Advances in Management & Applied Economics, Vol. 15, No. 4, 2025, 43-62
ISSN: 1792-7544 (print version), 1792-7552(online)
https://doi.org/10.47260/amae/1543
Scientific Press International Limited

The Impact of Renewable Energy Subsidy Policies on Indirect Carbon Emissions in the Power System

Yuanying Chi[1], Chenfeng Zhang[1], Mengwan Zhang[1]*, Yanzhao Zhang[1] and Yuxi Wu[1]

Abstract

As a core policy instrument for low-carbon transition in China's power systems, the mechanism through which renewable energy subsidies mitigate indirect carbon emissions remains underexplored. This study empirically examines the impact of renewable energy generation subsidy policies on indirect carbon emissions in power systems using panel data from 30 Chinese provinces (2011-2020). The findings reveal that: (1) Renewable energy subsidies directly suppress indirect carbon emissions and reduce emissions indirectly by curbing energy consumption. (2) Regional heterogeneity shows stronger emission reduction effects in central and western China due to heavy industry agglomeration and reliance on electricity transmission. (3) Electricity consumption heterogeneity indicates significant emission reductions in medium-to-high consumption areas constrained by rigid energy demand. Policy recommendations include establishing a dynamic subsidy mechanism for central/western China, implementing "energy storage-quota" differentiated strategies for high/low consumption areas, and reorienting subsidies toward technological innovations such as hydrogen energy and energy storage.

JEL classification numbers: P28.
Keywords: Renewable Energy, Subsidy Policy, Power Systems, Indirect Carbon Emissions, Carbon Neutrality Goals.

---

[1] College of Economics and Management, Beijing University of Technology, Beijing 100124, China. *Corresponding author.

Article Info: *Received:* May 16, 2025. *Revised:* May 28, 2025.
Published online: June 2, 2025.

1. Introduction

In recent years, global climate change and carbon neutrality imperatives have intensified pressure on countries to accelerate energy transition. At the 75th United Nations General Assembly in 2020, China pledged to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, with the low-carbon transition of its power system being pivotal. Data from the National Energy Administration reveals that CO2 emissions from energy consumption accounted for 88% of China's national emissions in 2020, while the power sector alone contributed 42.5%, underscoring the urgency of decarbonizing electricity systems. According to the GHG Protocol[1], carbon emissions are categorized into direct and indirect emissions. Direct emissions from power systems arise from fossil fuel combustion during generation and transmission[2], whereas indirect emissions - per ISO 14064 standards - refer to greenhouse gases in electricity consumption, reflecting upstream emission responsibilities[3],[4].

Since enacting *the Renewable Energy Law* in 2006, China has renewable energy generation subsidies to foster sectoral growth and reshape carbon emission structures[5]. While existing studies confirm that such subsidies mitigate direct emissions[6], their impact on indirect emissions and regional heterogeneity remains unexplored. This study addresses this gap by analyzing provincial panel data (2011-2020) from 30 Chinese regions to dissect how renewable energy subsidies influence indirect emissions. The findings offer empirical insights for designing spatially targeted policies, optimizing energy portfolios, and advancing China's carbon neutrality goals.

2. Literature Review

Academic research has extensively explored the role of renewable energy subsidies in power system decarbonization, with a predominant focus on direct carbon emissions. Studies employing decomposition methods like the logarithmic mean Divisia index (LMDI) attribute emission reductions to factors such as electricity generation, coal consumption decline, population and policy interventions[7]-[12]. Empirical evidence consistently validates the efficacy of subsidies: Yang and Liang (2023)[13] quantified the carbon rebound effect following subsidy withdrawal, while Aryanpur et al. (2022)[14] projected a 31% emission reduction through subsidized demand-side management. Hitaj and Löschel (2019)[15] reveal that feed-in tariffs significantly boost renewable capacity - e.g., a 0.01€/kWh subsidy increased wind installations by 796 MW in Germany. Fuinhas et al. (2017)[16] found that renewable energy policies have an emission reduction effect on per capita carbon emissions. However, indirect fiscal instruments like carbon taxes may inadvertently hinder renewable investments, as shown in Kk et al. (2014)[17].

Spatiotemporal heterogeneity in subsidy effects has gained attention, particularly in China. Zheng et al. (2024)[18] identified regionally divergent impacts of environmental regulations on direct emissions, whereas Yang (2022)[6] linked short-term emission declines to coal plant retrofits driven by subsidy policies.

