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Working Paper 120
http://ceep.bit.edu.cn/english/publications/wp/index.htm

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July 2018

This paper can be cited as: *Wang K., Yang K., Wei Y.-M., Zhang C. 2018. Shadow prices of direct and overall carbon emissions in China's construction industry: a parametric directional distance function-based sensitive estimation. CEEP-BIT Working Paper.*

This work was supported by the National Natural Science Foundation of China (Grant Nos. 71471018, 71521002 and 71761137001), the Social Science Foundation of Beijing (Grant No. 16JDGLB013), the Joint Development Program of Beijing Municipal Commission of Education, the Fok Ying Tung Education Foundation (161076), the National Key R&D Program (Grant No. 2016YFA0602603), and the International Clean Energy Talent Program of Chinese Scholarship Council. The views expressed herein are those of the authors and do not necessarily reflect the views of the Center for Energy and Environmental Policy Research.

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Shadow prices of direct and overall carbon emissions in China's construction industry: a parametric directional distance function-based sensitive estimation

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Abstract: Construction industry, together with building materials industries supplying it, is one of China's largest emitters of CO_2. Structural change in construction industry has been promoted to mitigate CO_2. This paper estimates CO_2 shadow price of construction industry and its supporting materials industries in China so as to help them to mitigate CO_2 cost-effectively. A parametric directional distance function model, taking into account all possible directional vectors, is applied to address issues regarding arbitrary selection of direction that will affect estimation of shadow price. Results show that there is larger potential for CO_2 reduction in supporting material industries than in construction industry itself and shadow price of overall CO_2 is much lower than that of direct CO_2. The existence of enlarging heterogeneity in shadow prices among different regions provides strong support for introducing a national carbon trading market, thereby helping construction industry and building materials industries to reduce their abatement costs.
Keywords: Abatement cost; Building material industry; Construction industry; Shadow price

1 Introduction

In recent years, policymakers, entrepreneurs, and academics have been progressively paying attention to mitigating global climate change, with reduction of carbon emissions being widely recognized as an increasingly essential issue in dealing with global warming. Based on USEIA (2010), the amount of global carbon emissions in 2035 will be 42.7% higher than in 2007, surging to 42.4 billion metric tons. As the biggest emitter of carbon dioxide (CO_2), China is committed to reducing its CO_2 emissions per unit of GDP (i.e., carbon intensity) by 18% of 2015 levels by 2020 under the 13th Five-Year Plan period during 2016–2020 (SCC, 2016). The Chinese government is increasingly proactive in participating in the international climate negotiations and taking on heavy responsibility. For instance, at the Paris climate summit in 2015, China guaranteed that its peak of carbon emissions will appear no later than 2030, and its carbon intensity will decrease by 60%–65% by 2030 compared with the 2005 level (NDRC, 2015; Lomborg, 2016). Emissions reductions in carbon-intensive industries are generally believed to be key to meeting these objectives (Wang et al., 2016a; Wang et al., 2017a; Xian et al., 2018). The Chinese construction industry, which accounts for approximately 30% of total energy consumption and 25% of the greenhouse gas (GHG) emissions of the whole country, is one of the most carbon-intensive industries in China (CCIA, 2010; CHI, 2010). According to the China Energy Statistical Yearbook, building energy consumption has increased continuously in recent years, reaching 76.96 million tons of coal equivalent in 2015, with an annual growth rate of 7.8% for the last five years. In particular, the amount of energy consumption and consequent carbon emissions by the construction enterprises has increased comparatively fast as a result of the need for growth in infrastructure construction. The Chinese government has already realized the contribution that the construction industry has made to carbon emissions and has promoted structural change in the construction industry to mitigate carbon emissions. In more detail,

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green buildings and green construction technologies are being encouraged (MOHURD, 2017). The carbon emissions from the construction industry include carbon emissions from the production building materials, in addition to the emissions from construction activities (Spence and Mulligan, 1995). Taking steel and cement as examples, the production processes of these commodities accounts for 30% and 15%, respectively, of the total industry energy consumption. The Report on Building Energy Consumption (CABEE, 2017) states that the steel consumed in the construction industry accounts for more than 50% of the total steel consumption, and the proportion is 60–70% for cement. The report also points out that carbon emissions reduction in the construction industry is critical for achieving the peak of carbon emissions in 2030. Overall, the construction industry, together with the building materials industries supplying it, is one of China’s largest consumers of energy and emitters of carbon emissions.

Given the remarkable contribution to carbon emissions made by China’s construction industry, together with the building materials industries, studies on carbon emissions reduction in the construction industry have appeared rapidly in recent years. Some scholars have reported the specific amount of carbon emissions in the construction industry. Chuai et al. (2015) assessed the total anthropogenic carbon emissions from the construction industry and found that they increased from 39.05 million tons to 1.04 billion tons from 1995 to 2010, respectively, contributing 27.87%–34.31% of the total carbon emissions in China. Zheng et al. (2018) pointed out that there are relatively fewer studies evaluating the carbon emissions from the construction activities themselves than the studies relating to the carbon emissions in building usage. They estimated carbon emissions through material use in Shenzhen and found that the carbon emissions reached 132.4 million tons in 2013. Lu et al. (2016a) stated that the carbon emissions of China's building and construction industry reached 11,500 million tons in 2012, representing 3.4% of the national emissions, with an average annual emissions growth rate of 6.9% for the last 19 years, and that building materials consumption contributed most (63%) to the total increase of carbon emissions. As for energy saving and CO_2 mitigation, González and Navarro (2006) stated that the carbon emissions from construction activities can be reduced by 30% through the use of environmental friendly materials. Shi et al (2017) investigated the factors driving CO_2 emissions changes in the construction industry and found that energy intensity made the greatest contribution to the reduction of carbon emissions. To sum up, these studies imply that there is extensive potential for carbon emissions reduction both in the construction industry and in the building materials industries. However, mitigating carbon emissions cost-effectively will greatly depend on the CO_2 emission abatement costs. Though a growing number of studies have appeared, no study has attempted to evaluate the costs of abatement of CO_2 emissions from the construction industry. Hence, the lack of relevant studies seems a significant gap to fill.

The implementation of the Kyoto Protocol established in the United Nations Framework Convention on Climate Change in 1997 has made the evaluation of CO_2 emission abatement costs a popular study area. Mandell (2011) states that, for infrastructure construction, estimation of the shadow price may be suitable for assessing the cost of abatement of carbon emissions. The shadow price is the marginal cost of abatement of carbon emissions, interpreted as the quantity of profit that entrepreneurs need to abandon for a certain quantity of carbon emissions reduction (Boussemart et al., 2017). Against the background of the carbon pricing mechanism, trading systems and carbon taxes are two effective approaches that governments take to control carbon emissions and stimulate environmentally friendly technologies. Estimation of the CO_2 shadow price can be helpful for these two approaches. If an emitter with high abatement costs find that shadow price of carbon emissions is higher than the price in the carbon market, he can buy emission rights from an emitter with low abatement costs to avoid extra cost, which means that the shadow price either reveals the willingness to pay for entrepreneurs or helps them to ascertain whether the price is fair. Therefore, the marginal abatement cost can identify the range of acceptable trading prices and determines the advantage of the permit trading policy over a command-and-control policy through the effort of emissions abatement (Wang et al., 2016b; Wang et al., 2016c; and Wang et al., 2016d). Similarly, the main problem in the alternative approach is how to formulate the standard of the carbon tax, and then again evaluation of the CO_2 shadow price can provide a useful reference for determining the implicit value of tax supported by economic models. To sum up, as the carbon pricing mechanism has been implemented to reduce carbon emissions, mathematical modelling of abatement costs can provide more accurate and more enlightening information for mitigating the emissions effectively (Wang et al., 2018b). Therefore, we will focus on the derivation of the CO_2 shadow price for the construction industry to provide useful information for policy makers and entrepreneurs.

The shadow price estimation is based on the production technology and the production frontier. At first, scholars used output or input distance functions to represent the production technology and derive the shadow price (e.g., Färe et al., 1993; Park and Lim, 2009; and Hailu and Veeman, 2000). However, there are some weaknesses in the use of output or input distance functions. The typical weakness is the assumption of proportional increase or decrease between desirable and undesirable outputs without taking into account the different changes in them. Nevertheless, the directional distance function, which allows desirable and undesirable outputs to hit the production frontier with non-proportional changes along a directional vector, was developed to suit product activities in practice. Studies based on this function then emerged (e.g., Lee et al. 2002; Wei et al., 2013; Wang et al., 2011; Guan et al., 2018; Zeng et al., 2018; Wang and Wei, 2014; and Wang and Wei, 2016). Therefore, we use the directional distance function to represent the production technology in this study.

Though the directional distance function is more reasonable and flexible, it has some shortcomings. For example, the shadow prices may vary for different selections of directional vectors, but the selections are not fixed in real production process. In detail, different directional vectors mean that entrepreneurs can adjust the outputs in different ways, such as expanding desirable outputs and contracting undesirable outputs or contracting them together, corresponding to diverse strategies of emissions reduction. The most common strategies for emissions abatement in environmental economics textbooks are separable purification activities and end-of-pipe purification activities (Førsund, 2008). Separable purification means the use of either environmentally approved technology or pure ingredients, which can be explained as investment in improving technology. End-of-pipe purification is the transformation of major undesirable outputs by means such as dissolving, decomposing, and transportation towards receptors, which adds extra costs for pollutant abatement. Besides, under the pressure of environmental regulation, entrepreneurs may cut down outputs to reduce emissions and meet the standard set by environment regulators. Improving efficiency for environmental resources allocation is also popular with entrepreneurs, explained as the shift of point on the production frontier (Wang et al., 2018a). To sum up, entrepreneurs may employ different strategies to mitigate emissions. Pittman (1981) estimated the shadow prices of water pollution for the pulp and paper mills in Wisconsin and Michigan and pointed out that the results may be biased without considering the different technologies used by pulp and paper mills. Therefore, the directional vectors that represent different strategies cannot be selected arbitrarily when modeling the production technology. It is worth noting that this issue has already gained attention from scholars. Feng et al. (2017) adopted a random-coefficient, random-directional-vector directional output distance function model to estimate the shadow prices of CO_2 emissions of electric utilities in the US from 2001 to 2014 and showed that the average annual prices range from \$62 to \$106. Färe et al. (2017) used parametric nonlinear programming to select the directional vector optimally and showed the difference between prices estimated with endogenously determined directional vectors and ad hoc vectors. Peyrache and Daraio (2012) proposed some empirical tools to quantify the sensitivity of the efficiency measurement to the selection of the direction.

