



Measuring the carbon shadow price of agricultural production: a regional-level nonparametric approach

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Received: 24 April 2023 / Accepted: 26 January 2024 / Published online: 9 February 2024
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Abstract

Climate change poses an urgent threat, necessitating the implementation of measures to actively reduce carbon emissions. The development of effective carbon emission reduction policies requires accurate estimation of the costs involved. In situations where actual prices of commodities are not available in the market, shadow pricing provides a useful method to calculate relative prices between commodities with and without price information. However, most studies focus on the industry, with few contributions on agricultural sector. This paper estimates the shadow price of carbon emissions in the agricultural sector from a provincial perspective, incorporating the impact of livestock into the calculation of carbon emissions and shadow pricing. Our findings indicate that ignoring livestock may overestimate CSP values. On the whole, the level of carbon shadow price is rising, indicating good green development in China's agricultural sector. The two types of convergence results show that there is sigma convergence and beta convergence in the western and central regions, demonstrating a significant improvement in environmental performance.

Keywords Carbon shadow price · Convergence analysis · Chinese agriculture · Environmental performance

Introduction

As early as 2018, the Intergovernmental Panel on Climate Change (IPCC) emphasized that the challenge of controlling climate warming at 1.5 °C is unprecedented. The IPCC Sixth Assessment Report pointed out that this challenge has become more severe due to the continued increase in greenhouse gas emissions. Greenhouse gas (GHG) emission,

including carbon dioxide (CO₂) emission, has a significant effect on climate change (Lyu and Liu 2023). As the concentration of the GHG in the atmosphere increases, the heat is “trapped” and leads to gradually raising temperatures globally with negative effects on the natural environment and human society (Xue et al. 2022). Given the global spillover of the effects of the global warming (Hussain et al. 2023), different countries face increasing frequency of extreme weather events, rising sea level and alterations in ecosystems. All of these have an impact on agriculture, water supplies, and human health among other severe and widespread effects of climate change.

Therefore, it is essential to address carbon emission to slow down the rate of climate change and suppress its effects. To promote the implementation of low-carbon technologies and practices, a multifaceted approach incorporating policies, regulations, and incentives can be employed. For example, China has proposed a “double carbon” target, which aims to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060 (Zeng et al. 2023). However, when creating policies, economic costs must be taken into account. To ensure the development of evidence-based and rational policies, accurate quantitative analysis related to

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expenditures associated with achieving the carbon neutrality goal is imperative.

Since the actual prices of certain goods may not always be accessible on the market, shadow pricing offers an alternative method. A shadow price is the estimated value of a good or service that build upon the trade-off between goods with and without price information. It can be regarded as the marginal value or marginal cost of an additional unit of a resource or service (He and Ou 2017). A carbon shadow price (CSP) reflects the economic cost of carbon emissions. The negative externalities associated with carbon emissions (Ji and Zhou 2020), such as climate change, are not taken into account unless a trading scheme for the emission permits is established. The purpose of utilizing the CSP is to quantify the expenses due to carbon emissions mitigation. Such information may provide background for the widespread adoption of environmentally friendly technologies and practices with low carbon footprints. By assigning a monetary value to carbon emissions, governments can establish carbon taxes and evaluate the cost-effectiveness of policies aimed at reducing carbon emissions. Consequently, they can better assess the true costs and benefits of different projects, policies, or investments and make more informed decisions about how to reduce their carbon footprint (Zhang et al. 2014; He et al. 2021).

China is currently the leading carbon dioxide producer, accounting for over 25% of global greenhouse gas emissions (Du et al. 2022). As such, global-scale efforts to address climate change should take into consideration measures to reduce emissions in China. In addition, China has set ambitious targets for reducing its carbon emissions in the coming decades, including reaching peak emissions by 2030 and achieving carbon neutrality by 2060 (Shen et al. 2021). Achieving these targets will require a better understanding of the drivers of emissions and the effectiveness of different mitigation strategies. China's experience in transitioning to a low-carbon economy could provide valuable lessons for other countries facing similar challenges. These points suggest that the case of China is highly relevant for empirical analysis.

Agriculture is a significant contributor to carbon emissions, accounting for around 25% of global greenhouse gas emissions (Hamid and Wang 2022). CO₂ emissions from land-use changes, such as deforestation and conversion of grassland to cropland, are also related to agricultural activities. They lead to the release of carbon stored in soil and plants into the atmosphere. The direct agricultural emission appears due to the use of fossil fuels in agriculture, such as diesel used in tractors and other machinery. Livestock farming (manure management and enteric fermentation) are also important sources off the GHG emission. The use of synthetic fertilizers is related to indirect GHG emission as the production of these fertilizers requires large amounts of energy, which usually comes from fossil fuels. Therefore,

a complex assessment of the GHG emission linked to agricultural sector is needed (Ben Jebli and Ben Youssef 2017; Long et al. 2018; Waheed et al. 2018).

By reducing carbon emission in agriculture, the stakeholders can mitigate the climate change and ensure sustainable development of agriculture. It is important to promote sustainable agricultural practices that are beneficial for the environment, farmers, and consumers. There may also be economic benefits realized as the reduction of the carbon emission and climate change may improve the operation environment for agriculture. Also, improving soil state through carbon sequestration can increase yields and reduce fertilizer and pesticide use, leading to cost savings for farmers. Therefore, it is important to identify effective solutions to reduce carbon emissions in agriculture.

Considering that emission reduction activities are generally carried out at the regional or provincial level (Castejana et al. 2020), analyzing the CSP at the province level is relevant in China. Policymakers and businesses can understand the economic costs associated with carbon emissions in those regions. The calculation of CSP can be applied to design and implement policies and incentives to encourage reduction of carbon emissions.

