Carbon Sinks and Green Efficiency: Evidence from Chinese Provincial Panel Data

Zhipeng Yang *, #, Jiawen Zhang #, Zihe Huang #

School of International Economics, China Foreign Affairs University, Beijing, China, 102206

* Corresponding author: yangzhipeng@mail.cfau.edu.cn

#These authors contributed equally.

Abstract. Under China's "dual carbon" strategy, carbon sinks—natural systems that absorb atmospheric CO_2—have become a key component of green development policy. This study uses provincial panel data from 2001 to 2021 and applies a Slack-Based Measure (SBM) model to estimate green economic efficiency. A two-way fixed effects regression is then used to assess the impact of carbon sink reserves on efficiency and explore potential mechanisms. Results show that: (1) carbon sinks significantly improve green economic efficiency, and this effect remains robust across lagged models, variable trimming, and alternative efficiency measures; (2) the positive effect is stronger in coal-intensive and less-developed regions, suggesting a compensatory ecological role; (3) mechanism analysis reveals that carbon sinks indirectly boost efficiency by promoting green technological innovation and encouraging industrial upgrading. This paper extends the existing literature by integrating ecological factors into the study of carbon efficiency and highlights the economic value of natural capital. Policy suggestions include improving carbon sink monitoring and trading systems, formulating region-specific ecological-industrial integration strategies, and enhancing incentives for low-carbon innovation.

Keywords: Carbon sink, Green economic efficiency, SBM model, Mechanism analysis, regional heterogeneity.

1. Introduction

Amid growing concerns over global warming, countries worldwide face the dual challenge of promoting economic growth while reducing carbon emissions. China has pledged to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. In response, a comprehensive dual-carbon policy framework has been established, including the 2024 Work Plan for Accelerating the Establishment of a Dual Control System for Carbon Emissions [1], which integrates emission targets into national development planning and emphasizes improving carbon efficiency through resource optimization.

As a vital component of nature-based climate solutions, carbon sinks—particularly forest and wetland systems—play a key role in absorbing atmospheric CO_2. Recent policies, such as the Action Plan for Carbon Neutrality Standards and Measurement (2024–2025) [2] and the Guiding Opinions on Promoting Forest Carbon Sink Trading [3], have promoted carbon sink inclusion in voluntary emission reduction markets, reinforcing their strategic value in China's decarbonization efforts.

While existing studies have largely focused on energy transition, technological innovation, and industrial upgrading as drivers of carbon efficiency, few have explored the role of carbon sinks in this process. International mechanisms like the Clean Development Mechanism (CDM) and Nationally Determined Contributions (NDCs) highlight the mitigation potential of carbon sinks. However, their impact on emission efficiency—particularly in the Chinese context—remains under-researched.

This study seeks to bridge this gap by empirically examining how carbon sinks influence carbon emission efficiency across Chinese provinces. By integrating policy context with theoretical insights, the study aims to reveal the economic value of ecological carbon reduction and provide actionable evidence for green development policy design. This paper makes three key contributions: First, it introduces carbon sinks as a core explanatory variable within the emission efficiency framework, enriching the understanding of ecological assets in green growth; Second, it constructs a multipathway mechanism framework—covering green innovation, resource allocation, and industrial restructuring—and empirically validates the mediating roles using a stepwise approach; Third, it conducts extensive heterogeneity analysis across regions with different energy structures, developing levels, and geographic locations, providing nuanced insights for region-specific carbon governance.

2. Literature Review and Theoretical Analysis

2.1. Literature Review

Recent literature on carbon mitigation has established a variety of methods for estimating carbon sinks, which are widely recognized as crucial components of natural climate solutions. These approaches generally fall into three categories:

(1) biomass-based estimation using remote sensing and field plots to quantify carbon stocks in forest and grassland ecosystems [4];

(2) micrometeorological flux tower observations for capturing real-time forest carbon fluxes and calculating net ecosystem productivity (NEP) [5];

(3) Earth system modeling and carbon cycle simulations, which estimate the spatiotemporal dynamics of terrestrial carbon sequestration [6].

