^t_{j,n}, \sum_{j=i}^{J} z_j = 1 \right\}. \tag{1}$$

For $m = 1, 2, \ldots, M$ $n = 1, 2, \ldots, N$ $j = 1, 2, \ldots, J$ z_j represents the weight of each industry observations provincial heavy, and $\sum_{j=i}^{J} z_j = 1$ means variable returns to scale production, Two inequality constraints represent inputs and outputs can be freely treatability. Directional distance function can be configured to:

$$\vec{D}\left(x, y; -g_x, g_y\right) = \sup\left\{\beta : \left(x - \beta g_x, y + \beta g_y \in p(x)\right\}\right.. \tag{2}$$

The style can follow $g = \left(-g_x, g_y\right)$ to achieve the maximum reduction in the maximum expansion of output and input, $g = \left(-g_x, g_y\right)$ represents a direction vector, β is scalar quantity, the larger the value, the lower the efficiency, conversely, the smaller the value, the higher the efficiency, Particularly, when $\beta = 0$, observations show that the sample surface is already in the production frontier. Therefore, based on China’s industrial environment directional distance function can be expressed as total factor productivity:

$$ETE = \left(x^t_j, y^t_j; g\right) = 1 - \vec{D}\left(x, y; -g_x, g_y\right). \tag{3}$$

Based on the relaxation model outputs and inputs increase or decrease in proportion to the hypothesis, this paper makes $\lambda_j = z_j + u_j$, we use the linear programming model *VRS* (Variable returns to scale) under the directional distance function to solve TFDI of Industrial environment of China. The following *VRS* linear programming model is then specified as:

$$\vec{D}\left(x,y;-g_x,g_y\right) = \max\beta$$
$$st.\left\{\begin{array}{c}(1+\beta)y_j^t \le \sum_{j=1}^{J} z_j^t y_j^t \\ (1-\beta)x_j^t \ge \sum_{j=1}^{J}\left(z_j^t + u_j^t\right)x_j^t \\ \sum_{j=1}^{J} z_j^t + \sum_{j=1}^{J} u_j^t = 1\end{array}\right\} \tag{4}$$

Therefore, China's TFPI of industrial environment under the directional distance function is expressed as:

$$M_0\left(x_{t+1},y_{t+1},x_t,y_t\right) = \vec{D}_0^{t+1}\left(x_{t+1},y_{t+1};-g_x,g_y\right)/\vec{D}_0^{t}\left(x_t,y_t;-g_x,g_y\right). \tag{5}$$

Among that, $\left(x_{t+1}y_{t+1}\right)$, (x_t, y_t) represent the input and output vectors of period t + 1 and period t, $\vec{D}_0^{t+1}$, $\vec{D}_0^{t}$ represent the directional distance function of period t + 1 and period t.

3 Empirical Analysis

3.1 Data and Index

The selected data sample is extracted from 30 provinces, autonomous regions, and municipalities directly under the central government ranging from 1999 to 2012, in which Tibet is not included because of data unavailability.

For the output indicators, we use the added value of the secondary industry of GDP (production method) in each province, as the "good" output, to measure the output of each province. As for unexpected "bad" output indicators, we select the provincial industrial SO2 emissions as the unexpected industrial "bad" output.

For input indicators, we select the classic capital and labor as inputs, of which we use the average annual balance of fixed assets net values of each province as the capital indicators; we use average annual labor input of all employees in industry department as labor indicators. In this paper, the data used are all from the Statistical Yearbook.