Based on the deliberations expressed above, this study is significant in the sense of several facets. The approximation of the costs associated with environmental performance and GHG emission mitigation allows taking further steps towards curbing the carbon emission. However, much of the empirical literature deals with the industrial sector. This paper applies a recent approach, viz., the by-production model, to analyze the China's agricultural sector with focus on the input variables. Also, the province-level analysis allows to deliver the policy implications that are relevant for different parts of country exhibiting varying resource endowments and infrastructure in general. Empirically, this paper calculates the shadow price of agricultural carbon emission for different regions in China from 1997 to 2020. The results can be beneficial for government agencies and researchers when identifying specific measures for decreasing carbon emission within the agricultural sector. The emission can be mitigated through changes in the input use.

The input construction in the present research rewards further attention. We focus on the effects of including the livestock input into analysis. As the livestock-related GHG emission comprises a substantial part of the total agricultural emission, it is important to check the effects of the inclusion of the corresponding input variable on the production technology and the resulting measures of performance.

The paper unfolds as follows. The “Literature review” section discusses the theoretical preliminaries for the measurement of the shadow price available in the literature. The “Methods” section constructs the research framework based on the frontier methods for the CSP analysis in the

by-production technology. The data are described in the “Data” section. The results for the case of China’s agriculture are outlined in the “Empirical results” section. Finally, the “Conclusion and policy implications” section concludes.

Literature review

Estimating the shadow price of undesirable outputs in a production system is essential in designing effective environmental policies. By putting a monetary value on the abatement of the, e.g., carbon emission, policymakers can determine the appropriate level of regulation and taxation to reduce the negative externalities associated with production. This helps to achieve a more efficient allocation of resources and promote sustainable development (Zhang et al. 2023). The shadow price of pollutants (or other non-marketed by-products) refers to the monetary value associated with the environmental and health damages caused by the release of pollutants. It is a useful tool for policymakers and economists to determine the appropriate level of pollution control and regulation. The shadow price of pollutants has been employed widely in research on climate change, air pollution, and land desertification. Early research on shadow prices focused primarily on air pollutants such as SO₂ or water pollutants (Lee 2005; Kaneko et al. 2010). As the importance of carbon emission reduction continues to increase, recent empirical studies on greenhouse gases have gradually increased. Shadow prices have been employed in a variety of ways, such as estimating the cost of carbon emissions reductions across different economic sectors, establishing the optimal level of greenhouse gas emission tax, and assessing the economic advantages of mitigating air pollution.

The data availability implies that carbon shadow pricing, in most cases, focuses on industry or a macro perspective. Lee (2011) studied the power generation industry in South Korea and utilized the Shephard output distance function to determine the CSP associated with it. Deng and Du (2020) used the sequential Luenberger Productivity Indicator to measure the green production efficiency of the Belt and Road countries, which is based on the data of carbon emissions. Furthermore, they followed an assumption that it is feasible to simultaneously achieve a reduction in CO₂ emissions and an increase in GDP. Cheng et al. (2020) utilized a non-parametric model which relied on by-production approach to calculate CSPs at both provincial and regional levels. Notably, the authors developed a novel DEA model, which allowed investigating carbon emission reduction costs in China’s industrial sector between 2003 and 2017. Within the framework of by-production technology, Wang et al. (2022a, b) examined the gap between the observed carbon shadow price and that obtained by using the aggregate direction across 152 countries worldwide from 1991 to 2019. Their findings revealed a global increase in CSPs, though there were notable

differences in the extent of the gap between the observed and “aggregate” ones across the countries.

Even though agriculture is an important contributor to the GHG emission, there has been little research on CSP and agricultural emissions in China. In a study conducted by Wu and Lin (2019), regional shadow prices of CO₂ in China were estimated using the environmental production technology alongside the directional distance approach. The study covered 29 provinces in China from 2006 to 2015. Similarly, Gu et al. (2019) utilized the parametric directional output distance function to estimate the shadow prices of CO₂ for 308 rice growers in Shanghai from 2008 to 2015. However, since most undesirable outputs are jointly reduced, Wei and Zhang (2020) proposed a new separation method that enables the separation of individual directional shadow prices from the cost of joint reduction of multiple undesirable outputs. In addition to this, livestock is not usually considered in input indicators in much of the literature on CSP in agriculture (Shen et al. 2018), and this needs to be improved.

When estimating shadow prices, parametric and nonparametric methods can be used. Production frontier is necessary when calculating shadow prices, and both approaches rely on the input and output data for each decision-making units (DMU) to establish the frontier. The difference among the two approaches relates to the way they establish the production frontier. For using the parametric approach, one needs to assume a certain functional form to relate the inputs and outputs. The stochastic frontier analysis discussed by Aigner et al. (1977) and Meeusen and Broeck (1977) can be given as an example of the latter strand. It is beneficial from the viewpoint of the noise as the random error in accounted for the in the parametric specification. The parameters defining the production frontier can then be used to derive the underlying shadow prices. Thus, the choice of the functional form may affect the resulting shadow prices.

The non-parametric approach gets rid of the reliance on that particular function form and defines the frontier in a flexible data-driven manner. Still, the frontier is subject to the axioms imposed during the optimization as the constraints. The deterministic production frontier is built by mathematically solving the optimization exercise by the virtue of linear programming. This approach is largely founded on the data envelopment analysis (DEA) that Charnes et al. (1978) first proposed in the constant returns to scale setting. The formulation of this model does not involve any specific functional form that must be chosen prior to the optimization. Therefore, it may be applicable for diverse contexts where the underlying functional form is not known. The earlier literature has extensively applied the DEA-based approach for analyzing the environmental production technologies involving unintended outputs (Lee et al. 2014; Shen et al. 2018). Therefore, this study also estimates carbon shadow price by this approach.