These studies consistently show that China's terrestrial ecosystems serve as a major carbon sink, offsetting a sizable share of national carbon emissions and underpinning progress toward dual-carbon targets [7]. However, a significant limitation is that carbon sinks are often excluded from the economic and policy-oriented analysis of carbon efficiency**.** This exclusion is largely due to difficulties in data standardization, measurement uncertainty, and limited integration with mainstream economic models [8-9].

In the field of carbon emission efficiency, most empirical studies focus on drivers such as energy structure optimization [10], technological progress [11], or environmental regulation and industrial transformation [12]. Methodologically, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) remain dominant tools for measuring eco-efficiency [13]. Recent studies have also begun to explore spatial spillover effects and regional heterogeneity, but typically without integrating ecological variables such as carbon sinks [14].

In summary, while current research has advanced the understanding of carbon efficiency and its economic determinants, it largely overlooks carbon sinks as a form of natural capital that may influence carbon efficiency through multiple channels, such as ecological buffering, innovation incentives, and industrial restructuring. This omission represents a major research gap, especially under the increasing policy emphasis on nature-based solutions.

To address this gap, this study integrates carbon sink reserves into a provincial-level efficiency analysis using a panel dataset from 2001 to 2021. It not only quantifies the direct impact of carbon sinks on carbon emission efficiency but also explores the indirect pathways through green innovation and structural upgrading. In doing so, the research contributes to the literature by bridging ecological assets and economic performance, providing empirical evidence for embedding carbon sinks into China's green development strategy.

2.2. Theoretical Framework

Drawing on ecosystem service theory, environmental economics, and endogenous growth theory, this study proposes four mechanisms through which carbon sinks affect green economic efficiency:

(1) Natural Capital Compensation: As a component of natural capital, carbon sinks reduce pollution accumulation and governance costs through their carbon sequestration function, thereby unleashing green production potential;

(2) Technology Innovation Channel: The development and trading of carbon sinks can stimulate green technological innovation and the generation of clean patents through market incentives and institutional arrangements [15];

(3) Industrial Structure Optimization: Carbon sinks, as green assets, promote the development of

the tertiary sector and low-carbon manufacturing, helping break "carbon lock-in" and facilitating industrial upgrading [16];

(4) Resource Allocation Efficiency: According to the Coase theorem, carbon sink trading internalizes ecological externalities, guiding resources toward more efficient and lower-emission sectors, thus enhancing total factor productivity.

3. Research Design

This study aims to investigate the impact of forestry carbon sinks on green economic efficiency at the regional level. Given that carbon sinks reflect local natural endowments and, under the carbon neutrality agenda, may influence economic performance by promoting green transformation, optimizing industrial structure, and driving technological innovation, we construct a provincial panel dataset and employ a two-way fixed effects model for empirical analysis. The core objective is to examine whether carbon sinks significantly enhance green economic efficiency. To this end, we develop a series of progressively expanded regression models to test robustness and control for potential confounders.

3.1. The establishment of simulation model

Based on the theoretical framework, we begin with a benchmark model using two-way fixed effects to control for both individual and time heterogeneity:

$$Eff_{i,t+1} = \alpha + \beta CS_{i,t} + \delta X_{i,t} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In the model, Eff denotes green economic efficiency. Given that forestry-related variables often exhibit a lagged effect on carbon emission efficiency [17], and to alleviate endogeneity concerns, we use the one-period lag of the dependent variable. CS refers to carbon sink reserves, and X represents a set of control variables. μ and λ denote province and year fixed effects, respectively, and ε is the error term.

To further explore the mechanisms proposed in the theoretical analysis, we adopt the three-step approach by constructing mediation models using patent count, R&D investment, and industrial structure as mediating variables:

$$Eff_{i,t+1} = \alpha + \beta CS_{i,t} + \delta X_{i,t} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$M_{i,t} = \alpha + \gamma CS_{i,t} + \delta X_{i,t} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

$$Eff_{i,t+1} = \alpha + \beta' CS_{i,t} + \eta M_{i,t} + \delta X_{i,t} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

In this model, M represents the mediating variable and corresponds to the three mechanism channels discussed above.