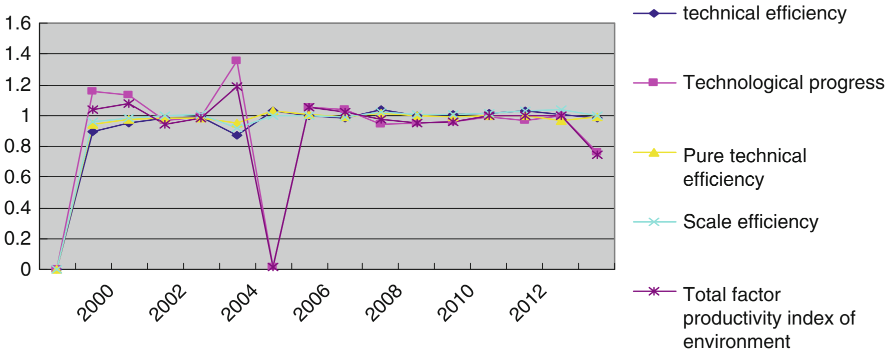

Fig. 1 1999–2012 TFDI of industrial environment and its resolution: time trend (Notes: The average is the geometric average of each year)

3.2 *Results and Discussion*

Here we also consider the variable returns to scale and calculate the industrial total factor productivity, technical efficiency, technological change, pure technical efficiency and scale efficiency of our 30 provinces and cities from 1999 to 2012 based on DEA model of directional distance function (Fig. 1).

Along with the acceleration of China's industrialization and the adjustment of the policy, in 1999–2000 years, China's industrial total factor productivity is increased, reaching 1.076 in 2000 and the main reason for the rise is the increase of technical efficiency index, rising to 5.2 %. In 2003, China's industrial total factor productivity index reaches the maximum value, 1.185, the average growth rate is 18.5 %, and technical progress is the main driving force of its growth, of which the reason lies in GDP growth of 9.1 % and the growth rate of investment 26.7 % in 2003, which greatly promotes the technological progress. But the advantage of backwardness is insufficient, technology progress regresses, investment is overheated in China in 2004, so the path goes into low quality with high growth, which reduces industrial environmental total factor productivity index, in 2004 the total factor productivity index is 0.014, the lowest level over the years. Along with our country adopts a series of measures to reduce the overheating investment in some sectors, in 2005–2006 year industry total factor productivity index rises, 2 years' the average growth rate is 3.5 %, and the key is the progress of technology has been greatly improved. Because of the financial crisis in 2007–2008 globally, the international environment has changed, leading to China's deterioration of industrial environment total factor productivity in 2008, total factor productivity index drops to 0.953. After 2008, China adopts some policies and measures and as a result the total factor productivity has a slight rise. Our country brings in overseas advanced technology and relies on technical progress mainly based on innovation to improve technical efficiency and scale efficiency and then increase the total factor productivity. In 2012, the total factor productivity index reaches 0.998, but it still needs increasing.

Table 1 1999–2012 TFDI of industrial environment and its resolution: area differentiation

	Technical efficiency index	Technological progress index	Pure technical efficiency index	Scale efficiency index	Total factor productivity index of environment
Northeast	0.976	0.781	0.978	0.998	0.762
East	0.982	0.892	0.993	0.989	0.876
Central section	0.976	0.779	0.98	0.996	0.760
West	0.960	0.633	0.973	0.987	0.608

From Table 1, we can see industrial total factor productivity size sequence is northeast east > middle > West, showing Eastern labor and capital using efficiency is high, and also the eastern area takes the leading position in environment treatment technically. While the western industrial environmental total factor productivity index is the lowest with serious decline, the average falling range up to 30.6 %, because the production technology is backward, technological progress, technical efficiency and pure technical efficiency are low, and growth is still “extensive” form, and the economic growth is at the cost of resources and energy, suggesting that the labor and capital using efficiency is not high, and also the technology for controlling and treating the pollution emissions is backward.

4 Conclusion

In the long run, the index to China’s industrial environmental TFP may appear a certain amplitude fluctuations, especially in the process of reform. A larger fluctuations will occur when some important events or policy adjustment have been made. From the regional differences of view, industrial environment TFP in various regions of China is in decline, showed that the area of the production technology in China is still very backward, and embodied in labor productivity, capital productivity and the productivity of pollution control. In contrast, the eastern region often play the “advanced” role, industrial environmental TFP is highest, the northeast region, the west central again, the lowest, they play a “catch-up” role. Industrial environmental TFP mainly comes from technological progress, followed by the technical efficiency.

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