The level of the shadow price is important in devising the policy implications. Still, yet another question deserves attention when analyzing the shadow prices, namely, their dispersion across the regions (or other entities). In an optimal case, these shadow prices should be equal. In the presence of the market imperfections, the shadow prices diverge. Therefore, the earlier research has also focused on convergence of the shadow prices. The studies on convergence have first been carried out in the case of the economic growth and productivity analysis (Baumol 1986; Barro 1992). The classical theory of convergence argues that the Solow model can be used as an example in the neoclassical growth theory to show that economies with different initial positions may approach the same development path. Over time, more nuanced analyses of the convergence required elaborated approaches, especially the quantitative models. For example, Hao and Peng (2017) employed σ -convergence and spatial β -convergence analysis to examine the convergence in per capita energy consumption in 30 Chinese provinces from 1994 to 2014. Cui et al. (2021) utilized σ -convergence and β -convergence methods to analyze the spatial and temporal distribution of NO₂ from 2004 to 2020. Therefore, the calculation of the CSP allows for further analysis, including the convergence analysis. It can provide theoretically sound background for the assessment of the movement towards the balanced growth path.

In this paper, the non-parametric framework is implemented by resorting on the DEA. However, the said technique has multiple extensions. The conventional DEA models are built on the assumption of the strong disposability (i.e., for a given production plan, any production plan with less desirable output and/or more inputs or unintended outputs is feasible). In this case, the involvement of the unintended outputs requires consideration of the assumption related to the disposability of those outputs. The assumption of the strong disposability, however, does not meet the requirements imposed by the materials balance principle as the generation of the undesirable outputs for a given level of the desirable outputs becomes unbounded (Murty et al. 2012; Dakpo et al. 2016). Weak disposability assumption relates the desirable and undesirable outputs by introducing a coefficient that governs a simultaneous contraction of those variables. The additional assumption of null-jointness implies that one cannot achieve zero pollution unless the production is halted. Even though these assumptions render a more realistic approach for certain conditions (i.e., when it is impossible to suppress the pollution without decreasing the desirable output), it is still possible to face certain shortcomings. Specifically, one may obtain negative shadow prices depending on the region

to which a certain observation is projected (Chen 2014). Such a case implies that undesirable outputs contribute to an increase in the shadow profit which is not reasonable in the sense of the economic theory.

In the light of considerations above, Murty et al. (2012) proposed the by-production model that attempts to alleviate the shortcoming of the strong and weak disposability models without involving into ad hoc assumptions. The by-production model is similar to the network DEA structures as it contains two sub-technologies that operate parallel to each other: one sub-technology links the inputs and outputs, whereas the other describes environmental pollution in the sense of the use of the pollution-generating (“dirty”) inputs. The latter sub-technology deals with the bad outputs. This framework takes in to account the materials balance principle and allows to impose the shape of the pollution-generating sub-technology that does not render negative shadow prices.

Based on the above analysis, the analysis of the CSP in the agriculture, including Chinese agricultural sector, can be considered as an important research avenue requiring further methodological solutions for reasonable estimates. Therefore, looking at the carbon shadow price for carbon emission from the Chinese agriculture at the province level can offer valuable insights into both economic and environmental effects of carbon emissions. Such information may assist the policy makers and academia in devising measures for low-carbon development in regard to the wider climate change mitigation commitments.

Methods

By-production model

The evaluation of CSP starts from setting the production technology and production function. Referring to Murty et al. (2012) and Murty and Russell (2018), this paper chooses the by-production approach. It is assumed that there are N decision-making units indexed by $n = 1, 2, 3, \dots, N$. Then, the inputs are divided into two categories. One category represents the “clean” inputs with their quantities denoted by x^c , and the other category comprises the “dirty” inputs with quantities denoted by x^d . Note that the former category of inputs is important for generation of the desirable outputs, whereas the second one has a role in generating both desirable and undesirable outputs. The quantities of desirable and undesirable outputs are denoted by y and z , respectively. The production technology is then modelled as follows:

$$T = T_1 \cap T_2 = \{(x^c, x^d, y, z) \in \mathfrak{R}_+^{C+D+G+B} : (x^c, x^d) \text{ can produce } y^g; x^d \text{ can generate } z\};$$

$$T_1 = \{(x^c, x^d, y) \in \mathfrak{R}_+^{C+D+G} | f(x^c, x^d, y) \leq 0\};$$

$$T_2 = \{(x^d, z) \in \mathfrak{R}_+^{D+B} | g(x^d, z) \leq 0\},$$
(1)

where $f(\cdot)$ and $g(\cdot)$ are continuously differentiable functions. T_1 and T_2 satisfy a series of basic economic axioms, including convexity, closure, etc. Due to the different production scale of each DMU, the accuracy of measuring environmental performance may be diminished when assuming constant returns to scale (Wang et al. 2016). Therefore, this paper relies on the assumption of the variable returns to scale.

In addition, T_1 assumes that inputs and desirable outputs are freely (strongly) disposable, that is, for a given output, more inputs can be used to produce it. This assumption is expressed as follows:

$$\text{If } (x^c, x^d, y, z) \in T_1, \text{ then } (\tilde{x}^c, \tilde{x}^d, \tilde{y}, \tilde{z}) \in T_1 \text{ when } (-\tilde{x}^c, -\tilde{x}^d, \tilde{y}) \leq (-x^c, -x^d, y) \tag{2}$$

Unlike T_1 , T_2 satisfies the cost disposability assumption rather than the free disposability assumption. This means that a reduction in undesirable output requires a allows for reducing the levels of the “dirty” inputs, yet this is related to a reduction in the desirable output given the relationship

$$\bar{D}(x^c, x^d, y, z; 0, 0, g_y, g_z) = \max\{\delta \in \mathfrak{R}_+ : (x^c, x^d, y + \delta g_y, z - \delta g_z) \in T\} \tag{4}$$