Different from these studies, we attempt to estimate the shadow price of CO_2 emissions, taking into account all possible directional vectors, to address the critical and unsolved issues regarding the arbitrary selection of direction that will affect the results in a non-negligible way. The reasons why estimating the shadow price in all possible directions is significant are as follows: 1) Our study is at province level, at which level construction enterprises have various measures of reducing carbon emissions; 2) An enterprise is likely to change its strategies in accordance with the different production phases; 3) It is impossible to accurately detect which direction an enterprise may choose. So, the consideration of all feasible vectors allows us to identify all possible strategies of production and carbon emissions reduction in construction enterprises. The results not only include the upper and lower boundaries but also present the distribution of shadow prices in different directional vectors, which is more comprehensive than previous studies that estimated the shadow price by following the single path of simply reducing undesirable outputs and increasing desirable outputs.

The major contribution of this study is that it estimates the shadow price of direct carbon emissions from the construction industry and the shadow price of overall carbon emissions from this industry, together with its supporting materials industries, taking into consideration of all possible directional vectors that indicate multiple abatement strategies. The remainder of this paper is organized as follows. Section 2 presents the derivation of the carbon shadow price and the theoretical background. Section 3 introduces the data for estimation and discusses the shadow price of direct and overall carbon emissions from China's construction industry. Moreover, the sensitivity of the shadow price to the selection of directional vectors is described in this section. Section 4 investigates factors influencing the shadow price and evaluates the disparities and convergence of shadow prices among different provinces. The last section presents the conclusions and policy implications.

2 Method

We start by describing the production model that our shadow-pricing method is based on. We define $x=(x_1,x_2,...,x_N)\in R_+^N$ as the denotation of inputs, $y=(y_1,y_2,...,y_M)\in R_+^M$ as desirable outputs, and $b=(b_1,b_2,...,b_J)\in R_+^J$ as undesirable outputs. Thus, we can represent the technology by the output sets $P(x)$, where $P(x)=\{(y,b): x\ can\ produce\ (y,b)\}$.

The general assumptions that the output set is convex and compact (closed and bounded) guarantee the tradeoffs between the good and bad outputs under the given inputs. And the inputs are freely disposable, which means if $x^{'}\geq x$, then $P(x^{'})\supseteq P(x)$. The output set also has additional assumptions, as follows. First, the bad outputs are always produced together with the good outputs. In other words, if (y, b) is involved in the output sets with no bad output produced, then the good output must be not produced. Formally, if $(y,b)\in P(x)$, and b=0, then y=0. Second, it is assumed that the good outputs and bad outputs have the property of joint weak disposability. For example, if $(y,b)\in P(x)$ and $0\leq\theta\leq1$, then $(\theta y,\theta b)\in P(x)$, which means it is feasible to contract the good outputs and bad outputs together proportionally. In other words, any reduction of bad outputs involves a cost. Although several pollution-producing technologies for modeling undesirable outputs have appeared in recent years, such as materials balance principles, weak disposability and by-production technologies, weak disposability is still a proper way to model the pollutants discussed in this paper. Weak disposability highlights the symbiosis between desirable and undesirable outputs, that is, the pollutant cannot be abandoned easily. Since carbon dioxide is hard to clear up, the assumption seems more suitable for carbon abatement. Moreover, the other approaches need detailed data that are difficult to collect at the province level. The last assumption is that good outputs are freely disposable. In other words, we can reduce good outputs with no reduction in bad outputs. Formally, if $(y,b)\in P(x)$, then for $y'\leq y$, $(y',b)\in P(x)$.

Imposing all the assumptions above, the production technology is represented by the directional output distance function. Let $g=(g_y,g_b)$ represent a directional vector, then the function can be defined as:

$$\vec{D}_0(x,y,b;g_y,g_b)=\max\{\beta:(y+\beta g_y,b-\beta g_b)\in P(x)\} \tag{1}$$

This function indicates the feasible maximum expansion of desirable outputs and reduction of undesirable outputs with the given technology. To explain the distance function, we assume that a producer M is producing the desirable output at levels y and undesirable output at levels b under the feasible given amount of input *x*, which is illustrated in Figure 1. Expanding or contracting y and b along the directional vector, M can achieve the point $(b-\beta^* g_b, y+\beta^* g_y)$ on the boundary of $P(x)$, where $\beta^*=\vec{D}_0(x,y,b;g)$ and $\beta>0$. In addition, it is noteworthy that the directional vector can turn in all feasible directions, which represents the multiple strategies for CO_2 emissions reduction and production efficiency improvement (Wang et al., 2017b), as we mentioned in section 1. In this study, instead of arbitrarily choosing a specific direction for the efficiency measure, we model the directional vector turning from (1, 1) to (-1, -1), as explained in Figure 2 (also shown as from 0° to 180°), to identify all possible adjustments on desirable and undesirable outputs. The practical meanings of these representative directions are as follows:

(I): Direction (1, 1) and those between (1, 1) and (1, 0): Expanding desirable outputs and undesirable outputs simultaneously;

(II): Direction (1, 0): Expanding desirable outputs and maintaining undesirable outputs unchanged;

(III): Directions between (1,0) and (0, -1): Expanding desirable outputs and contracting undesirable outputs simultaneously;

(IV): Direction (0, -1): Contracting undesirable outputs and maintaining desirable outputs unchanged;

(V): Directions between (0, -1) and (-1, -1) and direction (-1, -1): Contracting desirable outputs and undesirable outputs simultaneously.

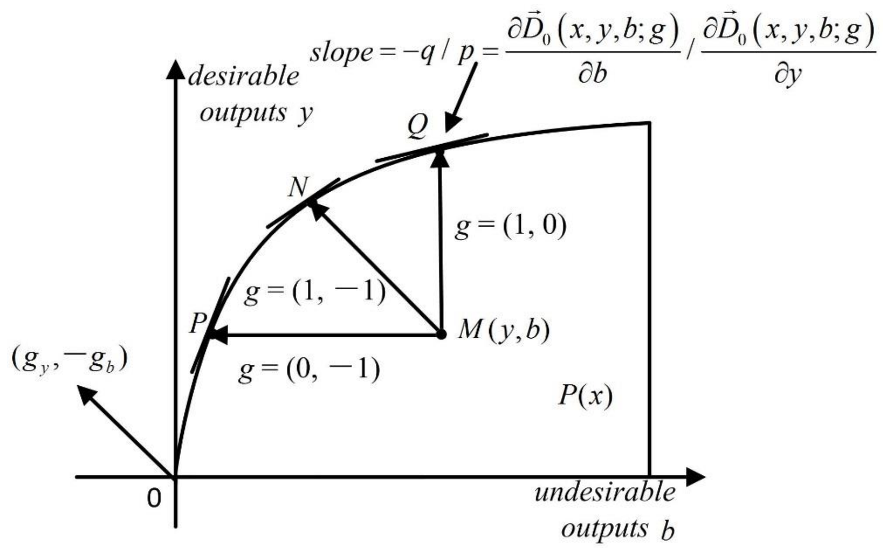

Figure 1 Directional output distance function

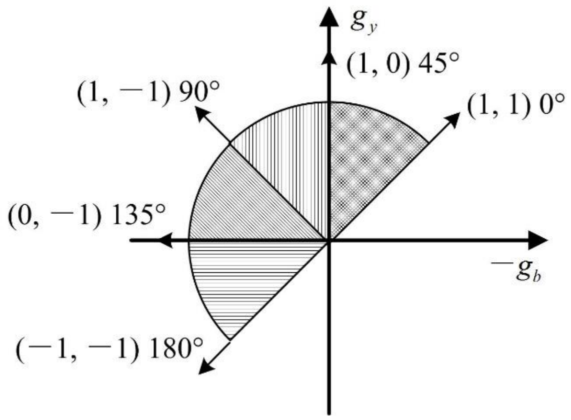

Figure 2 Range of representative directional vectors

The directional distance function satisfies the properties inherited from the technology $P(x)$. According to Bellenger and Herlihy (2010), these properties are as follows:

(a) $\vec{D}_0(x,y,b;g_y,g_b)\geq 0$ if and only if (y,b) is involved in $P(x)$;

(b) $\vec{D}_0(x,y',b;g_y,g_b)\geq \vec{D}_0(x,y,b;g_y,g_b)$ for $(y',b)\leq(y,b)\in P(x)$;

(c) $\vec{D}_0(x,y,b';g_y,g_b)\leq \vec{D}_0(x,y,b;g_y,g_b)$ for $(y,b')\leq(y,b)\in P(x)$;

(d) $\vec{D}_0(x,\theta y,\theta b;g_y,g_b)\geq 0$ for $(y,b)\in P(x)$ and $0\leq\theta\leq 1$;

(e) $\vec{D}_0(x,y,b;g_y,g_b)$ is concave in $(y,b)\in P(x)$;

(f) $\vec{D}_0(x,y+\alpha g_y,b-\alpha g_b;g_y,g_b)=\vec{D}_0(x,y,b;g_y,g_b)-\alpha,\alpha\in R$.

Property (a) shows that the directional function is nonnegative for feasible output vectors. Property (b) is consistent with the strong disposability of good outputs; this is a monotonicity property. It shows that inefficiency does not increase if good outputs expand while bad outputs and inputs remain at the original level. Property (c) is the same as (b), and it shows that inefficiency does not decrease if bad outputs expand while good outputs and inputs are held constant. Property (d) corresponds to the weak disposability of desirable and undesirable outputs. The concavity property (e) allows definition of the sign of the elasticity of substitution of the outputs. Finally, property (f) means translation invariance. If y increases by the amount αg_y and b decreases by the amount αg_b, then the corresponding value of the directional distance function will decrease by α. This property corresponds to homogeneity of the standard Shephard output distance function. The derivation of this property can be seen in Färe et al. (2006a).