Internationally, studies from Turkey[19], Australia[20], America[21] and the UK[22] further corroborate subsidies' direct emission mitigation effects. Despite these advances, critical gaps persist: no studies systematically examine how subsidies restructure energy demand to curb indirect emissions, nor do they address regional disparities across China. This study fills these gaps by analyzing 2011-2020 provincial data to quantify indirect emission pathways, dissect regional heterogeneity through mediation models, and propose spatially adaptive subsidy frameworks, thereby advancing the scholarly discourse beyond direct emission-centric paradigms.

3. Indicator Measurement and Empirical Context

3.1 Measurement of Renewable Energy Generation Subsidies and Current Status

China's renewable energy subsidy mechanism, governed by *the Interim Measures for the Administration of Renewable Energy Electricity Price Surcharge Funds*, adopts a “regional benchmark tariff” framework. Subsidies are determined as the difference between provincial renewable energy feed-in tariffs and local desulfurized coal-based benchmark tariffs. Given the negligible contribution of offshore wind (≤5% of total wind capacity during the study period), this study focuses on solar PV and onshore wind subsidies, excluding offshore wind. The subsidy calculations are defined as follows:

$$EPS_{it} = EPSPV_{it} + EPSWD_{it} \tag{1}$$

$$EPSPV_{it} = PVFIT_{it} - DCFUB_{it} \tag{2}$$

$$EPSWD_{it} = WDFIT_{it} - DCFUB_{it} \tag{3}$$

where, $EPSPV_{it}$ and $EPSWD_{it}$ represent provincial feed-in tariffs for solar and wind, respectively, and $DCFUB_{it}$ denotes the desulfurized coal benchmark tariff. Provincial resource zoning, mandated by *the Wind Power Project Construction Management Measures* and *the State Council Guidelines on Promoting Healthy Development of the PV Industry*, categorizes regions into four-tier zones for onshore wind (based on wind power density and average wind speed) and three-tier zones for solar PV (based on annual solar irradiance), as detailed in Table 1. This methodological alignment ensures consistency with national policy frameworks while isolating the subsidy mechanisms driving emission reduction pathways.

Table 1: National Distribution of Solar PV and Onshore Wind Resource Zones

Technology	Resource Zone	Covered Regions
Solar PV	Zone I	Ningxia; Haixi Prefecture, Qinghai; Jiayuguan, Wuwei, Zhangye, Jiuquan, Dunhuang, Jinchang in Gansu; Hami, Tacheng, Altay, Karamay in Xinjiang; Inner Mongolia Autonomous Region (excluding Chifeng, Tongliao, Xing'an League, and Hulunbuir).
	Zone II	Beijing; Tianjin; Heilongjiang; Jilin; Liaoning; Sichuan; Yunnan; Chifeng, Tongliao, Xing'an League, Hulunbuir in Inner Mongolia; Chengde, Zhangjiakou, Tangshan, Qinhuangdao in Hebei; Datong, Shuozhou, Xinzhou in Shanxi; Yulin, Yan'an in Shaanxi; Qinghai, Gansu, Xinjiang (excluding Zone I regions).
	Zone III	All regions not classified under Zone I or II.
Onshore Wind	Zone I	Inner Mongolia Autonomous Region (excluding Chifeng, Tongliao, Xing'an League, Hulunbuir); Urumqi, Ili Kazakh Autonomous Prefecture, Changji Hui Autonomous Prefecture, Karamay, Shihezi in Xinjiang.
	Zone II	Zhangjiakou, Chengde in Hebei; Chifeng, Tongliao, Xing'an League, Hulunbuir in Inner Mongolia; Zhangye, Jiayuguan, Jiuquan in Gansu.
	Zone III	Baicheng, Songyuan in Jilin; Jixi, Shuangyashan, Qitaihe, Suihua, Yichun, Greater Khingan Mountains Region in Heilongjiang; Gansu (excluding Zhangye, Jiayuguan, Jiuquan); Xinjiang (excluding Urumqi, Ili Kazakh Autonomous Prefecture, Changji Hui Autonomous Prefecture, Karamay, Shihezi); Ningxia Hui Autonomous Region.
	Zone IV	All regions not classified under Zone I, II, or III.

Data Source: National Energy Administration

The subsidy allocation for provinces spanning multiple resource zones is calculated based on the proportional distribution of land area across zones, referring to the method of Dong et al.(2021)[23]. For each province, the installed capacity of solar PV and onshore wind is assumed to correlate with the total area of its prefecture-level cities. The weighted average subsidy level is derived by assigning weights according to the area ratios of the overlapping zones. This method, by incorporating the area ratios of the resource zones, can reasonably reflect the subsidy levels of different resource zones. The area ratios of the resource zones for these nine provinces are shown in Table 2.