Here, $(g_y, -g_z)$ is the direction vector of the output combination, which means that the desirable output is increased relative to g_y and the undesirable output is contracted relative to g_z while adjusting δ . The level of inputs is held fixed. Thus, the distance from the DMUs to the production frontier is measured by δ (it is relative to the directional vector). The observed output values are used

ion T_1 . This suggests that the undesirable output cannot be discarded freely as it is the case for the desirable output. This assumption is formally expressed as follows:

$$\text{If } (x^d, z) \in T_2, \text{ then } (\tilde{x}^d, \tilde{z}) \in T_2 \text{ when } (\tilde{x}^d, -\tilde{z}) \leq (x^d, z) \tag{3}$$

Directional distance functions

The concept of sustainable development, especially, the strong sustainability approach, requires that multiple objectives connected to the economic, social, and environmental domains are met. This calls for adoption of the relevant approaches in the production modelling. In the context of the emission analysis, the conflicting goals of emission reduction and economic growth can be unified in the sense of the directional distance function (Zhu and Lin 2021). Following Boussemart et al. (2017) and Wang et al. (2022a, b), the output-oriented DDF for the environmental production technology is defined as follows:

as the direction making the analysis based on the proportional distance function.

Linear programming problem

The CSP can be established by looking at the curvature of the production frontier. The DEA allows constructing this frontier in the by-production framework. For each DMU (a certain province), the linear programming problem under the assumption of VRS is set as follows:

$$\begin{aligned} D(x^c, x^d, y, z; 0, 0, g_y, g_z) = & \min_{\pi_y^g, \pi_x^c, \psi_x^d, \omega_x^d, \omega_z^b, v_1, v_2} \left[\sum_{c=1}^C \pi_x^c x_{it}^c + \sum_{d=1}^D \psi_x^d x_{it}^d - \sum_{g=1}^G \pi_y^g y_{it}^g - v_1 + \sum_{b=1}^B \omega_z^b z_{it}^b + v_2 \right] \\ \text{s.t. } & \sum_{g=1}^G \pi_y^g y_{it}^g - \sum_{c=1}^C \pi_x^c x_{it}^c - \left(\sum_{d=1}^D \psi_x^d x_{it}^d + \sum_{d=1}^D \omega_x^d x_{it}^d \right) + v_1 \leq 0, \forall i = 1, \dots, N, \\ & \sum_{d=1}^D \omega_x^d x_{it}^d - \sum_{b=1}^B \omega_z^b z_{it}^b - v_2 \leq 0, \forall i = 1, \dots, N, \\ & \sum_{g=1}^G \pi_y^g g_y^g \geq 0.5, \\ & \sum_{b=1}^B \omega_z^b g_z^b \geq 0.5, \\ & \pi_y^g \geq 0, \forall g = 1, \dots, G, \\ & \pi_x^c \geq 0, \forall c = 1, \dots, C, \\ & \psi_x^d \geq 0, \forall d = 1, \dots, D, \\ & \omega_z^b \geq 0, \forall b = 1, \dots, B. \end{aligned}$$

Here, $\pi_x^c, \psi_x^d, \pi_y^g, \omega_z^b$ are the shadow prices of clean input, dirty input, intended output, and unintended output, respectively. It should be noted that the shadow values in the formula above have no direct economic meaning. However, their ratio is the shadow price that can provide valuable information for policymaking (Cui et al. 2022). The CSP

can be understood as the marginal transformation rate of the intended and unintended outputs which is the ratio of the multipliers in the formula. As the desirable output is the GDP (or value added for a sector-level analysis), one can easily fathom the economic meaning of CSP as the value of the intended output (GDP) that needs to be forgone for every

unit reduction of the unintended output (CO₂). Then, the relative shadow price the *b*th unintended output is defined as:

$$SP_b = \frac{\omega_{z,i}^b}{\pi_{y,i}^g} \quad (5)$$

Data

To estimate CSP, this study uses agricultural data from 31 Chinese provinces. The time period covered is 1997–2020. Note that this time period covers the reforms when the agricultural taxes were lifted, and the sector became a net receiver of public support.

The production technology for Chinese agriculture includes seven input indicators: labor force, cultivated land area, total mechanical power, diesel oil, fertilizer, pesticides, and livestock. Human labor does not produce CO₂ emissions directly. Unlike industries or processes that depend on fossil fuel-powered machinery, human labor itself does not release carbon dioxide into the atmosphere. Therefore, according to Boussemart et al. (2015) and Cui et al. (2022), except for the labor force, which is a clean input, the rest of the inputs are considered as the polluting ones. There are two outputs of different types: CO₂ emission as an undesirable output and GDP as a desirable output. Note that GDP is measured in real terms based on the deflator of 1997. According to Zhang et al. (2019) and Xiao et al. (2022), the livestock includes pigs, cows, sheep and horses, and their carbon emission coefficients are 34.1, 418.3, 35.2, and 133.9 kg C per head per year. All data come from the National Bureau of Statistics China Statistical Yearbook.

Table 1 shows the descriptive statistics for the input and output variables used. The general pattern is that of relatively high standard deviation, indicating a high degree of dispersion of production data among the 31 provinces. The

highest relative standard variation is observed for machinery and the intermediate inputs, e.g., diesel, fertilizers, and pesticides. At the provincial level, the minimum land area is 885,500 hectares, and the maximum is 149,101,300 hectares, which is approximately 168 times the minimum. The province with the highest carbon emissions (Henan) is approximately 94 times larger than the province with the lowest carbon emissions (Beijing). The livestock herd varies from 383 thousand up to 98.9 million heads. This may have an impact on carbon emission and the CSP. Thus, the consideration of this variable is important when modelling the CSP in the frontier-based framework. In general, different factor endowments and specialization determine the input–output mix across the provinces. These also impact the potential for the reduction in carbon emission.

Empirical results

The inclusion of the emissions from the livestock farming substantially alter the total CO₂ emission in China's agriculture (Table 2). Thus, one may expect that the use of the livestock as an input may explain substantial share of the inefficiency. In general, the CO₂ emission increases twofold when the livestock is accounted for. The livestock sector has an important role in determining the level of the total agricultural carbon emission in China. Still, one can note that the importance of the CO₂ emission from the livestock farming declines over time.