To derive the carbon emissions shadow price, we utilize the relationship between the directional distance function and the revenue function. Let $p=(p_1,...,p_M)\in R_+^M$ represent the prices of desirable outputs and $q=(q_1,...,q_J)\in R_+^J$ represent the prices of undesirable outputs. The revenue function can be written in the form of the directional distance function:

$$R(x,p,q)=\max_{y,b}\{py-qb:(y,b)\in P(x)\} \tag{2}$$

The revenue function represents the largest feasible revenue that can be obtained under the desirable price p and undesirable price q. Hence, with a feasible directional vector given, the revenue function can be expressed as:

$$R(x,p,q)\geq(py-qb)+p\cdot\vec{D}_0(x,y,b;g)\cdot g_y+q\cdot\vec{D}_0(x,y,b;g)\cdot g_b \tag{3}$$

The left side of Equation (3) means the maximal feasible revenue. The right side is the result of adding the improvement of technical efficiency to the actual revenue. The additional revenue can be decomposed into two parts: one is the profit of increase in desirable outputs along g_y, and the other is the gain corresponding to the decrease of undesirable outputs along g_b.

According to the duality relationship between the revenue function and the distance function, we can relate the directional distance function and the maximal revenue function as shown:

$$\vec{D}_0\left(x,y,b;g\right)=\frac{R\left(x,p,q\right)-\left(py-qb\right)}{pg_y+qg_b}=\min_{p,q}\left\{\frac{R\left(x,p,q\right)-\left(py-qb\right)}{pg_y+qg_b}\right\} \tag{4}$$

Equation (4) is an un-constrained minimization question. Assuming that the directional distance function and the revenue function are differentiable, the first-order condition about desirable output is Equation (5) and the first-order condition about undesirable output is Equation (6).

$$\nabla_y\vec{D}_0\left(x,y,b;g\right)=\frac{-p}{pg_y+qg_b} \tag{5}$$

$$\nabla_b\vec{D}_0\left(x,y,b;g\right)=\frac{q}{pg_y+qg_b} \tag{6}$$

Thus, if we assume that the shadow price p_m is the market price of the mth desirable output, we can derive the shadow price of the jth undesirable output from the ratio of Equations (5) and (6):

$$q_j=-p_m\cdot\left(\frac{\partial\vec{D}_0\left(x,y,b;g\right)}{\partial b_j}\Big/\frac{\partial\vec{D}_0\left(x,y,b;g\right)}{\partial y_m}\right) \tag{7}$$

In Figure 1, the ratio is illustrated by the slope of the tangent line on the frontier, representing the marginal transformation between the desirable outputs and carbon dioxide, which can be explained as the opportunity cost of desirable outputs when cutting down one unit of CO_2. From Figure 1 we can find that, if M goes along a different direction path to achieve the frontier, the points on the frontier are different (P, N, and Q, for example), and, obviously, the shadow price will be diverse due to the change of slope. As a result, the shadow price may be either overestimated or underestimated in the practical production process due to the arbitrary selection of a directional vector.

To estimate the directional distance function, both parametric and non-parametric approaches can be considered. Zhou et al. (2015) use both parametric and non-parametric methods to estimate and compare the shadow prices of Shanghai industrial sectors. Their results show that the carbon abatement costs are affected remarkably by which method is chosen. Compared to the parametric approach, the non-parametric approach has the advantage that it is not essential to specify the functional form. However, as the key point in our study is to estimate the shadow price of the undesirable outputs, we will choose the parametric approach because of its differentiability. In addition, there are other problems with the non-parametric method, such as how to deal with the outliers. Since the quadratic function is twice differentiable and satisfies the translation property, we use it to estimate the parameters for the directional distance function.

Assume there are $k=1,\dots,K$ units (provinces in our case study), with $n=1,\dots,N$ inputs, $m=1,\dots,M$ desirable outputs, and $j=1,\dots,J$ undesirable outputs. The unit k's quadratic directional distance function can be expressed as follows:

$$\begin{aligned}\vec{D}_0&=\left(x_k,y_k,b_k;g_y,g_b\right)\\&=\alpha+\sum_{n=1}^{N}\alpha_n x_{nk}+\sum_{m=1}^{M}\beta_m y_{mk}+\sum_{j=1}^{J}\gamma_j b_{jk}+\frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N}\alpha_{nn'}x_{nk}x_{n'k}+\frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M}\beta_{mm'}y_{mk}y_{m'k}\\&+\frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J}\gamma_{jj'}b_{jk}b_{j'k}+\sum_{n=1}^{N}\sum_{m=1}^{M}\delta_{nm}x_{nk}y_{mk}+\sum_{n=1}^{N}\sum_{j=1}^{J}\eta_{nj}x_{nk}b_{jk}+\sum_{m=1}^{M}\sum_{j=1}^{J}\mu_{mj}y_{mk}b_{jk}\end{aligned} \tag{8}$$

According to Aigner and Chu (1986), linear programming can be used to estimate the unknown parameters. We choose the parameters to minimize the sum of the distances between the production frontier and each unit observed.

$$\min \sum_{k=1}^{K}[\vec{D}_0\left(x_k, y_k, b_k; g_y, g_b\right)-0]$$

$$\begin{aligned}
\text{s.t.}\ &(i)\ \ \vec{D}_0\left(x_k, y_k, b_k; g_y, g_b\right) \geq 0, k=1,\ldots,K, \\
&(ii)\ \ \partial\vec{D}_0\left(x_k, y_k, b_k; g_y, g_b\right)\big/\partial b_j \geq 0, j=1,\ldots,J, k=1,\ldots,K, \\
&(iii)\ \ \partial\vec{D}_0\left(x_k, y_k, b_k; g_y, g_b\right)\big/\partial y_m \leq 0, m=1,\ldots,M, k=1,\ldots,K, \\
&(iv)\ \ \partial\vec{D}_0\left(x_k, y_k, b_k; g_y, g_b\right)\big/\partial x_n \geq 0, n=1,\ldots,N, k=1,\ldots,K, \\
&(v)\ \ \sum_{m=1}^{M}\beta_m g_{ym} - \sum_{j=1}^{J}\gamma_j g_{bj} = -1, \sum_{m'=1}^{M}\beta_{mm'} g_{ym'} - \sum_{j=1}^{J}\mu_{mj} g_{bj} = 0, m=1,\ldots,M, \\
&\qquad \sum_{j'=1}^{J}\gamma_{jj'} g_{bj'} - \sum_{m=1}^{M}\mu_{mj} g_{ym} = 0, j=1,\ldots,J, \sum_{m=1}^{M}\delta_{nm} g_{ym} - \sum_{j=1}^{J}\eta_{nj} g_{bj} = 0, n=1,\ldots,N, \\
&(vi)\ \ \alpha_{nn'} = \alpha_{n'n}, n \neq n', \beta_{mm'} = \beta_{m'm}, m \neq m', \gamma_{jj'} = \gamma_{j'j}, j \neq j'.
\end{aligned} \tag{9}$$

The restriction (i) indicates the feasibility, which requires the output and input vectors to be feasible for the units. Monotonicity conditions are imposed in restrictions (ii) and (iii). They state that either a decrease in bad outputs or an increase in good outputs indicates greater efficiency. The restriction (iv) gives the positive monotonicity of the inputs for the mean level of input usage. It means if keeping the good and bad outputs unchanged, an increase in inputs will leads to greater inefficiency. The restriction (v) is due to the translation property. This restriction will change if different directional vectors are chosen. The restriction (vi) imposes symmetry conditions (Färe et al., 2006b).

3 Data and shadow price

3.1 Data

Our study focuses on the shadow prices of carbon emissions from the construction industry sectors in China's thirty provinces during 2004–2014. We employ the carbon emissions as the undesirable outputs. We define the direct carbon emissions as the emissions from the energy consumed in either construction activities or the construction phase of buildings. We define the indirect carbon emissions as the emissions from the upstream industries related to construction industry, for example, the building materials manufacturing industries. In addition, we also need the input and output data for the construction industry. Based on comprehensive previous studies and the availability of data, we finally use four inputs—fixed assets investment, labor, energy consumption, and approval construction land—in addition to one desirable output—architectural added value—for estimation. The units are billion yuan, ten thousand people, ten thousand tons of standard coal, hectares, and billion yuan, respectively. All the basic data are obtained from the China Energy Statistical Yearbook, the China Statistical Yearbook, and the China Statistical Yearbook on Construction.

In recent studies, estimation of carbon emissions from the construction industry has involved three main approaches: input–output analysis (Chen et al., 2017; Zhang and Liu, 2013, Nässén et al., 2007), life cycle assessment (LCA) (Zhang and Wang, 2016; Hong et al, 2017; Wu et al., 2012) and the IPCC coefficient method (Lu et al., 2016b; Ye et al., 2011). The input–output model was proposed by Leontief (1936) for addressing the economic interrelationships between industries in an economic system at country level. LCA is a framework for evaluating the environmental impacts of a product, process, or service throughout its life cycle, and it is accomplished in line with International Standards. Since the data of these two approaches are difficult to collect at the province level over eleven years and our main focus is on energy-related direct carbon emissions, the IPCC coefficient method is selected for calculation. We employ the carbon emission factor of consumption (IPCC, 2006) and the calorific value (NRDC, 2008) to estimate the direct carbon emissions from the energy used in onsite construction, and the types are specified in the Energy Balance Table. However, heat and electricity are converted from primary energy, and there is no carbon emissions factor for them in the IPCC method. So, according to the Energy Balance Table, we first assessed the carbon emissions in the production of heat and electricity of the nation via the IPCC method and then used the proportion of energy consumption from construction to the energy consumption of the whole of society to calculate the amount of carbon emissions from heat and electricity that are consumed in construction. Following Feng (2015), this paper attempts to define the materials supplying construction as cement, steel, glass, wood, and aluminum. The carbon emissions from the process of producing these materials include energy-related and industrial process-related emissions. The CO_2 emissions factors of these materials are obtained from Wang (2008), Li and Xu (2009), Chen et al. (2006), and Wang (2012), respectively. In addition, because steel and aluminum are recyclable materials, we calculate the carbon emissions of the unrecovered part via the recovery factor (Li, 2007). The estimation of carbon emissions is shown in Equation 10 and Equation 11, and the symbols utilized are interpreted in Table 1.

