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Allocating provincial CO_2 quotas for the Chinese national carbon program*

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In order to improve the efficiency of climate change initiatives China launched its national carbon market in December 2017. Initial CO2 quota allocations are a matter of significant concern. How should we allocate CO_2 emissions reduction responsibilities among Chinese provinces, assuming that provinces will not or cannot trade these responsibilities among themselves? In this paper, we allocate CO_2 quota from the perspective of cost minimisation. First, we estimate the national CO_2 marginal abatement cost (MAC) function and deduce the interprovincial MAC functions. Second, we build an allocation model with nonlinear programming for cost minimisation. Finally, we obtain the allocation results under the emissions reduction target by 2030. The results are as follows. (i) The national MAC was 134.3 Yuan/t (at the constant price of 1978) in 2011, with an overall upward trend from 1990 to 2011. (ii) The interprovincial MACs differ significantly and decline gradually from east to west. Hebei has the largest emissions reduction quota, and Shandong has the largest emissions quota by 2030. (iii) Compared with other criteria of per capita, gross domestic product (GDP), grandfathering and carbon intensity, the proposed approach is the most cost-effective in achieving the reduction target, with cost savings of 37.7, 34.5, 47.9 and 33.87 per cent, respectively.

Key words: Chinese national carbon program, CO_2 quota allocation, interprovincial differences, marginal abatement cost.

1. Introduction

Global climate change is one of the most critical challenges for human beings' sustainable development. As a cost-effective means of reducing CO_2 emissions at the lowest cost, carbon markets have been receiving increasing attention from academics and governments alike. As the world's largest CO_2 emitter, China has been making unremitting efforts to reduce its CO_2 emissions. In 2009, it set the goal of decreasing its carbon intensity, defined as

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CO_2 emissions per gross domestic product (GDP), by 40–45 per cent by 2020 compared with 2005. Furthermore, in 2015 the Chinese Government committed to reducing the carbon intensity by 60–65 per cent by 2030 compared with 2005. To achieve these goals, China formally launched its national carbon market. This national trading program will assign emissions budgets across provinces. CO_2 quota allocation is a key part of building the carbon market (Zhou and Wang 2016). Therefore, determining how to allocate the CO_2 quota fairly and reasonably is one of the focuses of academic research.[1]

Previous studies have concentrated on the allocation principles and methods of emissions quota allocation. The proposed principles can be broadly classified into two categories: fairness; and efficiency. Some fairness criteria are proposed and applied in the study of CO_2 emissions quota allocation (Rose 1990; Rose and Stevens 1993; Rose *et al.* 1998; Ringius *et al.* 2002; Wei *et al.* 2014; Zhou and Wang 2016), include egalitarianism, historical responsibility, sovereignty, ability to pay, and vertical and horizontal equity. The efficiency principle aims at getting the lowest abatement cost and maximum revenue under the target of emissions reduction, using three criteria: carbon intensity (Den Elzen *et al.* 2003); cost-effectiveness (Okada 2007; Cui *et al.* 2014); and input–output efficiency (Feng *et al.* 2015; Miao *et al.* 2016). The allocation methods can be generally divided into three types: indicator, optimisation and game theory. The indicator methods include single and comprehensive indicator methods. The single indicator methods include GDP (Rose 1990; Rose *et al.* 1998), population (Baer *et al.* 2000; Ding *et al.* 2009), the historical CO_2 emissions (Grandfathering) (Böhringer and Lange 2005), outputs (Böhringer *et al.* 2014) and carbon intensity methods (Den Elzen *et al.* 2003). Triptych (Hof and Den Elzen 2010) and multicriteria decision analysis (MCDA) (Yi *et al.* 2011; Wei *et al.* 2012; Ni *et al.* 2015) are the two main comprehensive indicator methods. Compared with the single indicator method, the results via comprehensive indicators can be more acceptable for the emitters, since in this case, they can integrate multiple criteria. Various operation research models are used as optimisation methods to allocate CO_2 allowances, including linear or nonlinear programming (Tehrani 2007; Xu *et al.* 2015) and data envelopment analysis (DEA) (Feng *et al.* 2015; Miao *et al.* 2016; Wang *et al.* 2016). Furthermore, game theory has been introduced in exploring the optimal allocation mechanism especially under asymmetric information (Helm 2003; Mackenzie et al. 2008). Although allocation of tradable allowances does not determine their pattern of use, generally, the CO_2 quota allocation results obtained using the various methods are different. As a market mechanism, in theory, the carbon market can deal with global

[1] See Kampas and White (2003) and Cadarso *et al.* (2010) for applications to agriculture and freight transport.

climate change with the least cost. Thus, the cost minimisation method has gradually become a common trend for CO_2 quota allocation (Okada 2007; Li *et al*. 2010; Cui *et al*. 2014; Miao *et al*. 2016).

The MAC function is the basis of the cost minimisation method. There are three methods for estimating the MAC of a country or province. The first method is the computable general equilibrium (CGE) model. The CGE model estimates the MAC by using the CO_2 shadow price, which is obtained by changing the constraint of CO_2 emissions. The CO_2 shadow price can reflect the MAC*s* under different abatement levels (Kesicki and Stranchan 2011). Furthermore, this method can be classified into three solutions: the 'bottom-up'; 'top-down'; and mixed models. The partial equilibrium 'bottom-up' models, such as MARKAL (Tsai and Chang 2015), LEAP (Pan *et al*. 2013) and POLES (Criqui *et al*. 1999) design simulations for the cost of related technology and CO_2 emissions. They focus on the interrelationships between the energy and economic sectors. The 'top-down' models, such as EPPA (Ellerman and Decaux 1998) and DICE (Nordhaus 2014), describe the economic sectors elaborately using CGE models. The mixed models, such as NEMS (U.S. EIA., 2015), not only consider the relationships between different sectors embedded in the 'top-down' models but also integrate the characteristics describing the role of technology as accurately as possible, just like 'bottom-up' models. However, it is difficult to build these models and reach an exact conclusion without complete and high-quality data.

The second method is the data envelopment analysis (DEA) model. The main idea is to obtain the CO_2 shadow price estimated by directional distance functions. There are two ways to find the shadow price. One is the parametric approach, which needs to calculate the distance functions (Färe *et al*. 2006). The other is the nonparametric approach (Choi *et al*. 2012; Yao *et al*. 2015; Wang *et al*. 2016), which constructs a production possibility set in the DEA model without setting the form of the distance function. The direction distance function makes it more suitable for measuring the environmental performance and shadow price.

The third method is the engineering–economic methodology where engineering estimates of performance are linked in a market mechanism. Wei and Rose (2009) estimated the marginal energy conservation cost in China using the data of investment in energy conservation from 1981 to 2002. The authors explicitly point out that initial allocation will not change the pattern of use when trading is possible. Zhou *et al*. (2013) developed the Chinese interprovincial MACs in the quadratic function based on the Wei and Rose method.