The results based on the DEA model and by-production technology are shown in Table 3. The results suggest that the difference in the CSP is observed due to inclusion of livestock herd size as an input. Specifically, the mean CSP substantially increases (at least ten times) in case the livestock is ignored as an input. This implies that less GDP must be foregone per unit of carbon dioxide emissions reduced when livestock is considered. This result implies that the livestock input should be considered in case the

Table 1 Descriptive statistics for inputs and outputs

Type	Variable	Unit of measurement	Mean	Median	Std.dev	Min	Max
Clean input	Labor	10 ⁴ persons	957.54	785.89	739.11	27.00	3564.00
Dirty input	Land	10 ³ hectares	5136.33	4583.93	3684.04	88.55	14,910.13
Dirty input	Machinery	10 ⁴ kWh	2600.88	1840.11	2602.72	71.45	13,353.02
Dirty input	Diesel oil	10 ⁴ tonnes	59.56	43.41	62.16	0.46	487.03
Dirty input	Pesticides	10 ⁴ tonnes	4.93	4.36	4.19	0.04	19.88
Dirty input	Fertilizer	10 ⁴ tonnes	164.80	126.10	135.56	2.50	716.09
Dirty input	Livestock	10 ⁴ units	2786.41	2278.00	2006.35	38.29	9891.29
Intended output	GDP	100 million RMB	721.97	578.85	596.89	21.82	3317.04
Unintended output	CO ₂	10 ⁴ tonnes	1773.78	1630.41	1167.30	60.20	5643.59

Note: The exchange rate for US dollar to RMB is 1:7; GDP is deflated based on prices of 1997; fluctuations in exchange rates have been observed, and to aid the reader in currency conversion, average rates from recent years have been employed; this is also applied in subsequent charts

Table 2 Average CO₂ emission of 31 provinces during 1997–2020 (with and without livestock)

Provinces	1997–2002		2003–2008		2009–2014		2015–2020	
	With livestock	Without livestock	With livestock	Without livestock	With livestock	Without livestock	With livestock	Without livestock
Anhui	2446.07	1222.92	2185.51	1428.40	2149.12	1649.17	2024.33	1603.67
Beijing	181.76	106.49	172.04	93.89	147.92	84.79	88.38	53.65
Chongqing	795.39	334.77	820.96	391.90	887.33	472.15	919.03	548.35
Fujian	971.08	650.13	1066.80	760.88	1087.63	807.26	958.47	767.35
Gansu	1162.54	404.54	1417.67	506.22	1746.74	765.92	1828.84	809.36
Guangdong	1839.11	961.09	1819.00	1076.57	1907.28	1258.28	1755.12	1260.67
Guangxi	2286.31	740.63	2196.28	951.89	2183.95	1150.63	2073.34	1209.68
Guizhou	1583.98	294.64	1635.77	360.13	1482.93	450.51	1476.24	457.10
Hainan	389.05	129.06	459.78	230.13	520.05	323.88	452.13	308.02
Hebei	3236.16	1606.77	3776.44	2248.65	3205.82	2148.37	2856.20	1897.13
Heilongjiang	1705.96	764.17	2069.44	972.68	2474.74	1384.73	2481.92	1450.89
Henan	4753.14	1901.98	5205.44	2412.27	5313.17	3032.34	4667.73	3064.22
Hubei	2166.85	1244.13	2285.43	1412.78	2566.94	1679.57	2266.28	1481.73
Hunan	2169.85	903.00	2435.41	1101.36	2537.10	1279.97	2476.83	1278.86
Inner Mongolia	1584.59	412.44	2269.79	632.73	2763.87	977.39	3037.61	1176.27
Jiangsu	2053.02	1581.55	2045.52	1641.64	2038.78	1714.39	1879.74	1605.36
Jiangxi	1370.01	580.01	1342.54	697.58	1464.62	811.90	1366.76	747.21
Jilin	1373.13	558.53	1701.38	740.02	1886.47	1011.88	1848.62	1124.64
Liaoning	1274.52	704.02	1601.05	805.75	1884.49	1019.97	1703.71	969.95
Ningxia	272.68	119.90	360.37	153.21	431.82	210.18	498.00	215.95
Qinghai	896.11	40.07	925.96	42.67	955.47	58.34	1058.82	60.09
Shaanxi	1156.41	599.93	1237.21	681.02	1431.79	998.76	1489.08	1051.81
Shandong	4591.52	2456.14	4842.50	2910.20	4277.31	2886.72	3768.53	2555.63
Shanghai	188.73	143.39	164.21	134.72	152.35	116.89	117.89	94.48
Shanxi	963.85	428.08	910.81	493.64	899.85	591.39	932.82	587.56
Sichuan	3338.68	1004.10	3667.16	1131.84	3670.74	1289.60	3374.33	1240.17
Tianjin	184.04	118.61	229.40	141.88	222.86	149.29	173.80	104.38
Xinjiang	1700.86	582.00	2004.28	785.63	2263.17	1219.00	2915.00	1610.11
Xizang	1080.71	16.23	1218.61	20.63	1204.28	31.47	1144.41	34.75
Yunnan	2279.81	601.74	2413.03	797.21	2750.84	1117.41	2949.72	1187.69
Zhejiang	1059.38	832.78	1137.07	929.02	1161.54	966.02	1021.54	912.26
Average	1646.94	711.09	1794.09	860.88	1860.35	1021.23	1793.72	1015.13

livestock-related carbon emission is taken into account as the undesirable output.

Considering livestock as an input, Qinghai, Xizang, and Shandong are the three regions with the lowest average CSP of 34.27, 47.82, and 98.35 US dollars/tonne, respectively (over 2015–2020). These provinces should continue to implement the carbon emission reduction measures and look for new ones. If the cost of reducing carbon emissions when engaging in actual economic activities is lower than the price of carbon emission rights, then the remaining carbon emission allowances can be traded to achieve residual income (Wu et al. 2018). The national average marginal

carbon emission reduction cost during the period covered is 493.19 US dollars per tonne.