$$E_{dir} = \sum_{i=1}^{15} C_i \times \alpha_i \times \eta_i + E_{he} + E_{el} \tag{10}$$

$$E_o = E_{dir} + E_{ind} = E_{dir} + \sum_{j=1}^{5} M_j \times \beta_j \times (1-\varepsilon_j) \tag{11}$$

Table1 Meanings and units of symbols in Equations 10 and 11

Symbol	Meaning	Unit
E_{dir}	Amount of direct carbon emissions	10^4 ton
E_{ind}	Amount of indirect carbon emissions	10^4 ton
C_i	Amount of consumption of energy *i*	10^4 ton
α_i	Per unit calorific value of energy *i*	TJ/10^4 ton
η_i	CO_2 emissions factor of energy *i*	10^4 ton/TJ
E_{he}	Amount of carbon emissions in heat	10^4 ton
E_{el}	Amount of carbon emissions in electricity	10^4 ton
E_o	Amount of overall carbon emissions	10^4 ton
M_j	Amount of consumption of material *j*	10^4 ton
β_j	CO_2 emissions factor of material *j*	10^4ton/10^4 ton
ε_j	Recovery factor of material *j*	10^4ton/10^4 ton

The data on direct and overall carbon emissions from the construction industry in China's 30 provinces from 2004 to 2014 are presented in the Appendix.

3.2 Shadow price of CO_2 emissions

Involving the input and output data in the counting process, we obtain the parameters used in the quadratic functional form of the directional distance function by solving the linear programming. The calculated parameters can help us obtain the values of the directional distance functions, and then, according to Equation (7), we can derive the shadow price of the carbon emissions of construction industry for each province from 2004 to 2014. The different *g*-vectors from (1, 1) to (-1, -1) (as shown in Figure 2) are chosen to estimate all the possible shadow prices, providing more comprehensive shadow prices, since we do not know exactly what strategies for production and carbon emissions reduction that the entrepreneurs will adopt.

We present reasonable shadow prices in all possible directions in Figure 3. Specifically, the shadow prices of direct carbon emissions do not have nonzero values until the directional vectors turn 34 degrees from (1, 1). Furthermore, the shadow prices of direct and overall carbon emissions are abnormal after the directional vectors turn 164 degrees from (1, 1). Figure 3 shows that there is a rising tendency in the shadow prices associated with the direction turning from (1, 1) to (-1, -1), one degree at a time, which is as expected. Figure 1 illustrates the explanation of growth trend in shadow prices, where the slope of point *P* is the largest among *P*, *N* and *Q*. From the perspective of practical production, compared with strategies that expand good outputs and bad outputs at the same time, expanding good outputs and contracting bad outputs simultaneously will lead to higher shadow prices, since reducing the carbon emissions entails extra cost and resources. Then, strategies along the directions where entrepreneurs improve efficiency by contracting good and bad outputs together are much costlier because the profit obtained from good outputs will reduce. According to the change of color, we can see that the shadow prices vary greatly due to different directions. Furthermore, a one-way analysis of variance has been done to prove the sensitivity of prices to directions (see Appendix). We employ four representative shadow prices (average value for 2004 to 2014) obtained in the directions of (1, 1), (1, 0), (1, -1) and (-1,0), respectively, for estimation. The result shows that they differ significantly, which indicates that the shadow price is sensitive to the selection of directional vectors. In addition, according to the distribution and the change range of the shadow price, we reallocate all the possible shadow prices of direct carbon emissions and overall carbon emissions into groups, each of which covers a price range of 5000 yuan/ton and 500 yuan/ton, respectively. Then, we identify the group to which most prices belong and estimate the average values of shadow prices in this group. We define these values as the most possible values (MPV) of shadow price because they indicate the values most likely to appear during the process of direction change by 180 degrees from (1, 1) to (1, -1) (as shown in Figure 2). The MPVs of the shadow prices of direct and overall carbon emissions are illustrated in Figure 4. Most of the values of the direct carbon emissions of each province are obtained in the directions between (1, 0) and (1, -1), which represent the strategies of increasing desirable outputs and decreasing undesirable outputs simultaneously. These are considered as ideal directions since the construction enterprises could maximize their profits via these directions. Furthermore, most of the values of overall carbon emissions are estimated in the directions between (1, 1) and (1, 0). this indicates that the materials industries supplying the construction industry are likely to expand the carbon emissions when they choose the production and carbon abatement strategies. Therefore, there is potential for carbon emissions reduction for these industries and they can either improve their environmental technology to emit less CO_2 or allocate resources to environmental cleanup activities for mitigating CO_2 emissions.

Finally, we obtained the average values of shadow prices in all possible directions covering 30 provinces during 2004–2014; these are illustrated in Figure 5. From the results, we can observe that the shadow prices of direct and overall carbon emissions both exhibit growth trends during the sample years, which indicates that the carbon emissions reduction measures have taken effect, and the CO_2 abatement potential has been released. The costs of further emissions reduction will be more expensive because there is less potential to be exploited. Figure 5 shows that the shadow price of direct carbon emissions changed from 14,000 to 47,000 yuan/ton, while the shadow price of overall carbon emissions changed from 500 to 3,200 yuan/ton. The shadow prices of direct carbon emissions in Jiangsu and Zhejiang are very much higher than are those in other provinces. To make this figure easier to understand, we use the deepest color to represent the shadow prices of Jiangsu and Zhejiang in Figure 5; 47,000 yuan/ton is the highest shadow price of the provinces, except for Zhejiang and Jiangsu. The specific values of each province are reported in Tables 2 and 3. It is worth noting that the shadow price of direct CO_2 emissions is approximately 30 times higher than is that of overall CO_2 emissions. This phenomenon corresponds to the results in Figure 3 and Figure 4. The shadow prices associated with all possible directions of direct carbon emissions are much higher than are those of overall carbon emissions. Moreover, according to Figure 4, most provinces have large abatement potential because they probably choose the directions between (1,0) and (1,1), leading to the low shadow price. The high marginal cost of abatement of direct CO_2 emissions means it may be very costly for entrepreneurs to additionally cut down carbon emissions in the construction industry. Conversely, the low shadow price of overall carbon emissions reflects the fact that, compared with the construction industry, there exists substantial carbon emissions reduction potentiality in the production process of building materials industries. Hence, when construction enterprises carry out emission-reduction efforts and want to reduce carbon emissions by more than the present amount of emissions reduction, they can consider improving the environmental standards of the material production process, which can encourage suppliers to employ more advanced technology to satisfy the standards. As shown in Figure 5, one can observe lower shadow prices in 2011 and 2012. This phenomenon may have correlations with the global financial crisis triggered in 2008. The economic recovery in the following years brings more opportunity for development for material producers and construction enterprises, consequently leading to increases in energy consumption and associated CO_2 emissions; thus, the shadow price of CO_2 emissions in the construction industry fell in 2011 and 2012. Woo et al. (2015) suggested that the global financial crisis has had an effect on environmental efficiency. The above results show that marginal costs of carbon emissions abatement may have been affected by the crisis.

Comparing the two kinds of price, we can find something special in the shadow prices of Zhejiang, Jiangsu, Qinghai, Ningxia and Xinjiang. Zhejiang and Jiangsu have lower shadow prices of overall carbon emissions and higher shadow prices of direct carbon emissions, while Qinghai, Ningxia, and Xinjiang have much higher shadow prices of overall carbon emissions. The higher shadow prices of direct carbon emissions in Zhejiang and Jiangsu indicate that the carbon emissions reduction potential in the building activities of the two provinces has already been released. In addition, compared with other provinces, Zhejiang and Jiangsu have consumed more building materials, and, thus, the carbon emissions from their materials production processes are much higher, leading to lower shadow prices of overall carbon emissions. As for Qinghai, Ningxia, and Xinjiang, it is difficult to reduce carbon emissions because their present material carbon emissions are much lower than in the other provinces, resulting in higher shadow prices of overall carbon emissions.