While CGE models have been generally adopted to estimate MAC, designing simulations in CGE models need more complete data, which aims at obtaining the relationships across economic sectors. Generally, the DEA models do not consider technology advancement, which results in the transformation of production frontiers. In this paper, we intend to use the third method (i.e. the engineering–economic methodology) for the following reasons. First, compared with the CGE models, this method is less complicated and easy to implement. It does not necessarily profile the interplay between the different sectors. Second, the MAC is estimated indirectly by specifying the CO_2 shadow price instead of in a direct way as in the models above. The macro-investments are closely related to the costs of emissions control. Therefore, it is appropriate to use the macro-investments data to directly estimate the MAC with straightforward economic implications. More importantly, the engineering–economic methodology can provide robust results as demonstrated in the empirical analysis below.

We examine the distribution of costs for CO_2 abatement across Chinese provinces and identify the consequent cost-effective allocation of emissions (quotas) across provinces. The motivation is that, in practice, the Chinese national government is designing a carbon trading program that assigns emissions budgets among the provinces, and provinces have the opportunity to use markets to achieve their emissions outcomes. In future, provinces may have the opportunity to link their programs.

The aim of this study was to allocate the CO_2 quotas for the 30 provinces in China from the perspective of cost minimisation. The research objective lies in estimating a marginal abatement cost measure across regions, and then into applying an engineering method of the 'nonlinear programming' model to minimise the total national abatement costs. The research question was framed as follows: What is the most cost-effective allocation of emissions across Chinese provinces from the viewpoint of the national emissions reduction goal, assuming within-province cost-effective implementation is achieved?

The main contributions are twofold: (i) we estimate the national MAC with the engineering–economic methodology and deduce the interprovincial MAC functions; and (ii) we build a cost minimisation model under the national reduction target by 2030 with nonlinear programming to obtain the CO_2 emissions reduction for each province. Meanwhile, we verify that the proposed method is the most cost-effective compared with other criteria.

The rest of the article is organised as follows. Section 2 introduces the method. Section 3 describes the data and its sources. Section 4 provides results and discussion. Conclusions and policy implications are put forward in Section 5.

2. Methodology

2.1 Estimating the national MAC function

Inspired by the approach of Wei and Rose (2009), which is used to estimate the marginal energy conservation cost, we improve it to estimate the marginal cost of CO_2 emissions control. The abatement cost in a CO_2

emissions reduction project is the sum of the capital cost and the operating cost. The operating cost is only incurred by the running of the emissions reduction project and the operation of equipment. Once the project ends, there are no operating costs. Thus, it is usually estimated on an annual basis. The capital cost tends to happen at the beginning of the emissions reduction project. It can be converted into a capital recovery cost by discounting for each year in the lifetime period (Park 2015). The sum of the annual capital recovery cost and the operating cost is often called the equivalent annual cost. Therefore, the total abatement cost of the emissions reduction project is equal to the sum of the equivalent annual cost in the lifetime period. As the global benchmark for carbon markets, we refer to the crediting lifetime decision rules of clean development mechanism (CDM) projects[2] – any CDM project can choose a lifetime of either 10 years with no revalidation allowed or 7 years with the option of revalidating twice (UNEP 2002) – and we determine that the average lifetime of the emissions reduction projects in China is 10 years to avoid tedious calculation.[3] Therefore, the total abatement cost, TC_t, is expressed as:

$$\mathrm{TC}_t = \sum_{t=1}^{10} \mathrm{EC}_t = \sum_{t=1}^{10} (\mathrm{RC}_t + \mathrm{OC}_t) \tag{1}$$

where EC_t, RC_t and OC_t are the equivalent annual cost, capital recovery cost and operating cost in a year t, respectively. Operating costs are taken to be a fixed share of capital recovery costs.[4]

Given the present value of the capital I_{t} and investment rate r_{t} in a year t, we can calculate the capital recovery cost RC_t by the following function:

$$\mathrm{RC}_t = \frac{I_t r_t}{1 - (1 + r_t)^{-10}} \tag{2}$$

The operating cost, OC_t, including the management cost, wage and benefit, materials cost and other costs, is expressed as:

$$\mathrm{OC}_t = l * \mathrm{RC}_t \tag{3}$$

where l is the total percentage of the management cost, wage and benefit, materials cost and other cost accounts for the capital recovery cost, RC_t.

[2] CDM projects are used to estimate a marginal abatement cost for each province, as they best reflect in the world the cost and technological opportunities for emissions reductions.

[3] This 10-year assumption represents actual investment horizons in the CDM.

[4] These cost calculations provide an estimate of the amount of money spent on compliance. They can be seen as a proxy of the correct measure of true total abatement costs, lost profits to the firm or, more broadly, lost social surplus.

CO_2 emissions reduction is measured in comparison with the base year. TR_{t,t_0} is the emissions reduction in the year t compared with the base year t_0. $\mathrm{GDP_t}$ is the gross domestic product in a year t, which is calculated at the constant price. e_t and e_{t_0} are the carbon intensity, defined as the CO_2 emissions per GDP in the year t and t_0. The emissions reduction TR_{t,t_0} is defined by:

$$\mathrm{TR}_{t,t_0} = \mathrm{GDP}_t(e_{t_0} - e_t) \tag{4}$$

TR_{t,t_0} consists of several sources of emissions reduction caused by fundamental factors. We assume that the innovations and updates of energy conservation and CO_2 emissions reduction technology dominantly promote CO_2 emissions reduction. We intend to take into account the other important factors, such as industrial structure adjustments and carbon sinks, as well. We define direct emissions reduction as that which is only caused by technology and indirect emissions reduction as that which is caused by factors other than technology. Thus, direct emissions reduction, R_{t,t_0}, is discounted by the discount coefficient h_t based on TR_{t,t_0}:

$$R_{t,t_0} = h_t \mathrm{TR}_{t,t_0} \tag{5}$$

We calculate the national CO_2 emissions, E_t, through the consumption of three fossil primary energies: coal; oil; and natural gas. Let K_t be the reduction ratio, computed as the percentage that emissions reduction accounts over the sum of CO_2 emissions and emissions reduction. $\mathrm{MAC_t}$ is defined as the result of dividing the abatement cost $\mathrm{TC_t}$ by the direct emissions reduction $R_{\mathrm{t,t-1}}$. Thus, E_t, K_t and $\mathrm{MAC_t}$ are expressed as, respectively:

$$E_t = (k_{\mathrm{coa}} N_{\mathrm{coat}} + k_{\mathrm{oil}} N_{\mathrm{oilt}} + k_{\mathrm{nag}} N_{\mathrm{nagt}}) \times 44/12 \tag{6}$$

$$K_t = \frac{R_{t,t_0}}{E_t + R_{t,t_0}} \tag{7}$$

$$\mathrm{MAC}_t = \frac{\mathrm{TC}_t}{R_{t,t-1}} \tag{8}$$

where N_{coat}, N_{oilt} and N_{nagt} are the consumption of coal, oil and natural gas in a year t, respectively. k_{coa}, k_{oil} and k_{nag} are the carbon emission coefficients for coal, oil and natural gas, respectively.