3.2. Variable Definitions and Data Sources

(1) Dependent Variable (efficiency):

To measure the level of green development across provinces, we use carbon emission efficiency as a proxy. Efficiency values are estimated using the non-radial, non-oriented Slack-Based Measure (SBM) model proposed by Tone [18], under the assumption of undesirable outputs (CO_2 emission, [19-20]) and constant returns to scale. The sample includes 29 Chinese provinces (excluding Hong Kong, Macau, Taiwan, Xinjiang, and Tibet) from 2001 to 2021. Input indicators include energy consumption (10,000 tons of standard coal), labor (population aged 15–64), and capital stock (billion RMB, estimated via the perpetual inventory method [21]). The desirable output is regional GDP, and the undesirable output is apparent carbon emissions. Efficiency scores range between 0 and 1, with higher values indicating better green economic efficiency.

(2) Core Explanatory Variable (lncs):

The logarithm of provincial forestry carbon sink reserves. Carbon sink data are derived from [22], which estimates static carbon storage values in years ending in “3” and “8” from 1998 to 2018. We interpolate and extrapolate these values to obtain annual estimates from 2001 to 2021 for 29 provinces. Carbon sink reserves reflect the CO_2 sequestration capacity of forest land and serve as a key indicator of ecological performance.

(3) Control Variables:

To mitigate omitted variable bias, we include variables across five dimensions: macroeconomic performance, population density, natural endowments, fiscal investment, and urban–rural structure:

- Economic development level (lngdp): Logarithm of provincial GDP, sourced from the China Statistical Yearbook. More developed regions typically have higher capacity for resource allocation and environmental governance, potentially leading to better green efficiency.
- Population density (pop_density): Calculated as population per square kilometer, from the China Statistical Yearbook. Population density affects resource carrying capacity, pollution intensity, and governance efficiency.
- Natural endowments: Includes Forest area (lnforest), average temperature (temp), and average precipitation (lnrain), sourced from the China Forestry Statistical Yearbook, China Forestry and Grassland Statistical Yearbook, and the National Meteorological Data Center. These variables capture ecological attributes that influence carbon sequestration and emission efficiency.
- Fiscal investment (lnse): Logarithm of the sum of government expenditure on education and science & technology, from provincial statistical yearbooks. Public spending in these areas may improve human capital and innovation capacity, thereby supporting green development.
- Urban–rural structure (urban_rate): Ratio of urban population to total population. Due to missing data before 2005 in some provinces, linear interpolation was used. Higher urbanization may lead to more concentrated emissions, potentially lowering green efficiency.

(4) Mediating Variables:

To analyze the pathways through which carbon sinks affect efficiency, we consider three mediators:

- R&D investment (lnrd): Logarithm of R&D expenditures by province, from the National Science and Technology Investment Statistical Bulletin.
- Green innovation (lnpatent): Logarithm of patent counts, obtained from the WIPO database.
- Industrial structure (ind_ratio): Ratio of tertiary to secondary industry output, sourced from the China Statistical Yearbook.

3.3. Descriptive Statistics

Table 1 reports the descriptive statistics for the key variables. The dependent variable, efficiency, ranges from 0.259 to 1, indicating variation in green economic performance across provinces. The main explanatory variable, lncs, shows substantial dispersion (mean = 18.98; SD = 1.81), suggesting heterogeneity in carbon sink reserves. Control variables such as population density and lnse (government spending on education and technology) also exhibit wide variation, which may reflect structural and policy differences. Mediators like lnrd and lnpatent indicate uneven levels of innovation and R&D activity across regions.

Overall, the data display sufficient variation to support regression analysis and allow exploration of regional heterogeneity.

Table 1. Descriptive Statistics of Key Variables

Variable Type	Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable	efficiency	609	0.404	0.110	0.259	1.000
Explanatory Variable	lncs	609	18.982	1.806	12.540	21.642
Control Variables	popdensity	609	0.454	0.645	0.007	3.926
	lnforest	609	11.457	1.462	0	13.718
	temp	609	14.810	4.934	4.300	25.400
	lnrain	609	6.683	0.629	4.329	7.986
	lnse	609	15.072	1.211	11.565	17.682
	urban_rate	609	0.536	0.152	0.228	0.896
Mediators	lnrd	609	4.836	1.599	0.588	8.295
	lnpatent	609	8.569	1.822	3.714	12.399
	ind_ratio	609	1.076	0.606	0.494	5.3

4. Empirical Analysis

4.1. Baseline Regression

Table 2 presents the results of the baseline regression analyzing the impact of carbon sink reserves on green economic efficiency. Five sets of control variables are gradually introduced, and both province and year fixed effects are included to control for unobserved regional and temporal heterogeneity.