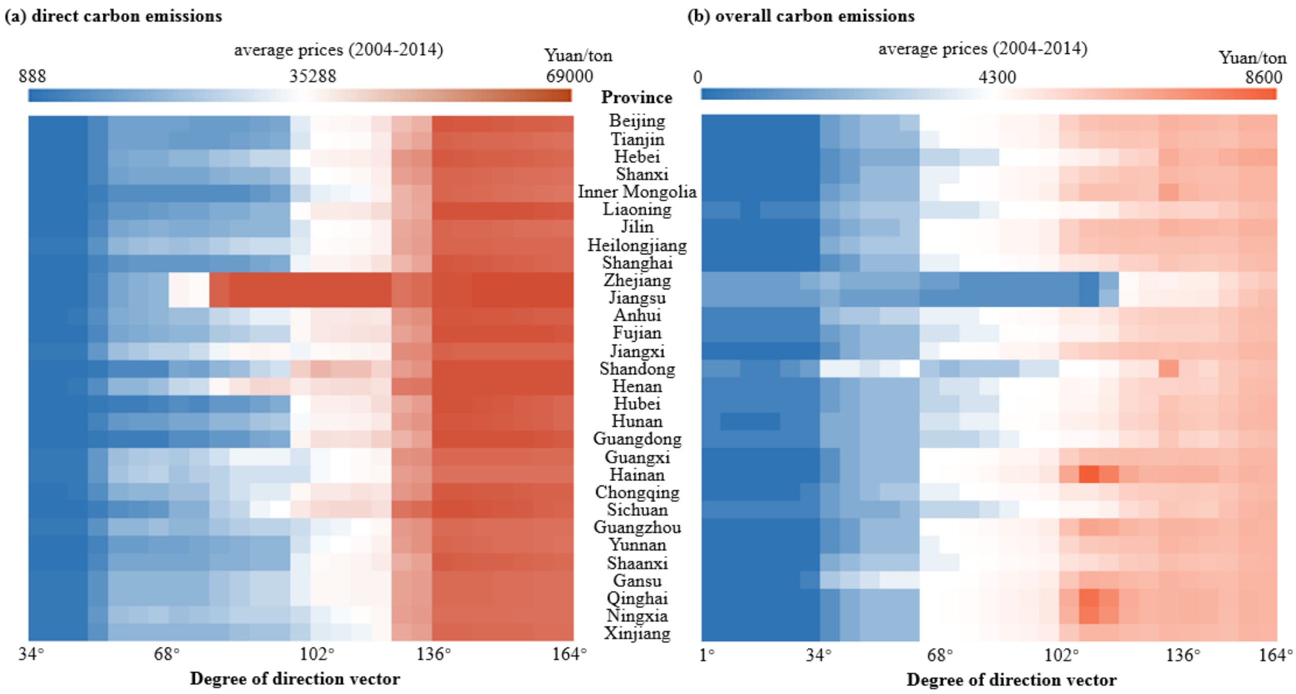

Figure 3 Sensitivity of average prices (2004–2014) to direction selection

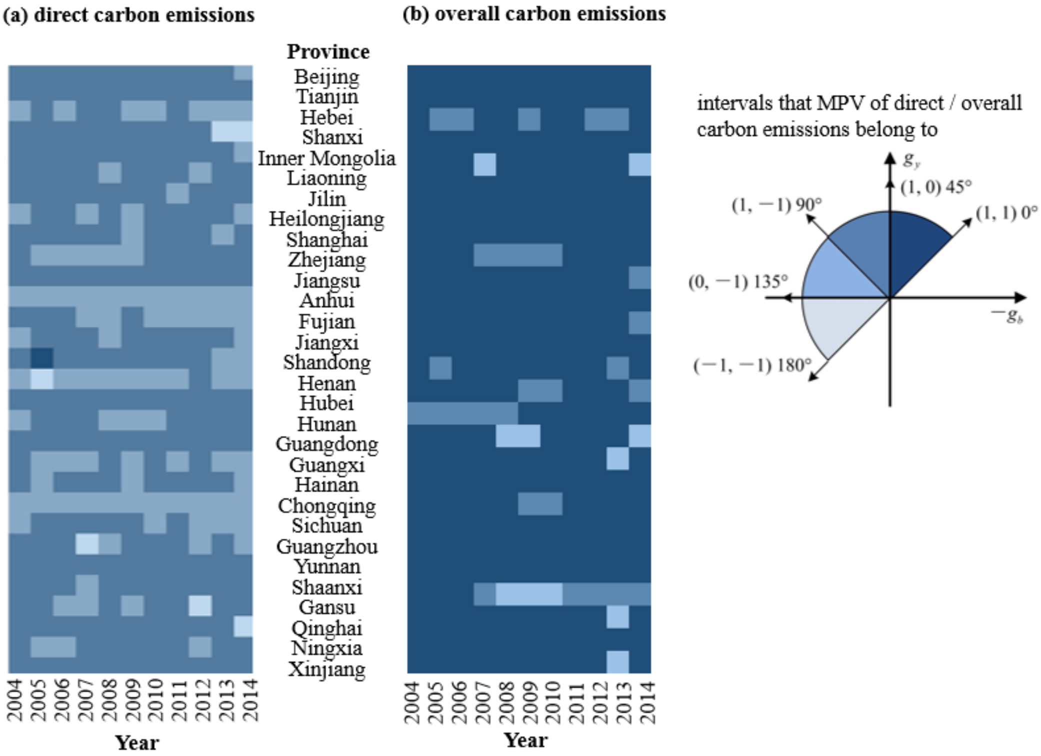

Figure 4 Intervals the most possible values belong to

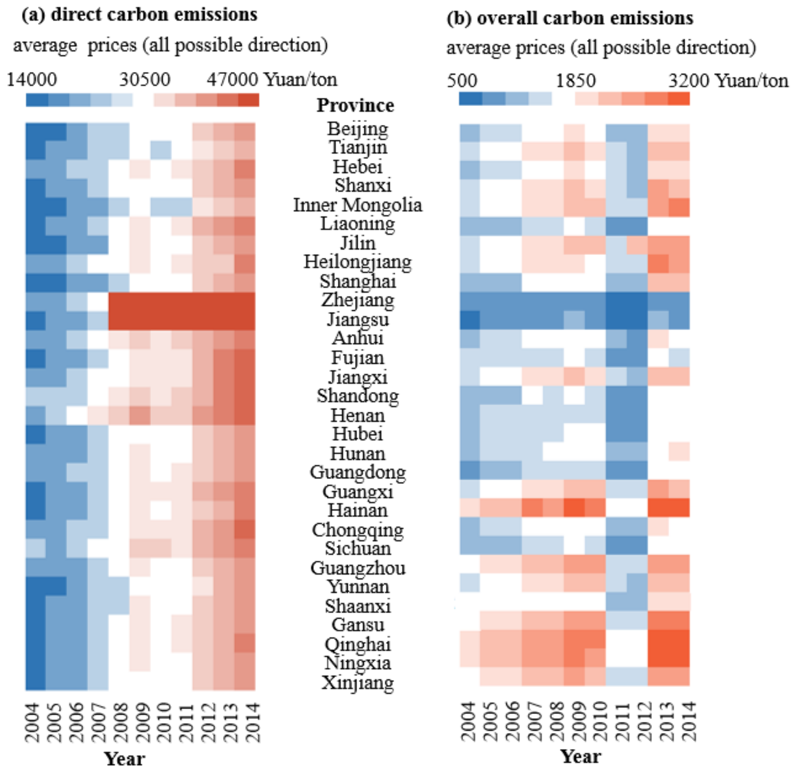

Figure 5 Average prices (all possible directions) in 2004–2014

Table 2 Average shadow prices (all possible directions) of overall carbon emissions (Yuan/ton)

Regions	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Beijing	1163	1320	1359	1615	1670	1850	1722	1079	1054	2019	1890
Tianjin	1483	1729	1721	1947	1995	2210	2087	1337	1278	2278	2227

Hebei	1245	1464	1476	1754	1643	1925	1804	1452	1198	2036	2087
Shanxi	1427	1632	1666	1907	1909	2147	1956	1328	1284	2403	2339
Inner Mongolia	1520	1770	1732	1958	1996	2203	2138	1399	1414	2610	2740
Liaoning	1160	1211	1203	1396	1444	1593	1462	955	923	1666	1799
Jilin	1522	1847	1832	2108	1956	2229	2145	1376	2266	2408	2405
Heilongjiang	1438	1714	1762	2072	1889	1997	1832	1384	1323	2716	2642
Shanghai	1133	1301	1290	1595	1594	1794	1749	1134	1115	2173	2130
Jiangsu	701	787	753	841	883	943	897	561	512	932	910
Zhejiang	662	758	745	864	930	1059	966	609	555	1056	1033
Anhui	1298	1457	1427	1639	1654	1841	1694	1082	1027	1856	1845
Fujian	1363	1452	1383	1524	1511	1627	1490	966.	882	1604	1557
Jiangxi	1470	1668	1682	1967	1894	2147	2055	1323	1204	2162	2135
Shandong	1103	1275	1301	1599	1440	1686	1463	994	922	1590	1627
Henan	1237	1381	1318	1440	1366	1500	1407	962	941	1702	1661
Hubei	1233	1418	1378	1559	1552	1736	1614	1002	917	1644	1664
Hunan	1160	1375	1357	1579	1595	1841	1767	1162	1113	1840	1874
Guangdong	954	1113	1135	1316	1357	1536	1550	992	918	1655	1667
Guangxi	1556	1772	1795	2097	2062	2299	2157	1410	1334	2420	2335
Hainan	2011	2326	2342	2736	2657	2995	2833	1825	1715	3142	3152
Chongqing	1296	1527	1534	1775	1758	1832	1692	1138	1086	1881	1816
Sichuan	1098	1300	1285	1514	1469	1688	1549	990	950	1765	1817
Guizhou	1651	1950	1954	2286	2348	2583	2443	1560	1472	2615	2588
Yunnan	1508	1757	1668	2014	2060	2303	2136	1428	1306	2222	2251
Shaanxi	1581	1719	1785	1849	1661	1831	1740	1181	1236	2103	2054
Gansu	1622	1889	1921	2275	2246	2565	2418	1563	1472	2704	2667
Qinghai	1954	2250	2249	2587	2586	2853	2666	1759	1660	3074	3056
Ningxia	1855	2167	2170	2537	2536	2780	2625	1685	1618	3001	2972
Xinjiang	1597	1917	1900	2233	2199	2452	2282	1416	1344	2439	2409

Table 3 Average shadow prices (all possible directions) of direct carbon emissions (Yuan/ton)