Moreover, we calculate the provincial CO_2 emissions, E_t^p, through the consumption of seven fossil energies: coal; coke; gasoline; kerosene; diesel; fuel oil; and natural gas:

$$E_t^p = (k_{\mathrm{coa}} N_{\mathrm{coat}} + k_{\mathrm{cok}} N_{\mathrm{cokt}} + k_{\mathrm{gaso}} N_{\mathrm{gasot}} + k_{\mathrm{ker}} N_{\mathrm{kert}} + k_{\mathrm{die}} N_{\mathrm{diet}} + k_{\mathrm{fue}} N_{\mathrm{fuet}} + k_{\mathrm{nag}} N_{\mathrm{nagt}}) \times 44/12 \tag{9}$$

where N_{cokt}, N_{gasot}, N_{kert}, N_{diet} and N_{fuet} are the consumption of coke, gasoline, kerosene, diesel and fuel oil in a year t, respectively. k_{cok}, k_{gaso}, k_{ker}, k_{die} and k_{fue} are the carbon emission coefficients for coke, gasoline, kerosene, diesel and fuel oil, respectively.

Inspired by Nordhaus (1991), we define the national MAC function as:

$$\mathrm{MAC} = \beta_1 + \beta_2 \ln(1 - K) \tag{10}$$

where K is the emissions reduction ratio. Once $\hat{\beta}_1$ and $\hat{\beta}_2$ have been estimated[5], we can obtain the national MAC function.

Notice the national MAC estimation is successfully obtained throughout the engineering–economic methodology. However, it is difficult to estimate the provincial marginal costs function independently by the engineering–economic methodology due to the limited availability of the primary data on provincial investments in emissions reduction.

2.2 Deducing the interprovincial MAC functions

The relative marginal abatement costs of the provinces depend on the extent to which the emission intensity of a given province is greater than or less than the national emission intensity. Hence, we assume that MAC depends on emission intensity and, in particular, that local MAC varies only with the difference of local carbon intensity from national carbon intensity (Bohm and Larsen 1994; Okada 2007). This approach is general and nonconfined to cooperative games. Besides, it can inform about the methodological choices made in this paper.

To deduce the interprovincial MAC functions, as shown in Figure 1, the MAC function is plotted by the emissions reduction ratio K on the horizontal axis and MAC on the vertical axis. x_{i} is the value of the emissions reduction ratio K_{i} of the province i. e is the national carbon intensity and e_{i} is the carbon intensity of province i.

If the carbon intensity, e_{L}, of the province L is lower than e, the MAC of this province is higher than that of the nation. Thus, its MAC curve starts at a point K_L^0 in the first quadrant, which is steeper than the zero point and

[5] Nordhaus (1991) proposes the function of MAC: MAC = $\beta_1 + \beta_2 \ln(1 - K)$. As a result, he estimates the MAC function of the United States : $\hat{\beta}_1 = -4.12$ and $\hat{\beta}_2 = -185.2$. We use this function to estimate the MAC function of China here. It should be noted that the variables MAC and K are both time series, and the autocorrelation problem may result in an unbiased but inefficient estimator by ordinary least square (OLS) regression. Thus, it is necessary to carry out the autocorrelation tests after OLS regression, for example Durbin–Watson (DW) and Breusch–Godfrey (LM) tests. Then, regression of the Newey–West or FGLS should be carried out if there is an autocorrelation problem.

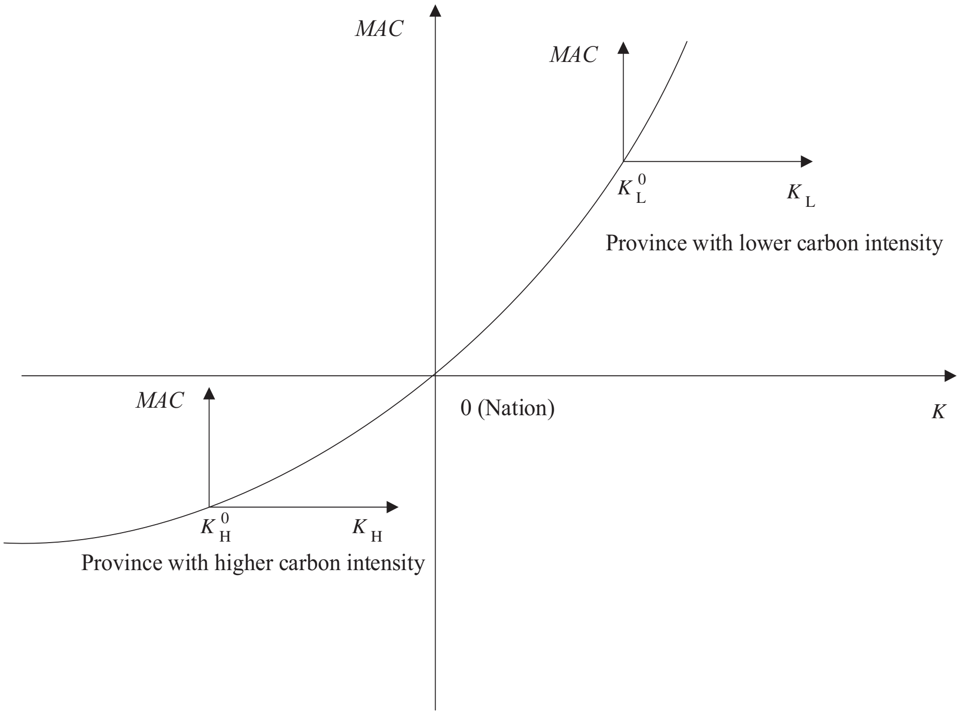

Figure 1 The curves of national and interprovincial MAC.

extends along the nation's curve. There is a relationship between e_L and e: $x_L = 1 - \frac{e_L}{e}$, and $x_L > 0$. On the contrary, if the carbon intensity, e_H, for the province H is higher than e, the MAC of this province is lower than that of the nation. Its MAC curve starts at a point K_H^0 in the third quadrant, which is flatter than the zero point and extends along the nation's curve. The relationship between e_L and e is: $x_H = 1 - \frac{e_H}{e}$, and $x_H < 0$. In brief, the MAC^i of any province $i$is expressed as:

$$\text{MAC}^i(K_i) = \text{MAC}(K_i + x_i) - \text{MAC}(x_i) = \beta_2 \ln(1 - \frac{K_i}{1 - x_i}) \tag{11}$$