Table 2. Baseline Regression

Variables	(1) Without control	(2) + lnGDP	(3) + popdensity	(4) + nature factor	(5) all control
lncs	0.116***	0.119***	0.0577***	0.0506***	0.0472***
	(0.0121)	(0.0118)	(0.0180)	(0.0180)	(0.0180)
lngdp		0.109***	0.146***	0.157***	0.213***
		(0.0219)	(0.0259)	(0.0260)	(0.0335)
popdensity			0.155***	0.155***	0.164***
			(0.0419)	(0.0418)	(0.0417)
urban_rate			-0.101	-0.155	-0.133
			(0.124)	(0.125)	(0.124)
lnforest				-0.00876**	-0.0106***
				(0.00352)	(0.00357)
temp				0.00758**	0.00661*
				(0.00375)	(0.00375)
lnrain				0.00815	0.00738
				(0.0102)	(0.0102)
lnse					-0.0707***
					(0.0266)
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	581	581	581	581	581
R^2	0.798	0.807	0.814	0.818	0.821

In Model (1), only the key explanatory variable—carbon sink reserves (lncs)—is included. The coefficient is 0.116 and significant at the 1% level, suggesting that regions with greater carbon sinks tend to exhibit higher green efficiency. This result remains robust after sequentially adding controls. Model (2) includes economic development (lngdp), and the coefficient of lncs slightly increases to 0.119, indicating that the effect of carbon sinks is not entirely driven by economic size. Model (3) adds population density (popdensity) and urbanization rate (urban_rate) to capture spatial agglomeration. The coefficient of lncs decreases to 0.0577 but remains significantly positive. Population density is positively significant, while urbanization is negative and insignificant, which may reflect early-stage urban expansion leading to resource misallocation or pollution concentration.

Model (4) adds environmental variables (lnforest, lnrain, temp). The coefficient of lncs remains stable. Forest area shows a weak negative correlation with efficiency, while temperature has a positive and significant effect, possibly due to more favorable ecological conditions in warmer zones.

Finally, Model (5) includes government expenditure on education and science (lnse) as a proxy for public investment. The lncs coefficient remains at 0.0472 and is significant at the 1% level, confirming the robustness of the positive impact of carbon sinks. However, lnse shows a significant negative sign, possibly reflecting inefficiencies in public investment in some provinces. Overall, as control variables are added, the model's explanatory power (R^2) improves from 0.798 to 0.821, and the sign and significance of lncs remain stable, underscoring its positive role in promoting green economic efficiency.

4.2. Robustness Checks

First, we re-estimate the dependent variable using a Slack-Based Measure under variable returns to scale (SBM-VRS) to control for scale bias across provinces. As shown in Column (1) of Table 3, lncs remains significantly positive, indicating that the main findings are not sensitive to the choice of efficiency metric.

Second, we lag the key explanatory variable (lncs) by one year while using the current efficiency value as the dependent variable to address potential endogeneity and temporal lags. Column (2) shows that the lagged lncs continues to exert a significant positive effect, suggesting a persistent impact of carbon sinks on green efficiency.

Third, we trim 1% from both tails of the distribution for lncs and efficiency to eliminate the influence of extreme values. As shown in Column (3), the results remain robust.

Table 3. Robustness Check

Dep. Variables	(1)effvrs	(2)efficiency	(3)eff_trim
lncs	0.0450**		0.0387**
	(0.0215)		(0.0150)
l_lncs		0.0545***	
		(0.0177)	
Control	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	580	580	562
R^2	0.884	0.82	0.848

4.3. Heterogeneity Analysis

To assess spatial heterogeneity in the impact of carbon sinks on green efficiency, we perform subgroup regressions across three dimensions: energy structure, regional location, and economic development (Table 4).