Regions	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Beijing	15007	17283	19234	21003	23416	26266	24712	26183	31284	35802	39614
Tianjin	16659	17543	19163	21364	22474	25256	23846	24696	29210	32992	36360
Hebei	18134	19440	20948	23231	25841	29084	26686	27695	33215	36954	40750
Shanxi	15032	17652	19290	21762	23993	27064	25022	26134	30732	34477	38107
Inner Mongolia	14552	15934	17397	19737	21755	24466	21049	23249	27618	31666	35896
Liaoning	16781	17871	19354	21306	24336	27932	26675	28161	35150	38618	42632
Jilin	15005	16639	17844	20204	24239	27526	25455	26301	32039	34397	37901
Heilongjiang	17833	19199	21100	23948	26278	30190	26820	28108	33706	31116	40855
Shanghai	14966	16470	19278	20435	23422	26782	25699	26635	31320	34933	38461
Jiangsu	27174	33562	39300	52951	61481	64143	61816	114147	86261	213395	120372
Zhejiang	28006	27667	32495	36291	40650	50713	49900	61805	92544	99500	171219
Anhui	17454	19853	21907	24376	27868	31159	28626	31235	35828	38514	42020
Fujian	17013	18785	20585	23648	26029	30161	29012	29973	35811	40463	46244
Jiangxi	18947	19901	21742	24275	26872	30468	28447	29724	36391	40967	45193
Shandong	22442	20657	23616	26124	28901	31772	29700	31066	36617	41277	43876
Henan	18732	22512	24736	28929	32670	37160	32101	33632	39171	43290	45064
Hubei	16194	17754	18982	21282	24355	26721	24288	25622	31223	34619	38783
Hunan	18985	18788	20580	22761	26624	29199	27128	26377	31408	34562	37173
Guangdong	17372	18736	20659	22235	24602	28167	25435	27669	32829	36910	39929
Guangxi	16349	18332	20242	22726	26187	29535	27524	29138	34594	39200	43575
Hainan	16988	18415	20296	22768	25410	28893	26682	27646	33026	36677	40437
Chongqing	18133	19528	21075	23601	26534	30021	28198	29865	35561	40168	44162
Sichuan	21448	20362	22577	23905	26402	30910	31696	29967	34420	40105	42636
Guizhou	17646	17330	18693	22300	24478	27300	25371	27143	32215	35616	38711
Yunnan	16997	17210	18787	20815	23187	26014	24515	25036	29292	34588	37893
Shaanxi	14902	17510	18945	22582	23394	27809	25526	26446	31445	36256	39169
Gansu	16632	18109	19915	22498	24974	28392	26094	27304	32722	36577	39926
Qinghai	16795	18276	20092	22523	25100	28438	26337	27661	32838	36684	40447

Ningxia	15959	18189	19976	22309	24484	27593	25738	27094	32372	36267	39843
Xinjiang	15746	17474	19165	21688	24142	26984	25180	26143	31106	34556	38086

4 Results analysis

4.1 Influencing factors of shadow price

It is of significant value to use regression analysis to investigate the factors influencing shadow prices. Taking into account the multiple selection of directional vectors, we choose four representative results: the average, maximum, and minimum values from (1,1) to (-1, -1), and the most possible value. Additionally, we consider the following influencing factors:

Per capita GDP: Du et al. (2015) states that per capita GDP, which reflects the development level of a city, has a non-linear relationship with CO_2 emissions, and, thus, it is significant to include per capita GDP in regression analysis to test whether this factor influences the shadow prices of carbon emissions. The data on GDP and population are derived from the China Statistical Yearbooks.

Urbanization rate: The urbanization rate reflects the urban population. The more citizens in an area, the more buildings that need to be constructed to accommodate people. Thus, the rate represents the demand of buildings, which may affect the CO_2 reduction cost in the construction industry. The necessary data are derived from the China Statistical Yearbooks.

Energy intensity: Energy intensity can represent technological progress in the use of energy. Generally, lower energy intensity implies more advanced environmental technology, which may have an effect on the cost of carbon emissions reduction. The data are derived from the China Energy Statistical Yearbooks and the China Statistical Yearbooks.

The ratio of total output value of construction industry over the total output value of secondary industry: This ratio can imply the development of the construction industry. A well-developed construction industry may have more investment in carbon emissions reduction, which can affect the degree to which the abatement potentials on carbon emissions are released. The data are derived from the China Energy Statistical Yearbooks.

Because of a small N=30 and a small T=10, which represent the provinces and year, respectively, in this article, we use the method of least squares with dummy variables (LSDV) to regress. The panel regression model is as follows.

$$PRICE_{it} = c_i + \beta_1 (preGDP)_{it} + \beta_2 \left(UR\right)_{it} + \beta_3 \left(EI\right)_{it} + \beta_4 (Ratio)_{it} + \varepsilon_{it} \tag{12}$$

where $PRICE$ denotes the shadow price, $preGDP$ denotes the per capita GDP, UR denotes the urbanization rate, EI is the energy intensity, $Ratio$ denotes the ratio of total output value of construction industry over the total output value of secondary industry, and the subscripts i and t, respectively, represent the construction industry sector in the ith province of the tth year. ε_{it} is the error term.

The results are presented in Table 4 and Table 5. From the tables, we can see that the same influencing factor has different levels of significance for four shadow price values. For example, per capita GDP is significant at the 1% level for the average value and the maximum value of the shadow price of overall carbon emissions, but it has no significant effect on the minimum value and the MPV. Table 6 shows that energy intensity has a positive influence on the MPV, contrary to the influence on average and maximum values. It may be connected with the magnitude of values. In detail, the MPV of the shadow price of overall carbon emissions belongs to the interval of increasing desirable and undesirable outputs simultaneously, and the shadow price in this interval is much lower than in others. Thus, average and maximum values are higher than MPV, resulting in an opposite effect as energy intensity have on the MPV. Except for the MPV, significant factors all have the same influence on the shadow prices of direct and overall carbon emissions, and the influences are as expected. The high per capita GDP means that this area is well-developed, and it then may be confronted with stricter environmental monitoring and the requirement for more detailed environmental information disclosure. As a consequence, the government will face considerable pressure from the public and will be assigned for reduction targets for pollutants other than CO_2. Disposing of other pollutants, such as SO_2 and NO_X, could facilitate the consumption of energy and the amount of carbon emissions will increase consequently, thus resulting in lower shadow prices and higher carbon emissions reduction potential. The high urbanization rate shows that numerous buildings have already been constructed to accommodate citizens, which means that potential for reduction of carbon emissions has been released completely, and the marginal cost for further abatement of carbon emissions will be higher. Moreover, the more attention the government pays to construction, the more advanced technology the construction industry will have; the advanced environmental technology can help the construction industry to release its carbon emissions reduction potential. The negative effect implies that a province with higher energy intensity will have lower costs when cutting down an extra unit of carbon emissions. The high energy intensity means the government should invest in advanced environmental technology to improve energy efficiency, which can facilitate the release of abatement potential on carbon emissions. Therefore, during the process of improving energy efficiency, the shadow price will climb because of the release of potential.

Table 4 Regression of the shadow price of overall carbon emissions

Variable	Average	Maximum	Minimum	MPV
Per GDP	-1553.449***	-3645.755***	-12.372`	-28.783
UR	-172.683	776.411	-3.068	473.695
EI	-306.421***	-647.464**	1.149	81.310**
Ratio	2641.697**	4540.527	8.692	648.064
Adjusted R^2	0.667	0.134	0.915	0.384

***p<0.01; **p<0.05; *p<0.1

Table 5 Regression of the shadow price of direct carbon emissions

Variable	Average	Maximum	Minimum	MPV
Per GDP	-14262.660***	-42119.330***	-771.659***	-8477.013
UR	173843.100***	368227.100***	3558.045***	100792.200***
EI	391.381	-5919.840**	-164.812***	-3066.101
Ratio	35110.990***	100203.700***	1674.412***	64008.140
Adjusted R^2	0.882	0.890	0.887	0.747

***p<0.01; **p<0.05; *p<0.1

4.2 Convergence of shadow price

In addition to the regression analysis, we use convergence to analyze the shadow price. The concept of convergence has been applied in the field of pollutant studies in recent years. Most studies use convergence analysis to model and predict pollutant emissions and energy consumption. This paper attempts to use the convergence method to recognize the differences in shadow prices among 30 provinces and provides some reference for policy implications. We focus on the analysis of two types of convergence: sigma convergence and beta convergence.

In this paper, sigma convergence means that the difference between the shadow prices of provinces will reduce as time passes. We use the deviation coefficient, which is the ratio of standard deviation to average value, to test if sigma convergence exists in the provincial shadow prices of carbon emissions. Sigma convergence occurs when the deviation coefficient of shadow prices among provinces decreases over time. The results are shown in Figure 6 and Figure 7.

For the overall carbon emissions, there are no obvious changes in the heterogeneity of shadow prices. However, the curve of MPV shows a slight rising trend with fluctuation, which is different from the other curves in Figure 6. Compared with the shadow price of overall carbon emissions, the heterogeneity of the direct marginal abatement costs across provinces have a larger change range, especially the curves of the maximum and the average values, which have stronger fluctuations than the rest. Nevertheless, both Quah (1993) and Sala-i-Martin (1995) have stated that sigma convergence is a sufficient, but not necessary, condition for beta convergence. That means that the absence of sigma convergence cannot prove that the beta convergence does not exist. Since we also want to discuss the beta convergence of the shadow price, the regression-based beta convergence test is still necessary.

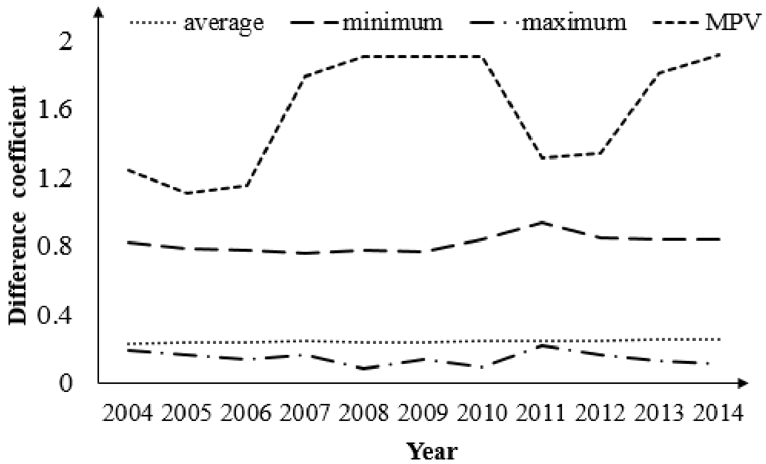

Figure 6 Sigma convergence of the shadow price of overall carbon emissions

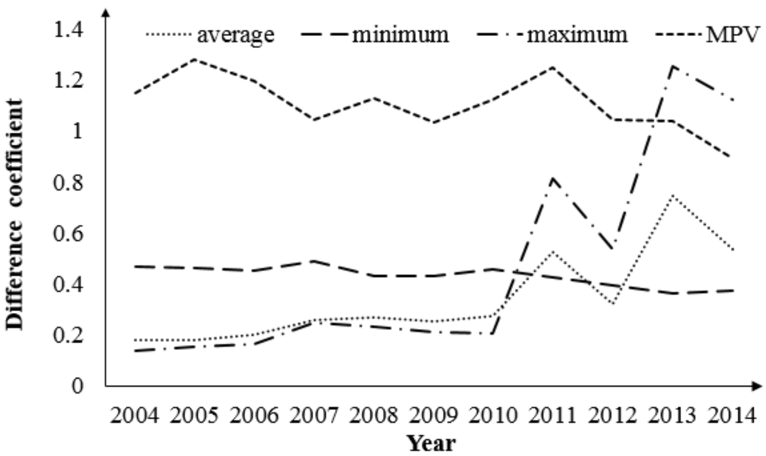

Figure7 Sigma convergence of the shadow price of direct carbon emissions

The existence of beta convergence means that the provinces with lower shadow prices will catch up with those with higher shadow prices. Deriving from the creative literatures of Barro (1991) and Mankiw et al. (1992), the concept of beta convergence can be categorized into unconditional beta convergence and conditional beta convergence. In this study, we will test the latter, suggesting that marginal abatement costs are reaching a unified long-run equilibrium by controlling for a series of structural conditions, such as population, affluence, technology and environmental regulations, that differ by region (Barro, 2015).