Additionally, the total abatement cost for the province i, C^i, is obtained by integrating the MAC^i of the emissions reduction ratio in [0, K_i]:

$$C^i(K_i) = -\int_0^{K_i} \text{MAC}^i(k)dk = \beta_2[\ln(1 - \frac{K_i}{1 - x_i})(1 - x_i - K_i) + K_i] \tag{12}$$

2.3 CO_2 quota allocation model: A nonlinear programming approach

A nonlinear programming model for CO_2 quota allocation was developed to minimise the sum of the abatement costs for n provinces under the national

CO_2 emissions reduction target:

$$\min TC = \sum_{i=1}^{n} -\beta_2[\ln(1 - \frac{K_i}{1 - x_i})(1 - x_i - K_i) + K_i]$$
$$s.t. \begin{cases} \sum_{i=1}^{n} R_i = R \\ 0 < K_i < 1 \end{cases} \tag{13}$$

where TC is the sum of the abatement costs for n provinces, and R and R_i are the national and interprovincial emissions reduction in target year t compared with the base year, t_0. Thus, K_i can be solved by the nonlinear programming method.

3. Data

In this study, the GDP, investment, and abatement cost are calculated at the constant price of 1978. However, we do not consider Tibet, Taiwan, Hong Kong, and Macao due to unavailability of data. The data are specified as follows:

1. *CO_2 emissions reduction target*: In 2009, China set the goal of reducing its carbon intensity by 40 per cent from 2005 levels before 2020. Furthermore, the Chinese Government announced explicitly in 2015 that the emissions reduction target by 2030 is to reduce the carbon intensity by 60–65 per cent compared to 2005. Thus, we select 60 per cent as the 2030 emissions reduction target.
2. *Investments*: The investments in technical updating and transformation of energy saving during 1980–2002 and 2003–2011 are collected from the *China Statistical Yearbook* (1981–2003) and the Annual Review of Low-Carbon Development in China (2011), respectively.
3. *Energy consumption*: The consumption of coal, oil, and gas in 1980–2011 is collected from the *China Energy Statistical Yearbook* (1981–2012).
4. *Population and GDP*: The nation's population and GDP during the period 1980–2014 are taken from the China Statistical Yearbook (1981–2015). The population and GDP of China are expected to increase at an average annual growth rate of 0.48 and 4.5 per cent, respectively. Meanwhile, we calculate the population and GDP of each province by 2030 through the population and GDP proportion of each province in 2013, respectively.
5. *Investment rates*: The annual investment rates during the period 1980–2011 are from the Almanac of China's Finance and Banking (1981–2012): 5.04 per cent from 1980 to 1981, 6.48 per cent from 1982 to 1984, 7.92 per cent in 1985, 10.08 per cent from 1986 to 1989, technical renovation investment rates from 1990 to 1995 and lending rates for the medium to long term more than 5-year rates in fixed assets from 1996 to 2011. If the

rate in one year changed several times, we set the average of the changed rates in this year as the annual investment rate.

6. *Referring to CDM projects as the global carbon market benchmark*: We estimate that the average percentage of the management cost, wage and benefit, material cost, and other cost accounts for the capital recovery cost are 15, 5, and 19 per cent, respectively[6]; thus, the sum of the percentages l is 39 per cent. According to Tian *et al*. (2014) and Zhang *et al*. (2014), the discount coefficient h_t is set as 90 per cent during the period 1990–1998 and 87.5 per cent during the period 1999–2011. The carbon emission coefficients are listed in Table 1.

4. Results and discussion

4.1 MAC function estimation

The national MAC function depends on the fraction of initial emissions abated and is estimated by regressing national total annual abatement expenditures (measured as described above) on the log of the abatement fraction.[7]

Using Equations (11) and (12) above, we calculate, the MACs and Ks, respectively in China from 1990 to 2011. Notice that the emissions reduction is negative from 2002 to 2005, which is a possibility given the log functional form during the nonlinear optimisation process. Data analysis further reveals that the overall trend of carbon intensity in China has declined gradually during 1990–2011. To avoid expanding the calculation deviation, we select the annual average rate of descent of carbon intensity during 2001–2006, which is adjacent to 2002–2005. Thus, we obtain the MACs and Ks as shown in Fig. S1.

Table 1 Carbon emission coefficients in units of t (C)/t (coal equivalent)

k_{coa}	0.7304
k_{oil}	0.5630
k_{nag}	0.4190
k_{cok}	0.8550
k_{gaso}	0.5538
k_{ker}	0.5714
k_{die}	0.5921
k_{fue}	0.4483

[6] The average ratio of the management cost, wage and benefit, material cost, and other cost to the capital recovery cost are estimated based on the data in the feasibility reports of the regular CDMs in China.

[7] Note this estimation strategy is robust when applied to first differences.

Furthermore, Equation (10) allows estimating of the coefficients β_1 and β_2 using the ordinary least square (OLS) and the Newey–West estimation. In order to underpin the robustness of results, we utilise, bootstrap regression and the least absolute deviation estimator (LAD)[8]. Both are appropriate in the case of small samples, as shown in Table 2.

The first column in Table 2 indicates that, in the OLS regression, the constant coefficient $\hat{\beta}_1$ is not statistically significant, but the bootstrap coefficient $\hat{\beta}_1$ is significant at the level of 1 per cent. We conducted the Durbin–Watson (DW) and Breusch–Godfrey (LM) tests for autocorrelation. The DW statistic is 0.52, and the *P*-value is 0.3 per cent in the LM test; thus, first-order autocorrelation exists. The second column is the Newey–West estimation; the constant coefficient is not significant yet, but the bootstrap coefficient is significant at the level of 5 per cent. The third column is the bootstrap regression, and it shows that $\hat{\beta}_2$ remains the same with OLS and NEWEY_1, and significant at the level of 5 per cent but $\hat{\beta}_1$ is not significant. The fourth column is LAD, and $\hat{\beta}_2$ is significant at the level of 5 per cent but $\hat{\beta}_1$ is still not significant. Consequently, we take the national MAC function as follows:

$$\mathrm{MAC} = -91.79 * \ln\left[1 - \left(\frac{k_i}{a_i(1-k_i)}\right)\right] \tag{14}$$

with k_i the emissions reduction ratio of province $i = 1,\ldots,30$, and a_i the abatement coefficient estimated. Indeed, we can deduct from Equations (10–12) the *MAC* functions for 30 provinces as shown in Table 3, which can be used to calculate the CO_2 emissions reduction quotas for 30 provinces by 2030 with the proposed model.

4.2 Allocation results

We solve the nonlinear programming problem stated in Equation (13) with the LINGO software (ver. 11), developed by LINDO Systems Inc, to obtain

Table 2 Sensitivity of β_1 and β_2 regression results with bootstrap methods

Coefficients	OLS	NEWEY_1	Bootstrap	LAD
β_2	−91.79***	−91.79**	−91.79**	−89.95**
β_1	5.351	5.351	5.351	2.725

Note: ***$P < 0.01$, **$P < 0.05$.