In addition, on average, the CSP values in 15 provinces are higher than the national average. This indicates that the average value is roughly dividing the provinces into two groups of similar sizes (in the sense of the number of provinces). The uneven distribution of the CSP levels creates conditions for the establishment and improvement of the carbon trading market.

Figure 1 depicts the average CSP across the different regions of China. Obviously, the average CSP in the three regions (eastern, central, and northeastern) is substantially

Table 3 Average CSP value of 31 provinces during 1997–2020 (with and without livestock)

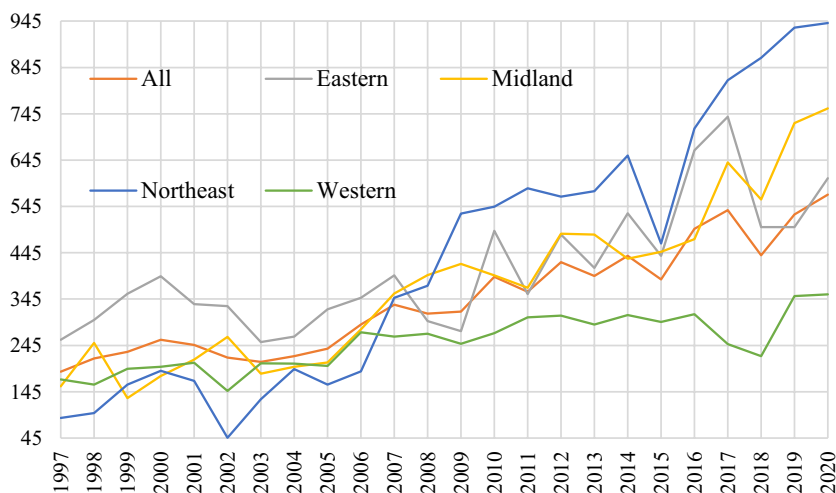
Provinces	1997–2002		2003–2008		2009–2014		2015–2020	
	With livestock	Without livestock	With livestock	Without livestock	With livestock	Without livestock	With livestock	Without livestock
Anhui	294.94	1500.05	533.72	6445.33	692.96	1270.48	933.19	990.81
Beijing	395.04	1409.91	442.90	6535.86	555.97	1115.94	721.03	18,422.08
Chongqing	321.25	1134.34	233.36	1090.06	288.34	7539.85	370.78	1494.85
Fujian	617.95	13,932.36	642.39	1430.88	283.87	1765.62	280.23	2334.49
Gansu	264.84	2387.47	304.22	866.45	431.07	1338.42	463.06	1762.81
Guangdong	171.41	7657.08	176.33	20,692.17	322.55	1450.34	515.84	2013.51
Guangxi	344.90	4695.41	489.72	1006.34	651.78	1084.86	677.55	1720.01
Guizhou	101.26	961.26	160.95	1758.57	193.16	1126.37	337.53	9181.42
Hainan	186.65	7094.09	196.42	1313.45	409.77	20,033.17	726.50	1609.91
Hebei	342.28	1789.17	47.49	1279.27	669.49	6729.29	545.96	1128.25
Heilongjiang	100.30	1113.97	252.53	940.70	636.29	16,347.46	865.71	1344.60
Henan	46.09	14,717.36	63.71	1328.54	165.54	1581.53	267.87	5615.03
Hubei	133.30	1074.12	215.75	14,552.91	577.51	1045.65	862.16	1124.82
Hunan	212.14	6978.05	239.89	911.84	296.33	14,036.49	378.81	844.20
Inner Mongolia	115.00	1292.52	233.84	8616.97	258.21	2302.44	311.90	694.82
Jiangsu	94.40	1508.92	299.08	1682.41	464.56	1713.93	592.96	7191.82
Jiangxi	142.95	16,435.57	104.69	1351.51	263.06	6137.12	458.24	1294.23
Jilin	120.61	17,476.70	347.00	1089.31	511.77	1115.06	726.00	1073.93
Liaoning	155.33	1414.22	97.43	684.38	580.39	1002.98	775.02	818.08
Ningxia	290.64	9131.15	308.89	3557.05	355.86	856.75	154.78	1883.20
Qinghai	58.93	1530.42	129.30	1267.22	60.07	7688.63	34.27	2188.54
Shaanxi	170.34	958.64	381.07	8188.74	544.98	703.53	567.43	1493.74
Shandong	58.59	1399.44	39.46	21,203.59	57.52	1436.57	98.35	2656.44
Shanghai	660.52	1721.43	631.63	2362.98	621.09	1439.73	837.12	6542.81
Shanxi	365.38	1791.70	467.43	6383.30	593.61	995.59	702.38	14,095.78
Sichuan	73.58	10,073.43	61.31	2190.85	78.35	844.76	141.20	1646.72
Tianjin	537.67	2360.65	468.82	1580.33	545.77	5852.90	1026.08	29,147.09
Xinjiang	115.22	959.39	155.39	738.39	153.64	1178.31	146.11	9968.85
Xizang	35.65	4790.46	40.55	1042.80	38.20	1340.31	47.82	10,125.04
Yunnan	265.95	8243.81	342.38	660.83	416.68	3790.40	317.65	1041.05
Zhejiang	222.88	11,593.46	189.96	1519.97	319.43	2559.61	405.54	1834.81
Average	226.32	5133.11	267.66	4008.81	388.32	3787.87	493.19	4622.06

higher than the national average, whereas the average level of the western region is lower than the national average. The reason is that because of the swift progress in the economy and sophisticated production technologies used in the eastern region, environmental impacts have been mitigated there (Zhou et al. 2021). Thus, further reduction in the agricultural carbon emission there requires higher investments compared to the case of underdeveloped regions with emission-intensive agriculture. There is still a large gap for emission reduction in the western region. Thus, to enhance the effectiveness of reducing carbon emissions, it may be beneficial to draw experience on agricultural practices in

the developed regions. Although the CSP level in Northeast China is the lowest at the beginning of the period covered, it rises with the fastest pace. Therefore, this region has seen serious improvements in the environmental performance in spite of the low initial level of environmental efficiency.