According to Huang et al. (2016), and also based on the influencing factors we discussed above, the conditional beta convergence can be tested by Equation (13).

$$PRIC_{it} = \alpha + \beta \ln PRIC_{i(t-1)} + \varepsilon_1 \left(GDP\right)_{it} + \varepsilon_2 \left(RATIO\right)_{it} + \varepsilon_3 \left(EI\right)_{it} + \varepsilon_4 \left(UR\right)_{it} + \mu_{it} \tag{13}$$

where $PRIC_{i(t-1)}$ represents the year lagged terms of shadow prices, GDP_{it} represents the GDP, and μ_{it} is the error term. The other symbols in this equation have the same meanings as in Equation (12).

If $0 < \beta < 1$, conditional beta convergence occurs. The shadow price of a province approaches the steady state at the speed λ, which can be estimated by λ=-lnβ. Similarly, when the N and T are small, LSDV may be a viable selection to test the model. Since we use the conditional beta convergence, the catch-up process is affected by the influencing factors. The nation was divided into three regions—eastern, central, and western regions—by China's seventh Five-Year Plan, and this division has played an important role in determining the priority of economic development and resource allocation in these regions, which has had an effect on the influencing factors in this paper. Hence, we will examine the beta convergence in the eastern, central, and western regions. In addition, according to the development of green buildings, we divide the nation into two regions: Region 1 denotes developed provinces (Shandong, Guangdong, Tianjin, Hebei, Jiangsu, Henan, Shanghai, Hubei, Shaanxi, and Anhui) and Region 2 denotes less-developed provinces (Beijing, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Zhejiang, Fujian, Jiangxi, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Gansu, Qinghai, Ningxia, and Xinjiang). The results are presented in Table 6.

Table 6 Conditional beta convergence of the shadow price

Values	Shadow prices	All regions	Eastern regions	Central regions	Western regions	Region 1	Region 2
Average	Direct	0.732***	0.801***	0.607***	0.573***	0.622***	0.716***
	Overall	0.260***	0.232**	0.270**	0.273**	0.211*	0.270***
Maximum	Direct	0.767***	0.836***	0.670***	0.631***	0.690***	0.754***
	Overall	0.255***	0.229**	0.426***	0.279**	0.298***	0.448***
Minimum	Direct	0.380***	0.415***	0.318***	0.121	0.384***	0.333***
	Overall	0.417***	0.459***	0.268**	0.262**	0.220***	0.262***
MPV	Direct	0.131**	0.124*	0.232**	-0.087	0.170	0.114**
	Overall	0.274***	0.345***	0.208	0.271**	0.342**	0.215**

***p<0.01; **p<0.05; *p<0.1

The findings show that the average value, maximum value, and minimum value of the shadow price all have good convergence, while the most possible value of the shadow price is a little different from the others. It can be seen that western regions seem to converge faster, which may be connected with three reasons related to the influencing factors. Firstly, economic growth may play a significant role since we considered the GDP. The Annual Report on Development in Western Regions of China (Xu et al., 2017) points out that, in 2015, the average annual rate of GDP in western regions reached 12.24%, which is higher than in eastern regions and central regions, which were 2.24% and 1.38% respectively. The rapid development largely depends on support from government. For example, the National Development and Reform Commission has been arranging for 100 million yuan to invest in the infrastructure construction in western regions every year since 2010. These conditions can accelerate the catch-up process, since the improvement of environmental friendly technology needs investment, and the regions that the government focuses on have priorities in terms of resource allocation. In addition, our original data show that the rates of decline of energy intensity in Qinghai and Xinjiang were the fastest among 30 provinces during 2004–2014, and that improving energy efficiency could accelerate the process of catching up. Finally, the western regions are less developed than are the eastern and central regions, leaving more room for advancement in the rate of urbanization and the development of the construction industry. Actually, the western regions performed well in these fields in sample years: during the 12th Five-Year-Plan period, the urbanization rate was up to 48.7%, and the railway and highway networks were extended by 12,000 kilometers and 215,000 kilometers, respectively (NDRC, 2017). Therefore, the shadow price of western regions has had a faster growth rate than in other regions. Moreover, for Region 1, the advanced green technology in the construction industry is the main factor behind a faster speed of convergence than in Region 2, while important roles are also played by other conditions of convergence, such as low energy intensity and high urbanization rate. Moreover, the selection of a directional vector in estimating marginal costs of carbon emissions abatement can lead to variable convergence speeds, even in the same region. Hence, when policy makers formulate environmental regulations between different provinces, the different production strategies of construction enterprises are an important condition that should be taken into account.

5 Conclusions and policy implications

To cope with the challenge of climate change, China has announced various emission reduction targets or plans, which are disaggregated at the province level. The construction industry, along with the material industries supplying it, is one of the most carbon-intensive industries, contributing massively to China's energy consumption and consequent carbon emissions. It is acknowledged that this industry should undertake heavy mitigation of carbon emissions to help the Chinese government realize its commitment that carbon intensity should decrease by 60%–65% by 2030 compared with the 2005 level. Assessment of the marginal costs of carbon emissions abatement can help prompt the construction industry to mitigate emissions effectively.

This paper estimates both the direct shadow prices and the overall shadow prices of the construction industry, together with those of the material industries supplying it, during 2004–2014 for China's 30 provinces by using a parametric directional distance function-based sensitively estimation that considers all possible direction selections. Directional vectors varying from (1, 1) to (-1, -1) are chosen to avoid either underestimating or overestimating the shadow prices. The results show that the shadow prices of direct and overall carbon emissions are sensitive to the selection of directional vectors. The wide range of shadow prices represents different costs of the probable carbon emissions mitigation strategies, such as reducing the desirable output to cut down carbon emissions and improving environmental technology to emit less CO_2, and our results provide the highest and lowest possible marginal abatement costs for policy makers and construction enterprises. From the average values, we can see that the shadow price of overall carbon emissions is much lower than is that of direct carbon emissions, which means that there is large potential for carbon emissions reduction in the supporting material industries. We also find that per capita GDP, the ratio of the total output value of construction industry to the total output value of secondary industry, urbanization rate, and energy intensity have significant effects on the shadow prices of direct and overall carbon emissions. We have analyzed the convergence on shadow price. The results show that sigma convergence does not exist while for the conditional beta convergence, the western regions seem to converge faster than other regions. In particular, we provide the corresponding policy implications as follows:

(i) When government assigns the construction industry their emission reduction missions, their relatively high cost of abatement should be considered. Though the construction industry is a carbon-intensive industry and emit a large amount of CO_2, it will pay a lot and be under considerable pressure when the target exceeds their present ability. Compared with construction industry, the building materials industries have relatively huge potential for carbon emissions reduction. Hence, when the Chinese government places the burden of reducing carbon emissions on the industrial sectors, they can pay more attention to the building materials industries. Increasing the discharge standard for pollutants and eliminating enterprises that fail to meet the standard are effective ways to urge materials industries to mitigate their carbon emissions by greater amounts.

(ii) In recent years, China has performed a series of powerful carbon mitigation policies and has had a remarkable improvement in carbon emissions reduction and environment protection. For example, it has launched sets of pilot carbon trading markets within several provinces and realized the target of reducing carbon intensity by 17% from 2010 levels (NRDC., 2016). Nevertheless, most scholars have expressed criticism that these gains have been obtained mainly by direct regulation and may not be cost-effective. Our study comes up with four factors that have significant influence on the shadow price of carbon emissions, and, thus, government can implement measures on these factors and facilitate cost-effective carbon mitigation. It is easier to achieve emissions reductions in developed areas, because per capita GDP has an obvious negative effect on the shadow price. Hence, we conclude that promoting economic development in an area can decrease the marginal abatement cost, thus helping construction enterprises to mitigate carbon emissions much more cost-effectively. Moreover, the shadow prices are high in the areas with low energy intensity. Therefore, if the government wants to release more of the potential for carbon emissions reduction in these areas, remaining dependent on increasing energy efficiency will cost a lot, while either strengthening environmental regulation or upgrading technology may be effective approaches to further emissions mitigation. Furthermore, we should pay great attention to the areas with low urbanization rates at present. With improvement of the urbanization rate, measures such as stricter government supervision and more environmental friendly technology should be adopted to slow down the increasing tendency of marginal abatement costs.

(iii) Though there is no sigma convergence during the study period, the convergence analysis proves the existence of conditional β convergence in China's provincial construction shadow prices. The results of convergence analysis give strong support to the necessity of introducing a national carbon trading market in China. The absence of sigma convergence indicates that the national carbon trading market needs to be proposed to eliminate the disparities of shadow prices among provinces. The beta convergence indicates that provinces with lower shadow prices will catch up with provinces with higher shadow prices. Since our results show that shadow prices have been increasing in recent years, the existence of catch-up progress implies that the abatement costs in the construction industry will rise continuously and rapidly. Implementing the mechanism of carbon trading can reduce the abatement costs and slow down the rising speed of shadow prices. To sum up, our findings give strong support for introducing a national carbon trading market in China, which can help the construction industry and the building materials industries to reduce their carbon abatement costs.