Table 2: Land Area Ratios of Inter-resource Zone Provinces in the Two Resource Zones

Resource Zone	Xinjiang	Inner Mongolia	Gansu	Hebei	Qinghai	Shanxi	Shaanxi	Jilin	Hei Longjiang
Solar PV Zone I	0.195	0.605	0.639		0.459				
Solar PV Zone II	0.805	0.395	0.361	0.53	0.541	0.297	0.39		
Solar PV Zone III				0.47		0.703	0.61		
Onshore Wind Zone I	0.219	0.605							
Onshore Wind Zone II		0.395	0.465	0.406					
Onshore Wind Zone III	0.781		0.535					0.255	0.428
Onshore Wind Zone IV				0.594				0.745	0.572

Data Source: Official Websites of Provincial People's Governments

As illustrated in Figure 1, the feed-in tariffs (FITs) for wind and solar PV exhibited a consistent downward trajectory from 2011 to 2020, reflecting both technological advancements and the gradual phase-out of national subsidies. Specifically, wind FITs declined from 0.6013 CNY/kWh to 0.4506 CNY/kWh, while solar PV FITs dropped more sharply from 1.15 CNY/kWh to 0.4455 CNY/kWh, representing reductions of 25.1% and 61.3%, respectively. Correspondingly, total renewable energy subsidies also decreased annually, with a pronounced reduction notably after 2016. This shift reflects the government's strategic transition from direct fiscal support to market-driven mechanisms, aligning with the broader phase-out of subsidies and industry maturation under China's renewable energy policy framework.

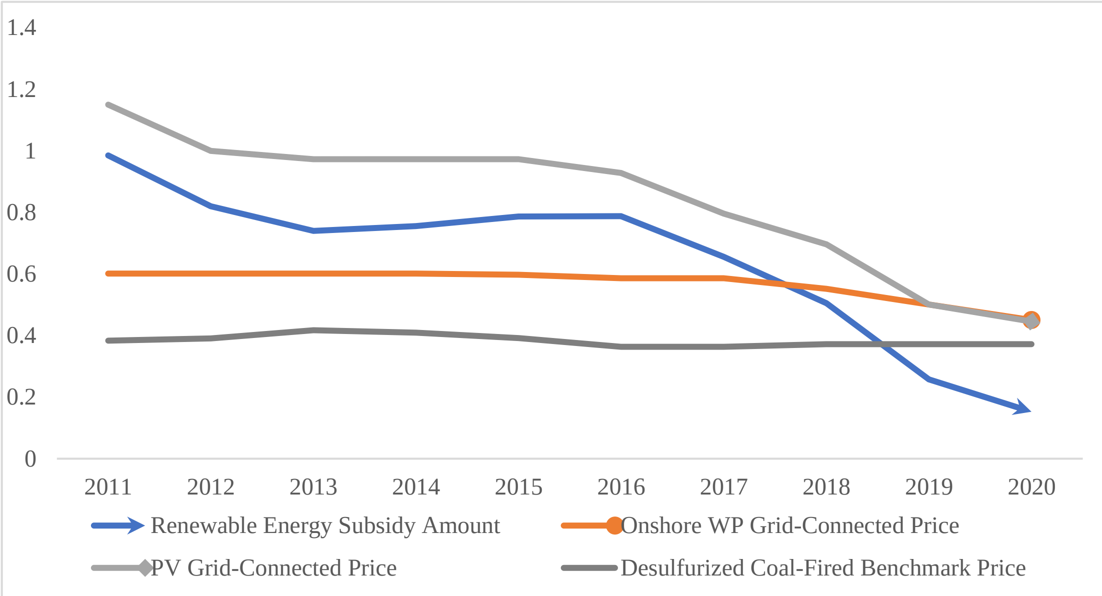

Figure 1: National Average Trend of Renewable Energy Generation Subsidies from 2011 to 2020

3.2 Measurement and Analysis of Indirect Carbon Emissions in Power Systems

As a quintessential secondary energy source, electricity generates carbon emissions primarily during production and transmission, with no direct emissions occurring at the consumption stage. For instance, emissions from power purchased and consumed by enterprises, though physically generated at power plants are classified as indirect carbon emissions under corporate carbon accounting frameworks, as these emissions are triggered by end-user electricity demand. For most non-energy-intensive enterprises, indirect emissions constitute the dominant share of their carbon footprints.