[8] To investigate the finite sample properties of statistics such as OLS estimators when we do not believe that asymptotic distribution can serve as a good approximation to what happens in finite sample, we can resort to bootstrap. One advantage of LAD compared to OLS is that LAD is more robust against outliers in the dependent variable, especially when the size of the observations is small.

Table 3 Abatement coefficient a_i estimated for each interprovincial MAC function by 2030

Province	a_i	Province	a_i
Beijing	0.51	Henan	1.83
Tianjin	1.12	Hubei	1.31
Hebei	3.17	Hunan	1.16
Shanxi	6.14	Guangdong	0.79
Inner Mongolia	4.38	Guangxi	1.36
Liaoning	1.95	Hainan	1.31
Jilin	1.85	Chongqing	1.22
Heilongjiang	2.07	Sichuan	1.42
Shanghai	1.01	Guizhou	3.56
Jiangsu	1.20	Yunan	2.17
Zhejiang	0.98	Shaanxi	2.43
Anhui	1.90	Gansu	2.61
Fujian	1.03	Qinghai	2.87
Jiangxi	1.34	Ningxia	7.02
Shandong	1.77	Xinjiang	4.23

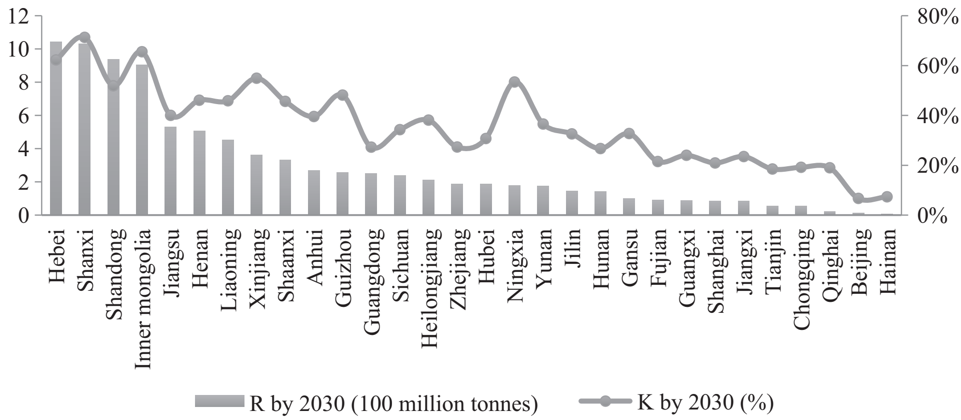

Figure 2 *K*s and *R*s of 30 provinces by 2030.

the global optimal solutions, K_i^* and R_i^*. For this study, we set 2013 as the base year.

Figure 2 reports the emissions reduction quota and ratio for each province. As regards the emissions reduction ratio, the highest is shown by Shanxi, with 71.33 per cent by 2030 compared with 2013, followed by Inner Mongolia and Hebei. Their emissions reduction ratios are all over 60 per cent. The carbon intensities of the three provinces substantially exceed that of the nation in 2013, and the MACs of these provinces are lower than those of the nation. Thus, the emissions reduction ratios of these provinces should be higher than others.

As regards the emissions reduction quota, the highest is found for Hebei, with 1.04 billion tonnes compared with 2013, followed by Shanxi, Shandong and Inner Mongolia. The emissions reduction quotas of these four provinces drastically surpass other provinces. Their MACs are among the highest across provinces, which is why the model has them abating more intensely than most others.

There are two characteristics of the proposed method: first, when the GDP are the same, the province with a higher carbon intensity has a higher emissions reduction ratio. For example, Shanxi and Yunnan had approximately equal GDP in 2013, but the carbon intensity of Shanxi is nearly three times as high as Yunnan in 2013; thus, the emissions reduction ratio of Shanxi is nearly twice that of Yunnan. Second, when the carbon intensities are the same, the province with a larger GDP has a higher emissions reduction ratio. Taking Hubei and Hainan as an example, the carbon intensities of these two provinces were approximated in 2013. GDP in Hubei was eight times that in Hainan in 2013; thus, the emissions reduction ratio of Hubei is 23 per cent higher than that of Hainan.

The MACs of 30 provinces by 2030 are reported in Figure 3. In relation to regional differences, the MACs in the western provinces (excluding Sichuan and Xinjiang) are lower than those in the central and eastern provinces. The MACs in the eastern coastal provinces (excluding Fujian and Shanghai) are higher than those in most inland provinces, and the highest MAC is in Shandong. This means that there is an inverse relationship between the marginal abatement cost and the economic development level. Furthermore, the interprovincial MACs obviously differ, the highest MAC (Shandong) being 15 times as high as the lowest one (Hainan). We verify here a classic property of emissions trading schemes, whereby cost-efficient abatement occurs primarily at the sources with the lowest cost.

Generally, a positive correlation exists between the reduction potential and the emissions reduction ratio. According to the emissions reduction potential, we can divide the 30 provinces into four classes, as shown in Figure 4.

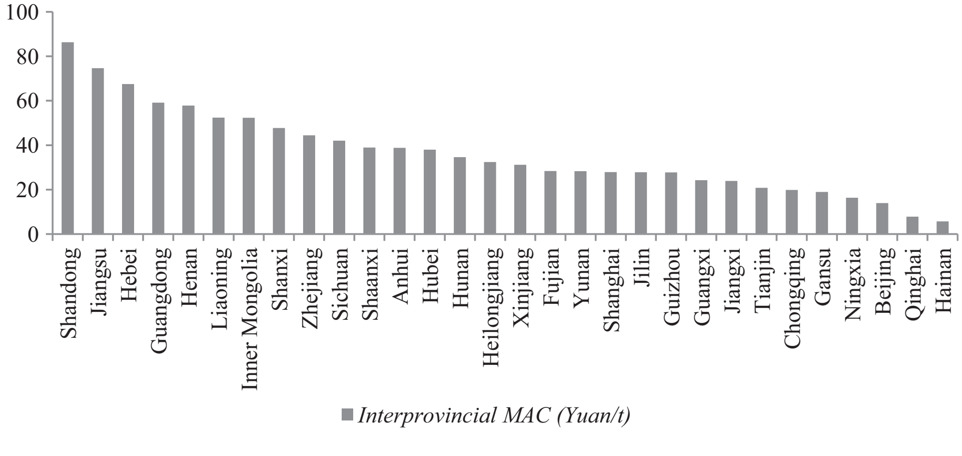

Figure 3 The interprovincial MACs by 2030.