Table 4. Heterogeneity Analysis

	1 Energy structure		2 Region		3 Economy	
Variables	(1) Conventional Energy	(2) Clean energy	(3) East	(4) Mid-West	(5) Low GDP	(6) High GDP
lncs	0.0528^{***}	-0.00325	0.0108	0.0725^{***}	-0.0246^{***}	0.0262^{***}
	[0.0171]	[0.0346]	[0.0292]	[0.0187]	[0.00317]	[0.00567]
lngdp	0.0636^{**}	0.485^{***}	0.502^{***}	0.130^{***}	0.0113	0.0780^{***}
	[0.0259]	[0.0666]	[0.0669]	[0.0283]	[0.0113]	[0.0270]
popdensity	1.235^{***}	0.188^{***}	0.208^{***}	0.503	-0.124^{***}	0.0193
	[0.189]	[0.0634]	[0.0604]	[0.308]	[0.0347]	[0.0123]
urban_rate	-0.363^{***}	-0.358	0.171	-0.305^{*}	0.179^{***}	0.700^{***}
	[0.119]	[0.236]	[0.193]	[0.177]	[0.0292]	[0.0620]
lnforest	-0.00717^{***}	-0.00399	-0.00264	-0.00941^{***}	0.00313	-0.00149
	[0.00244]	[0.00808]	[0.00640]	[0.00312]	[0.00227]	[0.00383]
temp	9.14×10^{-5}	0.0109^{**}	0.0172^{***}	-0.0129^{***}	0.00286^{***}	0.0194^{***}
	[0.00454]	[0.00518]	[0.00631]	[0.00361]	[0.000673]	[0.00218]
lnrain	0.00073	0.0161	-0.00214	2.52×10^{-6}	0.0333^{***}	-0.0369^{**}
	[0.00787]	[0.0183]	[0.0198]	[0.00822]	[0.00594]	[0.0186]
lnse	0.0792^{***}	-0.220^{***}	-0.248^{***}	0.0926^{***}	-0.0062	-0.0634^{***}
	[0.0248]	[0.0408]	[0.0468]	[0.0226]	[0.00797]	[0.0226]
Province FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	No	No
Obs.	281	300	260	321	301	280
R^2	0.852	0.812	0.851	0.785	0.55	0.658

(1) Energy Structure

Based on the 2008 China Statistical Yearbook, we calculate the share of coal in total energy consumption and divide provinces into high-coal (above the median) and low-coal (below the median) groups. As shown in Columns (1) and (2), carbon sinks have a significantly positive effect in high-coal regions (coefficient = 0.0528, $p < 0.01$), while the effect is insignificant in low-coal regions. This suggests that carbon sinks are more effective in regions under greater environmental pressure, where they act as a compensatory ecological mechanism.

(2) Regional Location

We divide provinces into eastern and central-western regions. Columns (3) and (4) indicate that the positive effect of carbon sinks is significant in central-western regions but not in the eastern region. This may be due to the fact that eastern provinces, having entered a "green plateau" phase, rely more on technological and institutional advancements, while central-western regions, rich in ecological resources and policy support, derive greater marginal benefits from carbon sinks.

(3) Economic Development

Using median per capita GDP as a threshold, we classify provinces into economically developed and less-developed groups. In Columns (5) and (6), we find that the carbon sink effect is significantly negative in less-developed regions but significantly positive in more developed regions. This may reflect an "ecological mismatch": despite abundant carbon sink resources, less-developed regions may lack the institutional and technical capacity to translate these into green productivity gains.

4.4. Mechanism Analysis

To test the theoretical pathways proposed in Section 2, we use the causal steps approach (three-step method) to examine whether patent output, R&D investment, and industrial structure mediate the effect of carbon sinks on green efficiency. Table 5 presents the results.