Current methodologies for calculating indirect emissions include the Grid Average Carbon Emission Factor (GACEF), widely adopted globally for its practicality in linking regional electricity mixes to consumption-based accountability. This method assumes uniform carbon responsibility per unit of electricity across a grid region over extended periods, serving as a robust reference for quantifying user-level indirect emissions[2]. The GACEF bridges direct emissions from power generation with indirect emissions from consumption, enabling coordinated mitigation strategies: reducing emissions at the generation stage while guiding demand-side decarbonization. The indirect carbon emissions of the power system (*PICE*) are calculated as:

$$PICE = A_{ele} \times E_{ele} \tag{4}$$

A_{ele} represents the net purchased electricity (in billion kWh) for province i in year t, sourced from provincial energy statistical yearbooks and regional energy balance sheets, and E_{ele} denotes the grid-average carbon emission factor derived from *Research on CO_2 Emission Factors for China's Regional Grids (2023)*[24]. As illustrated in Figure 2, indirect emissions exhibited a fluctuating upward trajectory from 2011 to 2020, rising from 434.5 million tonnes (Mt) to 920.0 Mt, while net purchased electricity surged from 577.5 billion kWh to 1,383.1 billion kWh over the same period. Notably, post-2017 data reveals accelerated growth in both emissions and electricity demand, underscoring the challenges of decoupling consumption expansion from carbon intensity under current grid emission factors. This divergence highlights the critical need for refining regional emission accounting methodologies and strengthening demand-side management to align with national decarbonization targets.

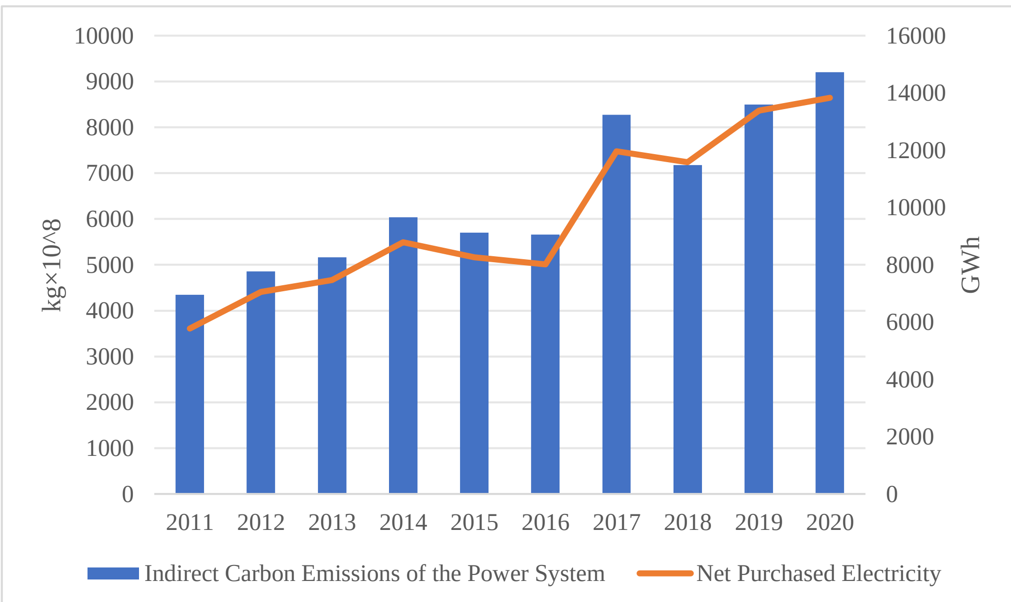

Figure 2: Trends in Provincial Average Indirect Carbon Emissions and Net Purchased Electricity in the Power System (2011 – 2020)

4. Model Specification, Variables, and Data

4.1 Model Specification

This study employs panel data analysis to investigate the impact of renewable energy generation subsidies on indirect carbon emissions in power systems. The baseline econometric model is specified as follows:

$$PICE_{it} = \alpha_0 + \alpha_1 EPS_{it} + \alpha_2 Z_{it} + \varepsilon_{it} \quad (5)$$

where $PICE_{it}$ represents the indirect carbon emissions of the power system in province *i* and year *t*, EPS_{it} denotes the intensity of renewable energy generation subsidies (CNY/kWh), and Z_{it} captures control variables including industrial structure, energy efficiency, and economic output. Province fixed effects, while ε_{it} is the stochastic error term.