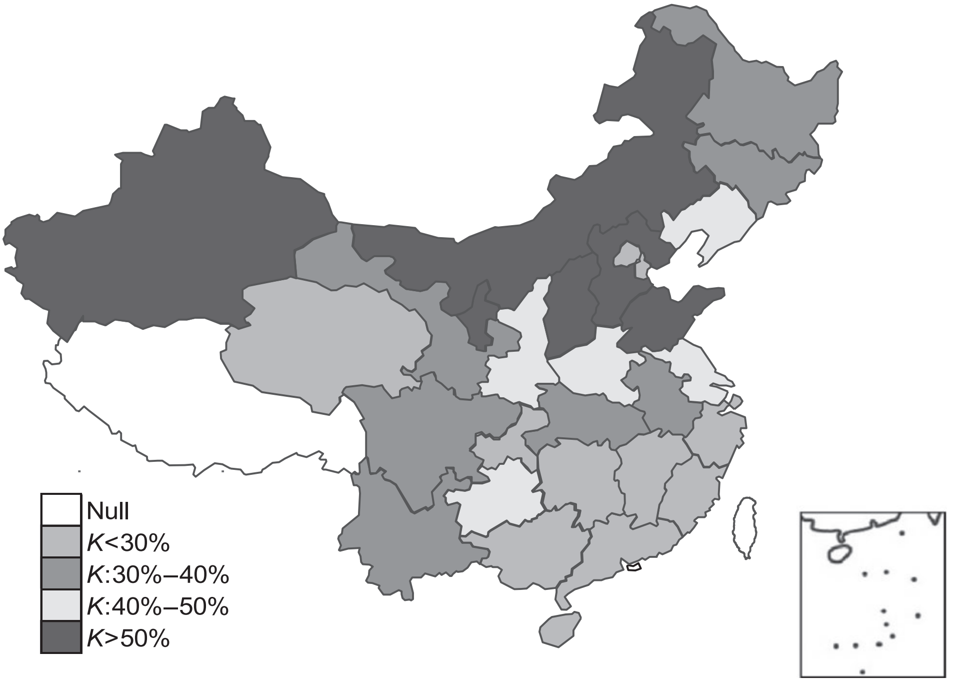

Figure 4 The interprovincial CO_2 emissions reduction potential in China. *Note:* $K > 50$ per cent includes Shanxi, Inner Mongolia, Hebei, Xinjiang, Ningxia, and Shandong. *K*: 40–50 per cent includes Guizhou, Henan, Liaoning, Shaanxi, and Jiangsu. *K*: 30–40 per cent includes Anhui, Heilongjiang, Yunnan, Sichuan, Gansu, and Hubei. $K <$ below 30 per cent includes Zhejiang, Guangdong, Hunan, Guangxi, Jiangxi, Fujian, Shanghai, Chongqing, Qinghai, Tianjin, Hainan, and Beijing.

Class-I *K* exceeds 50 per cent. Class-II *K* is 40–50 per cent. Class-III *K* is 30–40 per cent. Class-IV *K* is below 30 per cent. Corresponding province names can be found in the figure.

Figure 5 contrasts the burden that each province represents, in terms of carbon emissions and quotas, between 2013 and 2030, revealing leaders and laggards within the national Chinese carbon market. Ten provinces will shrink in the quota percentage compared with the CO_2 emissions percentage in 2013, and the shrinking proportion totals 11.7 per cent. Shanxi, Hebei and Inner Mongolia are the three largest contraction provinces that sum up to 8.8 per cent. Thus, emissions reduction in these three provinces will be the core task in future. In addition, the CO_2 emissions quota of the western provinces, including Guizhou, Yunnan, Shanxi, Ningxia and Xinjiang, will shrink to varying degrees, and Xinjiang will experience the largest decline, reaching 0.64 per cent. The province with the largest increase in the quota percentage is Guangdong, which will rise by 1.3 per cent compared with 2013. Shandong will have the largest CO_2 emissions quota, which will be 7.58 per cent by 2030, and the next will be Jiangsu and Guangdong. Shanxi, Hebei and Inner

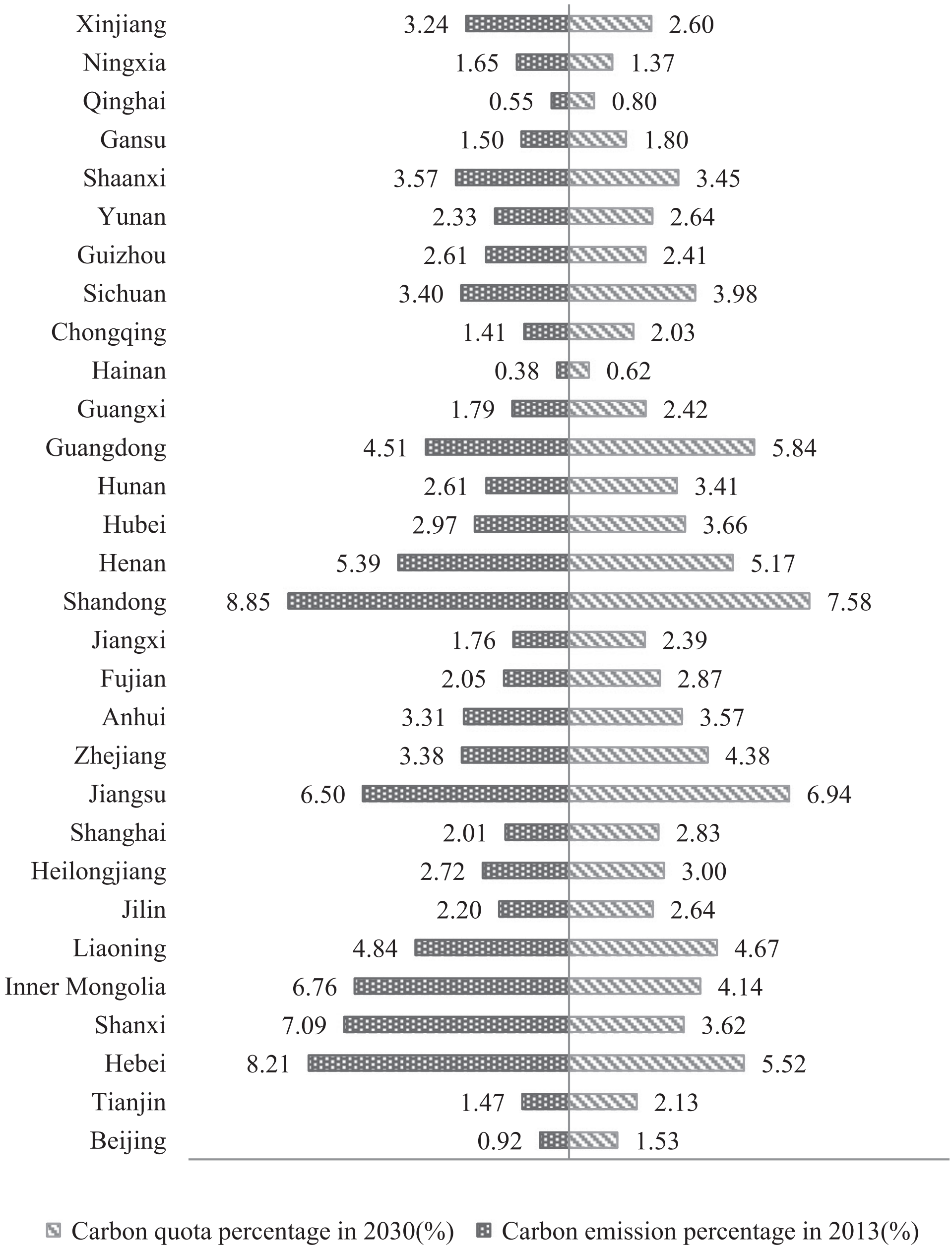

Figure 5 The percentage of the CO_2 emissions quota by 2030 and CO_2 emissions in 2013.