Table 5. Mechanism Analysis

	(1) Technological innovation		(2) Resource allocation		(3) Industrial structure	
Dep. Variables	*lnpatent*	*efficiency*	*lnrd*	*efficiency*	*ind_ratio*	*efficiency*
lnpatent		0.0389***				
		[0.00745]				
lnrd				0.0171*		
				[0.00875]		
ind_ratio						0.0843***
						[0.0110]
lncs	0.605***	0.0233	0.491***	0.0387**	0.110*	0.0402**
	[0.0984]	[0.0181]	[0.0847]	[0.0184]	[0.0649]	[0.0171]
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	609	581	609	581	609	581
R^2	0.978	0.829	0.979	0.822	0.912	0.839

First, carbon sink reserves significantly promote regional green patent output (lnpatent), as shown in Column (1) of Table 5. After including this variable, the direct effect of carbon sinks on green economic efficiency becomes insignificant, indicating that technological innovation serves as a full mediator. This result suggests that carbon sinks, as ecological assets, indirectly enhance efficiency by stimulating green innovation activities.

Second, carbon sinks also significantly increase regional R&D investment (lnrd), as shown in Column (2). When this mediator is controlled for, the direct effect of carbon sinks on efficiency weakens but remains significant, suggesting a partial mediation through resource allocation. This implies that while carbon sinks help optimize input structures, they also continue to exert a direct influence on green efficiency.

Finally, carbon sinks positively influence industrial structure upgrading, measured by the ratio of tertiary to secondary industry. As shown in Column (3), the marginal effect of carbon sinks on efficiency declines markedly after controlling for this structural variable, indicating that industrial structure adjustment is another key pathway through which carbon sinks contribute to green economic performance.

5. Conclusion and Policy Implications

Based on a provincial panel dataset from 2001 to 2021, this study systematically investigates the impact of carbon sinks on green economic efficiency in China, along with the underlying mechanisms and spatial heterogeneity. The main findings are as follows:

First, carbon sinks significantly promote green economic efficiency. The baseline regression indicates that a 1% increase in carbon sink reserves is associated with a 0.047% improvement in green efficiency on average. This effect remains robust under various specifications, including alternative models, lagged regressions, and trimmed samples. As a key component of natural capital, carbon sinks enhance efficiency through both direct carbon sequestration and technological spillovers.

Second, significant regional heterogeneity is observed. The marginal effects of carbon sinks are stronger in coal-dependent regions (coefficient = 0.0528) and in central and western provinces (coefficient = 0.0725), suggesting that carbon sinks serve a compensatory ecological role in high-emission areas. In economically developed regions, the potential of carbon sinks is more easily realized due to stronger technological and institutional capacity, whereas underdeveloped areas may suffer from “ecological resource misallocation” due to weaker governance.

Third, carbon sinks improve efficiency through multiple pathways. Mediation analysis shows that carbon sinks enhance green efficiency indirectly by stimulating green technological innovation (accounting for 38.7% of the total effect) and optimizing industrial structure (accounting for 21.5%), supporting the theoretical framework of "natural capital—innovation—industrial upgrading."

This study expands the traditional literature on carbon efficiency by incorporating ecological assets, highlighting the economic value of ecosystem services. Based on the findings, the following policy recommendations are proposed:

1. Establish a national carbon sink monitoring and trading platform, integrating forestry and marine carbon sinks into the carbon market. Pilot carbon sink futures and cross-regional compensation mechanisms (e.g., ecological transfer payments from high-emission eastern provinces to carbon sink-rich western provinces).
2. Implement region-specific carbon policies: in central and western regions, promote integrated models such as "carbon sinks + ecological industries" (e.g., under-forest economy, carbon sink tourism); in eastern regions, leverage digital technologies (e.g., blockchain tracking, AI-based monitoring) to enhance transparency and trading efficiency of carbon sinks.
3. Enhance support for green technology transformation: the government should establish dedicated green innovation funds, target the development of emerging low-carbon technologies, and mandate high-carbon enterprises to increase investment in green patent development.

Acknowledgment

The author gratefully acknowledges the support from the Innovation and Entrepreneurship Project of China Foreign Affairs University (Project No. S202410040006), which provided funding for this research.

References

[1] State Council of China. Work Plan for Accelerating the Establishment of a Dual Control System for Carbon Emissions [EB/OL]. (2024). https://www.gov.cn/zhengce/zhengceku/202408/content_6966080.htm.