Different shadow price levels and trends across the regions reflect the regional differences in the green development of Chinese agriculture. According to the differences and characteristics of economic regions, one can set CO₂ reduction targets in line with the regional development status (Xiong et al. 2022). In the short run, this may promote the rational use of the resources and ensure that the carbon emission mitigation

Fig. 1 Average CSP across the regions of China, 1997–2020 (USD/tonne)



at the national level is implemented with the lowest economic costs. Also, the regional differences indicate the potential for the creation of the market for trading the agricultural carbon emissions at a national level (Wang et al. 2016). In the long run, the regional economies may adapt to the prevailing trends and introduce more efficient farming practices leading to convergence in the CSP.

Finally, in order to analyze the convergence of carbon shadow prices in different regions, this paper conducts two kinds of convergence tests. The first is σ convergence, which examines how the variance of carbon shadow prices in different regions changes over time. As the variance relative to the mean declines, one can observe the decline in the dispersion of the data which indicates that the CSP is becoming more similar across the provinces of China. Referring to Maghyereh and Awartani (2012) and Lu and Xu (2019), this paper uses the coefficient of variation to test the σ -convergence:

$$CV_t = \frac{\sigma_t}{\mu} \tag{6}$$

Here, σ_t represents the standard variation of the CSP across the DMUs (provinces) in during the t th year, and $\bar{\mu}$ represents the average CSP for all the provinces in year t .

CV_t is the coefficient of variation of carbon emission shadow prices in year t which can also be considered as the relative coefficient of standard deviation. These calculations can be applied for each of the regions defined.

The results of the σ convergence test are shown in Table 4. The pooled ordinary least squares were fitted for the CV to obtain its stochastic trend. The resulting stochastic rate of growth is 0.22% per annum for the whole sample, and those for the eastern, central, northeastern, and western regions are 0.37%, -0.86%, -1.28%, and 0.03% per annum, respectively. If the value of the coefficient of variation in the latter year is smaller than that in the former year, then the gap is narrowing and there is sigma-convergence. According to the results, only western and central regions exhibit significant negative coefficients associated with the linear trend, suggesting that the CV in these two areas is decreasing in general. Thus, these regions have shown a σ convergence in the agricultural carbon shadow price. At the country level, no significant trend is observed. Thus, the CSP tends to converge within separate regions, yet this is not happening at the country level.

In addition to σ convergence, we further test whether provinces with lower initial level of the CSP exhibit higher growth rates and thus achieve a catch-up effect within the whole sample or a sub-sample. This can be checked by looking at the β convergence test. Referring to Cheng

Table 4 Pooled OLS for the σ convergence of the CSP across the regions of China

	(1)	(2)	(3)	(4)	(5)
	Whole sample	Eastern	Western	Midland	Northeast
Year	0.002 (1.651)	0.004 (1.237)	-0.009*** (-2.856)	-0.013* (-2.075)	0.000 (0.087)
_cons	-4.373 (-1.621)	-7.329 (-1.214)	17.464*** (2.878)	25.893** (2.090)	-0.423 (-0.073)
N	23	23	23	23	23
Adj. R ²	0.073	0.024	0.245	0.131	-0.047

Note: t statistics are given in parentheses; significance codes * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

et al. (2020), the relevant regression model is established as follows:

$$\frac{\ln(CSP_{i,t}) - \ln(CSP_{i,0})}{t} = \alpha + \beta \ln(CSP_{i,0}) + \varepsilon_{i,t} \quad (7)$$

Here, t represents the time index, $\ln(CSP_{i,t})$ is the logged value of the CSP in the i th province in year t , $\ln(CSP_{i,0})$ is the logged value of the CSP in the i th province for the initial time period; $\frac{\ln(CSP_{i,t}) - \ln(CSP_{i,0})}{t}$ represents the average annual growth rate during the time period in between 0 and t . The usual linear regression setting involves an intercept, α , the β convergence coefficient, β , and a random error, ε . If $\beta < 0$ and the coefficient is significant, it means that there is absolute β convergence, i.e., regions with lower CSP are catching up. In our case, the Hausman test suggests that a fixed effects model is preferred. According to the theory of absolute β -convergence, if the β coefficient is negative, it indicates the existence of absolute convergence, and positive indicates divergence. The results are provided in Table 5. The β coefficients are negative in the whole sample and in each sub-sample, and they are all significant at the 1% significance level, indicating that the CSP difference among regions in China shows a shrinking trend, both in the whole country as a whole, and in terms of the subregions in the East, Central, West, and Northeast. It means that provinces with a relatively low shadow price of agricultural carbon emissions are catching up with higher provinces by exhibiting relatively higher growth rates.

Interestingly, among the four sub-regions, only the western and central regions showed both σ and β convergence in the agricultural sector CSP. This phenomenon is determined by several factors. First, the differences in the degree of the economic development play a crucial role. All along, the northeast region has been dominated by the development of heavy industry, while the Eastern region shows developed economy with advanced infrastructure. Also, increasing urbanization in this region has reduced the relative importance of agriculture there. On the contrary, the western and central regions have retained a focus on agriculture, leading to convergence of their agricultural performance as evidenced by the CSP.

Regional differences in resource endowments can also affect agricultural production, with the eastern region having easier access to advanced technologies and higher competition for resources, whereas the opposite is observed for the less developed regions. The results suggest that the regions with σ convergence are those with the lower competition for energy resources. Additionally, economic conditions, including income levels and access to markets, can affect the ability of farmers to adopt sustainable practices, with higher income levels in the east leading to greater investment in sustainable technologies, while the center and western adopt simpler, more cost-effective methods that may be imitated by multiple provinces.