Mongolia, with a higher emission intensity in 2013, have more reduction potential. It is reasonable to reduce their CO_2 emissions. Meanwhile, Guangdong, with a lower emission intensity, has less reduction potential, and its GDP is comparatively large; thus, it is also reasonable to increase its CO_2 emissions.

4.3 Comparison with other criteria

To obtain the differences between the proposed method and other criteria, including the per capita, GDP, grandfathering and carbon intensity methods, we report allocations in Table 4.

Regarding abatement cost heterogeneity, the abatement cost of grandfathering is the highest, which will be 38.74 billion yuan by 2030. Following this are the per capita, GDP and carbon intensity methods. The cost minimisation method involves the lowest cost, with 20.18 billion yuan, which makes cost savings of 37.7, 34.5, 47.9 and 33.87 per cent more than the per capita, GDP and carbon intensity methods, respectively. In summary, because the outcome depends on the 'allocation' then there is an assertion of cost-effectiveness within provinces. Following the cost minimisation exercise, we proceed to explain differences in marginal abatement costs across provinces.

As for individual heterogeneity, significant individual differences exist across the five methods. The maximums of the CO_2 emissions quota are 10 per cent more than the minimums for any province following the five methods, and Beijing, Tianjin, Hainan, Chongqing, Gansu, Qinghai and Ningxia exceed 60 per cent. The GDP method is obviously beneficial to the provinces with a large GDP, such as Shandong, Jiangsu, Guangdong and Zhejiang, while the western provinces are allocated less than in the other methods. The provinces with high carbon intensities or large CO_2 emissions, such as Hebei, Shanxi, Inner Mongolia, Guizhou, Ningxia and Xinjiang, are allocated more in the grandfathering method than in other methods, while the provinces with low carbon intensities, such as Beijing, Zhejiang, Fujian and Hainan, are allocated less. Beijing and Hainan are allocated more in the emission intensity method than in the others. The provinces with high carbon intensities are allocated less in the proposed method than in the others, which implies that the proposed method focuses on the CO_2 emissions reduction potential.

This analysis shows that the most unequal is the grandfathering method, with a Gini coefficient[9] of 0.415. The variables GDP, per capita, carbon intensity and cost optimisation methods have Gini coefficients of 0.405, 0.401, 0.361 and 0.337 in turn. Thus, the proposed method is the most equitable one.

4.4 Sensitivity analysis

4.4.1 Changes of h_t

The discount coefficient h_t is set as 90 per cent during the period 1990–1998 and 87.5 per cent during the period 1999–2011 in the analysis above, which is regarded as the case of medium level. To examine the sensitivity of the results

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[9] The Gini coefficient is defined as $G = 1 - \frac{1}{n}(2\sum_{i=1}^{n-1} w_i + 1)$, where n is the number of sample groups; here, $n = 30$. w_i is the CO_2 emission quota percentage of province i. Note that the Gini coefficient is often used to measure inequality in income distribution in a population. We use a modified Gini "index" to measure inequality across provinces.

Table 4 CO_2 quota allocation and abatement cost of five methods by 2030

Province	Cost optimisation		Per capita		GDP		Grandfathering		Emission intensity	
	Red.	*Emi.*	*Red.*	*Emi.*	*Red.*	*Emi.*	*Red.*	*Emi.*	*Red.*	*Emi.*
Beijing	0.13	1.75	0.72	1.16	0.47	1.40	0.82	1.05	0.70	2.51
Tianjin	0.56	2.45	1.38	1.62	1.19	1.82	1.32	1.69	1.52	2.19
Hebei	10.43	6.32	7.79	8.96	7.94	8.81	7.35	9.41	4.31	8.35
Shanxi	10.32	4.15	7.05	7.42	7.16	7.31	6.34	8.13	8.36	7.12
Inner Mongolia	9.04	4.75	6.84	6.96	6.70	7.09	6.05	7.75	5.97	6.85
Liaoning	4.54	5.35	4.59	5.30	4.42	5.47	4.33	5.55	2.66	5.20
Jilin	1.47	3.03	2.00	2.50	1.99	2.50	1.97	2.53	2.52	2.62
Heilongjiang	2.12	3.44	2.42	3.14	2.50	3.05	2.43	3.12	2.81	3.08
Shanghai	0.86	3.24	1.83	2.27	1.57	2.53	1.80	2.30	1.38	2.79
Jiangsu	5.31	7.96	5.92	7.35	5.35	7.92	5.82	7.45	1.63	7.10
Zhejiang	1.89	5.02	2.92	3.99	2.61	4.29	3.03	3.88	1.34	4.17
Anhui	2.68	4.09	2.78	3.98	3.01	3.75	2.96	3.80	2.59	3.70
Fujian	0.90	3.29	1.72	2.47	1.61	2.58	1.84	2.35	1.40	2.83
Jiangxi	0.84	2.74	1.32	2.27	1.49	2.10	1.57	2.01	1.82	2.35
Shandong	9.37	8.69	8.18	9.88	7.94	10.12	7.92	10.14	2.40	9.19
Henan	5.07	5.92	4.57	6.43	4.86	6.13	4.82	6.17	2.49	5.76
Hubei	1.86	4.20	2.44	3.62	2.50	3.56	2.66	3.40	1.79	3.56
Hunan	1.42	3.90	1.96	3.37	2.13	3.20	2.33	2.99	1.58	3.28
Guangdong	2.51	6.70	3.50	5.71	3.17	6.04	4.04	5.17	1.08	5.49
Guangxi	0.88	2.77	1.33	2.32	1.52	2.13	1.60	2.05	1.85	2.37
Hainan	0.06	0.71	0.29	0.48	0.32	0.45	0.34	0.43	1.79	1.00
Chongqing	0.55	2.33	1.14	1.74	1.17	1.71	1.26	1.62	1.66	2.07
Sichuan	2.38	4.57	2.63	4.32	2.92	4.03	3.05	3.90	1.93	3.94
Guizhou	2.57	2.76	2.34	2.99	2.55	2.78	2.34	3.00	4.85	2.81