4.2 Variable Selection

4.2.1 Core Explanatory Variable

Renewable energy generation subsidies (EPS_{it}) are measured as the total subsidies for solar PV and onshore wind in province *i* and year *t*, calculated by summing the differences between provincial feed-in tariffs for solar PV ($PVFIT_{it}$) and onshore wind ($WDFIT_{it}$) and the desulfurized coal benchmark tariff ($DCFUB_{it}$).

4.2.2 Core Dependent Variable

Indirect carbon emissions from the power system ($PICE_{it}$) are quantified using the grid average carbon emission factor (GACEF) method.

4.2.3 Control Variables

Renewable Energy Generation (*repg*): Annual renewable electricity output (billion kWh) in province i, which influences cross-province electricity transfers and grid carbon intensity due to supply volatility.

Coal Consumption (*cc*): Provincial coal consumption (million tonnes), reflecting reliance on carbon-intensive thermal power and potential electricity import dependency.

Power Generation Structure (*ps*): Share of thermal power in total generation (%), affecting local energy efficiency and external electricity demand.

Government Intervention (*gie*): Ratio of provincial environmental protection expenditure to GDP (%), capturing policy-driven structural reforms in energy systems.

Population (*pop*): Resident population (million), driving electricity demand growth and cross-regional power transfers.

This variable framework isolates the subsidy-emission nexus while accounting for technological, economic, and policy confounders, ensuring robust identification of causal pathways.

Table 3: Variable Definitions for Econometric Model

	Variable Symbol	Description	Definition/Calculation
Explanatory Variable	*EPS*	Renewable Energy Generation Subsidies	Sum of solar PV and onshore wind subsidies
Dependent Variable	*PICE*	Indirect Carbon Emissions of Power System	Net Purchased Electricity×Grid-average Carbon Emission Factor
Control Variables	*repg*	Renewable Energy Generation	Total electricity generation excluding thermal power (billion kWh)
	cc	Coal Consumption	Annual coal consumption (million tonnes)
	ps	Power Generation Structure	Share of thermal power in total generation:
	gie	Government Environmental Intervention	Ratio of provincial environmental protection expenditure to GDP
	pop	Population	Year-end total population (million)

4.3 Data Description

This study utilizes a balanced panel dataset spanning 2011-2020, covering 30 Chinese provinces (Tibet, Hong Kong, Macau, and Taiwan are excluded due to data availability), yielding 300 province-year observations. All raw data are sourced from authoritative national institutions: National Bureau of Statistics, China Electric Power Yearbook, Energy Statistics Yearbook, and *the Research on CO_2 Emission Factors for China's Regional Grids* published by the Chinese Academy of Environmental Planning under the Ministry of Ecology and Environment.

5. Empirical Results and Analysis

5.1 Benchmark Results Analysis

This paper employs Stata 16 software to conduct the Hausman test on the random effects model and the fixed effects model. The Hausman test results ($X^2(4) = 39.21$, $p = 0.00$) strongly reject the null hypothesis of the random effects model, confirming the appropriateness of the fixed-effects model. As shown in Table 4, the baseline regression results indicate that renewable energy subsidies exert a statistically significant negative effect on indirect carbon emissions at the 1% significance level. This supports the hypothesis that subsidies drive renewable energy adoption, thereby displacing fossil fuel-based electricity and lowering carbon intensity. Among control variables, population size exhibits a significant positive correlation, suggesting that population-driven electricity demand amplifies indirect emissions. Notably, renewable energy generation shows an unexpected positive association, potentially due to rebound effects where renewable capacity expansion stimulates ancillary demand, offsetting emission reductions. Government intervention, however, significantly suppresses emissions, highlighting the role of environmental fiscal policies in accelerating decarbonization. Most control variables are statistically significant at conventional thresholds (1% or 10%), affirming model robustness and reliability.