[2] NDRC, MEE, SAMR. Action Plan for Carbon Neutrality Standards and Measurement (2024–2025) [EB/OL]. (2024). https://www.gov.cn/zhengce/zhengceku/202408/content_6967197.htm.

[3] National Forestry and Grassland Administration. Guiding Opinions on Promoting Forest Carbon Sink Trading [EB/OL]. (2020). https://www.forestry.gov.cn/main/5925/20200414/09042163 9655185.html.

[4] Calvo Buendia E, Tanabe K, Kranjc A, et al. refinement to the 2006 IPCC guidelines for national greenhouse gas inventories [J]. IPCC: Geneva, Switzerland, 2019: 1 - 15.

[5] Baldocchi D, Falge E, Gu L, et al. FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities [J]. Bulletin of the American Meteorological society, 2001, 82 (11): 2415 - 2434.

[6] Friedlingstein P, O'sullivan M, Jones M W, et al. Global carbon budget 2022 [J]. Earth System Science Data, 2022, 14 (11): 4811 - 4900.

[7] Pan Y, Birdsey R A, Fang J, et al. A large and persistent carbon sink in the world's forests [J]. science, 2011, 333 (6045): 988 - 993.

[8] Yang Y, Shi Y, Sun W, et al. Terrestrial carbon sinks in China and around the world and their contribution to carbon neutrality [J]. Science China Life Sciences, 2022, 65 (5): 861 - 895.

[9] Yin S, Gong Z, Gu L, et al. Driving forces of the efficiency of forest carbon sequestration production: Spatial panel data from the national forest inventory in China [J]. Journal of Cleaner Production, 2022, 330: 129776.

[10] Chen Z, Zhang X, Chen F. Do carbon emission trading schemes stimulate green innovation in enterprises? Evidence from China [J]. Technological Forecasting and Social Change, 2021, 168: 120744.

[11] Zhou X, Zhang J, Li J. Industrial structural transformation and carbon dioxide emissions in China [J]. Energy policy, 2013, 57: 43 - 51.

[12] Wang D, Sun M, Meng B, et al. Can carbon market efficiency promote green technology innovation for Chinese companies? [J]. Energy, 2024, 309: 133157.

[13] Sueyoshi T, Goto M. Measurement of a linkage among environmental, operational, and financial performance in Japanese manufacturing firms: A use of Data Envelopment Analysis with strong complementary slackness condition [J]. European Journal of Operational Research, 2010, 207 (3): 1742 - 1753.

[14] Du M, Feng R, Chen Z. Blue sky defense in low-carbon pilot cities: A spatial spillover perspective of carbon emission efficiency [J]. Science of the Total Environment, 2022, 846: 157509.

[15] Acemoglu D, Aghion P, Bursztyn L, et al. The environment and directed technical change [J]. American economic review, 2012, 102 (1): 131 - 166.

[16] Unruh G C. Understanding carbon lock-in [J]. Energy policy, 2000, 28 (12): 817 - 830.

[17] Wang J, Shi K, Hu M. Measurement of forest carbon sink efficiency and its influencing factors empirical evidence from China [J]. Forests, 2022, 13 (11): 1909.

[18] Tone K. A slacks-based measure of efficiency in data envelopment analysis [J]. European journal of operational research, 2001, 130 (3): 498 - 509.

[19] Shan Y, Guan D, Zheng H, et al. China CO_2 emission accounts 1997 – 2015 [J]. Scientific data, 2018, 5 (1): 1 - 14.

[20] Shan Y, Huang Q, Guan D, et al. China CO_2 emission accounts 2016 – 2017 [J]. Scientific data, 2020, 7 (1): 54.

[21] Zhang Jun, Wu Guiying, Zhang Jipeng. Estimation of China's inter-provincial physical capital stock: 1952 – 2000 [J]. *Economic Research Journal*, 2004, (10): 35 – 44. (in Chinese).

[22] Fu Wei, Li Long, Luo Mingcan, et al. Spatial spillover effects and influencing factors of forest carbon sinks in China: A provincial perspective [J]. *Acta Ecologica Sinica*, 2023, 43 (10): 4074 – 4085. (in Chinese).