Conclusion and policy implications

Economic development and sustainable development are the key objectives for agriculture and the whole economy to ensure that the economic activity provides for means of subsistence without dampening the ecosystem (Yijun et al. 2023). The increasing scale and scope of the effects of climate change imply that the links among the environment, economy, and society need to be improved with focus on the mitigation of the GHG emissions, particularly CO₂, which can be achieved through comprehensive frameworks involving regulations and incentives (Yijun et al. 2023). China, being a major emitter of carbon dioxide, plays a vital role in achieving global net zero carbon emissions. Therefore, it is crucial to develop China's agriculture with a focus on low carbon emission. As the market prices for carbon dioxide emission is not available in the agricultural sector yet, shadow pricing can offer evidence-based insights into the economics of the emission abatement. These shadow prices can aid national and local authorities in setting reasonable carbon taxes or creating carbon trading markets leading to an informed policymaking for setting the limits for the expense associated with mitigation of the carbon emissions. This research discussed the agricultural sector at the provincial level in China with focus on the role of the livestock herd as an input in the environmental production technology. This adds to the earlier discussion on the shadow pricing of the

Table 5 The fixed effects model for β convergence across the regions of China

Coefficient	(1) Whole sample	(2) Eastern	(3) Western	(4) Midland	(5) Northeast
β	-0.542*** (-15.964)	-0.603*** (-9.809)	-0.682*** (-11.383)	-0.460*** (-6.132)	-0.400*** (-4.339)
α	2.961*** (16.036)	3.411*** (9.812)	3.514*** (11.365)	2.588*** (6.230)	2.334*** (4.491)
N	713	230	276	138	69
Adj. R^2	0.239	0.274	0.300	0.187	0.189

Note: t statistics in parentheses; significance * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

carbon emission that was chiefly focused on the industrial sector or an international macro perspective. The findings may provide practical guidance based on scientific evidence.

According to the findings, the provinces covered in this study break evenly in the sense of the average marginal cost of carbon reduction (CSP) compared to the national average. Obviously, certain regions in China face more significant challenges in reducing carbon emissions than others. The overall average CSP in China is increasing, which implies a positive trend in environmental performance. By analyzing convergence in the agricultural CSP, it was found that the western and central regions exhibit both σ and β convergence, indicating increasing similarity in the provincial environmental performance within those regions.

The results revealed the differences in the shadow price of carbon across provinces in China. These differences may be subject to multiple factors among which one can mention differences in the general economic development which also determines the infrastructure development. The energy production and consumption patterns also vary across the regions due to the energy resource endowments. The developed regions may apply more low-carbon technologies and cleaner energy sources, leading to relatively high carbon shadow prices. However, the convergence among these provinces may not always be evident as the implementation of such technologies is rather costly. Conversely, relatively economically poor or energy-intensive regions in China may opt for common means for improving energy efficiency with higher convergence, yet the overall performance remains lower. Usually, such regions generate higher carbon emissions to meet their energy needs, resulting in a relatively low shadow price. Besides, the emission-intensive livestock farming is more prevalent in less urbanized provinces. As a result, Chinese provinces may implement different carbon control approaches. Some provinces may adopt stringent carbon emission control measures that are reasonable amid higher carbon shadow prices. The local government and communities need to be informed of the environmental performance in the relevant regions so that engagement in the activities related to the climate change mitigation would be proactively and collectively steered at various levels of management.

The research findings imply several policy recommendations that would encourage movement towards a net-zero agriculture in China. Noteworthy, the other regions of the world may also benefit from the lessons evident in the Chinese case. First, building on the carbon trading pilot projects initiated in some provinces and cities, the Chinese government could implement a carbon pricing mechanism to drive emissions reductions. In addition, the promotion of energy-efficient appliances and the upgrading of existing

infrastructure in agriculture and other sectors could also significantly reduce the emission.

Second, Chinese agriculture requires dedicated measures to implement the novel sustainable farming technologies. The examples of such technologies may include precision farming, use of tillage, organic farming. These measures are sector-specific and require positive attitude from both producers and consumers. The promotion of similar techniques can be adjusted for specific regions and guided by the estimates of the carbon shadow prices obtained in this study. The whole supply chain needs to be related to the environmental performance assessment and benchmarking in order to ensure that the uptake of innovations is effective in the Chinese agricultural sector. Obviously, ensuring the food security objectives must be maintained amid the sustainability concerns in order to ensure that the measures introduced to improve the sustainability remain viable in the long run.

However, it is essential to acknowledge the limitations of this research. The data used in this paper cover the period up to 2020. This may not fully reflect the current situation. Future studies should incorporate the latest information to draw more accurate and up-to-date conclusions. Also, the outputs may also be adjusted when the inputs are changed (e.g., the livestock related GHG emission).

Author contribution Introduction and literature review, Zhang Y. and Zhuo J.; methods and data, Baležentis T. and Shen Z.; empirical results and discussion, Zhang Y., Zhuo J., and Shen Z.; heterogeneity analysis, Zhang Y., Zhuo J., and Baležentis T.; conclusions and discussions, Zhang Y. and Zhuo J.; writing—original draft preparation, Zhang Y. and Zhuo J.; writing—review and editing, Baležentis T. and Shen Z. All authors have read and agreed to the published version of the manuscript.

Funding Shen Z. appreciates the financial support from Beijing Institute of Technology Research Fund Program for Young Scholars and the National Natural Science Foundation of China (No. 72104028).

National Natural Science Foundation of China, 72104028, Zhiyang Shen

Data availability The datasets generated and/or analyzed during the current study are not publicly available due to the confidentiality agreement of the patent data, but are available from the corresponding author on reasonable request.

Declarations

Ethical approval. Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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