Acknowledgement

We acknowledge the financial supports from the National Natural Science Foundation of China (Grant Nos. 71471018, 71521002 and 71761137001), the Social Science Foundation of Beijing (Grant No. 16JDGLB013), the Joint Development Program of Beijing Municipal Commission of Education, the Fok Ying Tung Education Foundation (161076), the National Key R&D Program (Grant No. 2016YFA0602603), and the International Clean Energy Talent Program of Chinese Scholarship Council.

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Appendix

Table A Carbon emissions factor and recovery factor of building materials

Material type	Cement	Steel	Glass	Wood	Aluminum
CO_2 emissions factor	0.822kg/kg	1.789kg/kg	0.966kg/kg	-842.800kg/m^3	2.600kg/kg
Recovery factor	-	0.800	-	-	0.850

Table B Amount of direct carbon emissions from China's construction industry (104 ton)

Regions	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Beijing	279.28	256.51	245.59	258.00	272.61	335.18	398.04	380.32	353.08	288.25	274.21
Tianjin	98.62	123.40	147.02	172.75	317.42	392.11	468.42	507.80	532.16	539.65	541.96
Hebei	188.74	218.51	217.34	249.87	262.98	290.90	386.77	473.89	479.00	451.08	427.62
Shanxi	304.83	195.64	222.82	230.08	277.29	333.13	403.56	440.03	464.89	493.53	441.94
Inner Mongolia	268.29	266.35	303.48	316.71	407.94	443.37	831.77	697.39	722.92	630.99	511.11
Liaoning	251.66	267.17	291.95	342.68	349.74	395.83	503.66	579.57	543.24	593.74	470.96
Jilin	244.45	238.07	265.83	279.53	174.43	188.00	252.41	280.88	309.40	435.20	432.08
Heilongjiang	47.10	43.66	49.41	48.64	50.14	64.98	96.29	140.36	152.10	875.81	159.64
Shanghai	341.99	333.64	239.22	370.47	383.76	403.92	307.54	521.64	537.26	554.11	521.78
Jiangsu	247.58	249.76	259.17	274.85	321.54	353.53	399.13	474.14	499.59	591.42	610.64
Zhejiang	220.94	470.92	508.66	545.63	585.97	653.54	878.04	946.38	959.51	1063.21	1078.22
Anhui	166.78	148.68	171.63	192.47	216.94	231.36	286.12	336.56	409.43	527.06	542.24
Fujian	116.57	106.93	136.66	150.16	288.72	298.17	372.24	440.06	416.56	511.25	535.74
Jiangxi	30.24	49.85	52.05	57.53	76.94	89.72	106.90	143.71	142.55	165.86	180.77
Shandong	384.52	525.73	536.38	539.01	568.12	639.91	760.34	851.51	746.33	703.40	733.28
Henan	86.64	74.46	98.92	113.50	124.11	163.11	271.08	361.65	357.82	436.69	552.69
Hubei	321.76	363.95	424.49	464.51	465.25	556.48	767.55	832.52	793.54	865.69	907.86
Hunan	137.38	282.80	300.07	311.10	270.15	312.70	443.43	552.55	595.64	712.55	786.18
Guangdong	382.23	452.66	478.00	535.50	563.32	561.82	702.36	734.42	748.20	744.65	805.87
Guangxi	75.57	95.85	112.43	104.10	74.15	84.68	96.67	118.23	119.87	108.70	104.44
Hainan	24.65	25.53	27.84	31.20	31.42	41.26	64.67	78.91	87.67	100.79	118.58
Chongqing	132.47	137.13	165.57	192.84	238.34	229.89	297.83	351.62	344.73	364.42	384.15
Sichuan	329.02	357.93	349.21	489.21	462.76	528.05	696.51	777.30	673.08	653.42	614.16
Guizhou	16.25	148.87	134.83	113.36	160.79	195.18	225.06	192.79	207.55	285.24	344.74
Yunnan	114.15	235.35	270.47	282.80	337.29	353.55	481.17	587.19	583.89	548.57	591.01
Shaanxi	268.13	179.99	245.38	155.30	338.67	289.50	424.64	399.71	428.28	438.46	465.42
Gansu	147.02	141.78	143.13	149.30	159.06	162.02	226.76	258.84	280.36	283.79	308.77
Qinghai	43.58	41.23	45.52	47.09	60.12	63.29	80.19	97.78	109.34	117.61	121.97
Ningxia	17.8	34.3	41.1	50.1	94.1	105.	136.	144.	145.	156.8	156.4

	3	7	7	7	4	90	14	32	78	9	5
Xinjiang	157.74	99.61	107.09	113.46	124.66	141.84	166.22	205.21	261.58	297.94	296.42

Table C Amount of overall carbon emissions from China's construction industry (104 ton)

Regions	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Beijing	1303.35	1427.41	1420.91	1761.29	2029.43	2948.38	3489.71	3593.99	2853.69	3319.45	3412.00
Tianjin	753.00	640.91	809.16	1200.65	1189.04	1654.02	1651.28	2336.45	2269.03	3187.53	4467.15
Hebei	1897.96	2499.82	4879.51	2420.49	3644.69	3785.28	10651.04	49455.46	47309.39	17288.64	6997.48
Shanxi	990.98	1431.14	1310.91	1645.28	2641.03	2619.08	4087.12	2716.80	2749.74	2818.30	3409.52
Inner Mongolia	651.02	486.65	577.31	851.46	2147.06	1294.92	1304.68	1417.06	1213.79	1078.62	1056.10
Liaoning	1869.37	1751.26	1996.31	2263.34	3159.60	4400.58	5631.80	9370.61	7432.98	14285.92	13917.23
Jilin	1474.01	192.65	613.47	608.41	1011.36	1349.40	1339.65	1479.72	94998.80	6295.51	6722.53
Heilongjiang	807.29	627.81	680.52	790.06	967.69	1045.41	1239.90	1524.56	1369.09	1416.08	1484.96
Shanghai	1417.05	1789.74	1667.16	1672.15	1758.06	1887.33	1984.35	2125.16	1878.52	1983.96	2056.85
Jiangsu	6291.63	6951.38	7800.87	10013.44	12912.29	13204.69	15215.81	63551.79	27107.27	21129.76	22426.52
Zhejiang	9102.08	10935.54	12885.08	13371.31	16401.33	17306.63	19886.02	24417.93	26149.25	29558.18	30399.91
Anhui	1335.78	1422.68	1668.25	2169.42	2380.05	2774.38	3851.68	4132.83	4054.30	5106.87	5502.91
Fujian	849.56	1658.75	2320.82	1873.44	3483.30	4358.10	5502.88	5417.65	6891.15	9291.89	12275.81
Jiangxi	907.65	1049.63	1260.83	1167.85	1340.68	1584.20	1802.31	2881.23	2877.04	3810.86	1824.80
Shandong	2784.05	3299.38	3832.19	2962.99	4982.05	6195.51	7023.99	6832.98	16687.92	8636.56	8932.44
Henan	1718.13	1783.73	2535.04	3747.67	4257.21	5229.95	6490.06	6552.89	8095.21	7646.32	20913.74
Hubei	2002.23	2820.93	2769.52	3207.78	2754.50	3262.94	3243.62	7360.16	14342.24	12952.29	15391.27
Hunan	4542.64	2608.03	3276.23	3515.14	3951.77	4774.98	5170.45	4704.05	5501.30	5941.76	6302.14
Guangdong	2531.23	3074.40	3256.52	3216.68	3083.36	3533.12	4614.81	7563.00	1268.43	6304.52	6718.31
Guangxi	822.49	805.29	863.63	876.09	993.85	1310.01	1575.75	1784.35	2437.21	1758.98	1949.19
Hainan	61.45	65.49	74.69	86.50	143.45	182.70	177.85	317.17	311.98	401.26	233.62
Chongqing	1405.92	1423.76	1469.16	1813.01	2284.30	2330.38	4265.09	4307.35	3950.30	4770.09	4979.30
Sichuan	2146.17	2256.45	2655.40	2955.10	3501.56	4415.48	9747.90	11924.37	17956.01	19030.53	21186.97
Guizhou	526.89	415.60	517.96	622.45	646.23	991.53	631.13	1073.18	1262.48	2329.29	2846.08
Yunnan	725.50	788.32	1097.34	999.56	1161.86	1381.67	1926.36	1584.20	2035.96	5041.34	5610.72
Shaanxi	675.78	1152.77	1172.07	1716.90	2778.58	2968.83	3278.67	5684.41	3605.16	3925.63	4480.46
Gansu	514.46	548.13	681.72	483.64	1144.54	773.07	745.12	1769.40	1148.66	1743.48	1884.08
Qinghai	110.02	93.16	87.55	158.94	247.35	348.59	513.26	259.75	277.61	291.99	315.39
Ningxia	179.	183.9	208.4	221.8	264.9	303.5	369.8	480.2	438.7	627.4	691.3

Xinjiang	92856.84	6439.97	5901.49	8617.39	7711.66	3722.14	6906.68	63058.42	61526.36	71403.64	62014.95

Table D One-way analysis of variance (shadow price of overall carbon emissions)

Shadow prices	Estimated in (1, 1)	Estimated in (1, 0)	Estimated in (1, -1)
Estimated in (1, 0)	344.8 (0.052)	-	-
Estimated in (1, -1)	1011.7 (0.000)	666.9 (0.000)	-
Estimated in (-1, 0)	3779.3 (0.000)	3434.5 (0.000)	2767.6 (0.000)

Note: The shadow prices represent a group of 30 provincial shadow prices (average value of 2004-2014).

Table E One-way analysis of variance (shadow price of direct carbon emissions)

Shadow prices	Estimated in (1, 0)	Estimated in (1, -1)
Estimated in (1, -1)	18910.8 (0.000)	
Estimated in (-1, 0)	60576.0 (0.000)	41665.3 (0.000)

Note: Shadow prices represent a group of 30 provincial shadow prices (average value of 2004-2014); Direction in (1, 1) is not included since shadow prices of direct carbon emissions do not have nonzero values until directional vectors turn to 34° from (1, 1).