Table 4 (*Continued*)

Province	Cost optimisation		Per capita		GDP		Grandfathering		Emission intensity	
	Red.	*Emi.*	*Red.*	*Emi.*	*Red.*	*Emi.*	*Red.*	*Emi.*	*Red.*	*Emi.*
Yunnan	1.74	3.02	1.90	2.86	2.16	2.60	2.09	2.67	2.96	2.68
Shaanxi	3.32	3.96	3.32	3.96	3.36	3.93	3.19	4.09	3.30	3.86
Gansu	1.00	2.06	1.28	1.79	1.42	1.64	1.34	1.72	3.56	1.79
Qinghai	0.21	0.91	0.51	0.61	0.53	0.60	0.49	0.63	3.91	0.83
Ningxia	1.80	1.57	1.66	1.70	1.67	1.69	1.47	1.89	9.55	1.74
Xinjiang	3.63	2.98	3.15	3.46	3.21	3.41	2.90	3.72	5.76	3.39
Total	89.46	114.62	89.46	114.62	89.46	114.62	89.46	114.62	89.46	114.62
Cost	201.78		324.06		308.10		387.44		304.95	

Notes: *Red*. is an abbreviation for reduction. *Emi*. is an abbreviation for emissions. 1. Reduction denotes the CO_2 emissions reduction quota by 2030 compared with 2013, and emission denotes the CO_2 emission quota by 2030. 2. The metrological units of reduction and emission are 100 million tonnes, and the metrological unit of cost is 100 million yuan calculated at the constant price of 1978.

Table 5 β_2 regression results

Coefficients	Case 1: Low level	Case 2: Medium level	Case 3: High level
β_2	−102.1	−91.79	−83.08

Table 6 β_2 regression results

Coefficients	Case 1: Low level	Case 2: Medium level	Case 3: High level
β_2	−88.49	−91.79	−95.09

to the changes of h_t, we only change h_t and keep other variables unchanged. Thereby, we specifically set h_t at a high level: 95 per cent (1990–1998); and 92.5 per cent (1999–2011), and at a low level: 85 per cent (1990–1998) and 82.5 per cent (1999–2011). The regression results of national MAC are reported in Table 5. It shows that $\hat{\beta}_1$ is always insignificant, and $\hat{\beta}_2$ increases with h_t, which means that national MAC decreases with h_t. Moreover, $\hat{\beta}_2$ in case 2 is 10.1 per cent higher than in case 1, and $\hat{\beta}_2$ in case 3 is 9.5 per cent higher than in case 2.

However, h_t does not influence the allocation results because h_t only has an impact on $\hat{\beta}_2$, which does not change the solutions (K_i) of the nonlinear programming.

4.4.2 Changes of l

The discount coefficient l is set as 39 per cent in the analysis above, which is also regarded as the case of medium level. Similarly, we further specifically set l at a high level: 44 per cent, and at a low level: 34 per cent. The other variables remain unchanged. The regression results are reported in Table 6. It shows $\hat{\beta}_1$ is still not significant in all cases, and $\hat{\beta}_2$ decreases with l, which means that the national MAC increases with l. Moreover, $\hat{\beta}_2$ in case 2 is 3.7 per cent lower than in case 1, and $\hat{\beta}_2$ in case 3 is 3.6 per cent lower than in case 2. Thus, the national MAC is less sensitive to the changes of l compared with that of h_t.

Similarly, l only has an impact on $\hat{\beta}_2$, which does not change the solutions of the nonlinear programming. Hence, the allocation results do not change with l.

5. Conclusions and policy implications

In this paper, we allocate CO_2 quotas for the Chinese national carbon market with nonlinear programming. First, we use a mixed engineering–economic approach to estimate the national MAC functions and deduce the inter-provincial MAC functions. Second, we build a cost minimisation allocation model with the constraint of the CO_2 reduction target to obtain CO_2 quotas of 30 provinces by 2030. Under our assumptions and calculation, this method emerges as the most cost-effective. The main conclusions are as follows:

First, the Chinese national MAC showed an increasing trend from 1990 to 2011, especially in 2008–2011, with the average annual growth of 55.3 per cent. In 2011, the national MAC reached 134.3 Yuan/t, which was the highest from 1990 to 2011, and the CO_2 reduction ratio of China was 51.7 per cent compared with 1990.

Second, there are significant differences in interprovincial MACs. By 2030, the lowest MAC is predicted to be in Hainan, while the highest will be in Shandong, which is 15 times as high as the former. Furthermore, the interprovincial MACs tend to decline from east to west.

Third, the 30 provinces can be divided into four classes according to their emissions reduction ratio potential. Shanxi has the largest emissions reduction quota, which is up to 1.04 billion tonnes. Next are Shanxi, Shandong and Inner Mongolia with 1.03, 0.94 and 0.90 billion tonnes. Meanwhile, Shandong has the largest CO_2 emissions quota, which will be 0.87 billion tonnes by 2030, followed by Jiangsu and Guangdong with 0.80 and 0.67 billion tonnes, respectively.

Finally, compared with the other four allocation methods, the proposed allocation model cannot only obtain the lowest Gini coefficient but also minimise the abatement cost. Specifically, this method offers cost savings of 37.7, 34.5, 47.9 and 33.87 per cent more than the per capita, GDP, grandfathering and carbon intensity methods, respectively.

Based on the conclusions above, we derive and argue for some policy implications. First, a single index distribution program sharply increased the abatement costs due to the considerable differentiation existing in the interprovincial MACs. Decision-makers should take into account the heterogeneity of MACs. Meanwhile, the allocation results of several methods are quite different. No method can embody all the principles and factors. Thus, the national carbon market needs a mix of allocation methods involving the basic attributes, and this paper can be considered as an important benchmark for one of the attributes – the efficiency principle, for allocating CO_2 quotas in the Chinese national carbon program.

Second, the provinces that have a greater emissions reduction potential, such as Hebei, Shanxi and Inner Mongolia, should be allocated higher emissions reduction quotas. The provinces that have lower emission intensities or larger GDP, such as Shandong, Jiangsu and Guangdong, should be allocated more CO_2 emissions quota.

Third, the national MAC is estimated by the data of macro-investment in energy conservation and CO_2 emissions reduction. However, the reliability of MAC directly depends on the quality of the data. Thus, it is necessary to improve and complete the objectivity and integrity of the related data.

While in this study we efficiently allocate CO_2 quotas at the provincial level, determining the allocation to various emission sources within each province remains unresolved. How to do so efficiently and equitably, conditional on the provincial allocations remains an open question for future research.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Fig. S1. MACs and *K*s of China during 1990–2011.