Table 4: Benchmark Regression Results

	(1)	(2)
	PICE	PICE
EPS	-1766.29***	-1021.56***
	(-4.26)	(-3.18)
repg		0.11***
		(5.92)
cc		0.03
		(0.79)
ps		-21.21
		(-0.02)
gie		5.52*
		(1.95)
pop		2.71***
		(4.45)
Constant	3301.97***	-10649.05***
	(12.35)	(-3.82)
Fixed Effects	Yes	Yes
N	300	300
R^2	0.159	0.305
Adj. R^2	0.156	0.291
F	18.127	22.179

*** $p<0.01$. ** $p<0.05$. * $p<0.1$.

5.2 Addressing Endogeneity

To mitigate potential endogeneity concerns, this study employs a two-stage least squares (2SLS) approach with urbanization level (*ul*) and energy consumption structure (*ecs*) as instrumental variables (IVs). Urbanization, measured as the urban population share[25], and energy consumption structure, defined as the ratio of coal consumption to total energy use[26], satisfy exclusion restrictions by influencing indirect emissions through long-term economic restructuring and energy supply-demand dynamics, while remaining uncorrelated with contemporaneous subsidy policies. The calculation formulas are shown in Equations (6) and (7):

$$ul = \frac{Urban\ Population}{Total\ Population} \tag{6}$$

$$ecs = \frac{Coal\ Consumption}{Total\ Energy\ Consumption} \tag{7}$$

To further verify the validity of the instrumental variables, this study not only reports the Kleibergen-Paap LM statistic and Kleibergen-Paap Wald F statistic but also conducts the Sargan overidentification test. The F-statistic in the first-stage regression is 44.36, significantly exceeding the threshold of 10, which rules out the weak instrument problem. Meanwhile, the Sargan test supports the exogeneity of the instrumental variables, indicating the validity of the instrumental variable selection. In Table 5, column (1) presents the original regression results, while column (2) shows the results using urbanization level and energy consumption structure as instrumental variables. Here, the core explanatory variable, *EPS* remains significantly negative at the 1% significance level, demonstrating that after addressing endogeneity, renewable energy subsidies continue to exert a significant inhibitory effect on indirect carbon emissions from the power system.

Table 5: Endogeneity Test Results

	(1)	(2)
	Original Regression	2SLS Regression
EPS	-1021.56***	-9,051.85***
	(-3.18)	(-7.60)
repg	0.11***	-0.01
	(5.92)	(-0.02)
cc	0.03	-0.03**
	(0.79)	(-1.99)
ps	-21.21	6,564.23***
	(-0.02)	(8.40)
gie	5.52*	13.72***
	(1.95)	(4.17)
pop	2.71***	0.63***
	(4.45)	(8.98)
Constant	-10649.05***	-400.29
	(-3.82)	(-0.36)
Kleibergen-Paap rk LM		69.90
P value		0.000
Kleibergen-Paap rk Wald F		44.36
Fixed Effects	Yes	Yes
N	300	300
R^2	0.305	0.147

*** $p<0.01$. ** $p<0.05$. * $p<0.1$.

5.3 Robustness Checks

To ensure the reliability of the research conclusions, this paper conducts robustness checks from three dimensions: variable substitution, model extension, and indicator reconstruction, with results shown in Table 6. First, considering that energy consumption structure (*ecs*) may affect policy effectiveness through electricity price transmission mechanisms[27], the core explanatory variable is replaced with *ecs*. The results, as shown in column (2), indicate that the substitute variable still exerts a significant negative inhibitory effect on indirect carbon emissions. Second, to exclude potential interference from primary energy supply, provincial coal production (*cp*) is incorporated as an additional control variable based on the power sector's coal-dominant structure[28]. Column (3) demonstrates that the negative effect of renewable energy subsidies remains significant after controlling for coal supply-side factors, confirming that the results are unaffected by omitted variable bias. Finally, the dependent variable is reconstructed as industrial carbon emissions (*ice*) to test the generalizability of policy effects across emission sources. Column (4) reveals no substantial changes in coefficient direction or significance levels, suggesting that the emission reduction effect of subsidies is consistent across dimensions.

Table 6: Robustness Test Results

	(1)	(2)	(3)	(4)
	Original Regression	Replace Core Explanatory Variable	Add Control Variable	Replace Dependent Variable
EPS	-1021.56***		-687.01**	-2286.90***
	(-3.18)		(-2.27)	(-5.77)
ecs		-4300.66**		
		(-2.37)		
repg	0.11***	0.12***	0.09***	-0.02
	(5.92)	(6.98)	(5.02)	(-0.69)
cc	0.03	0.06	-0.12	-0.03
	(0.79)	(1.32)	(-1.39)	(-0.79)
ps	-21.21	-988.53	-419.58	-5705.07***
	(-0.02)	(-0.69)	(-0.41)	(-4.35)
gie	5.52*	5.27*	4.69*	4.74
	(1.95)	(1.81)	(1.72)	(1.45)
pop	2.71***	2.54***	2.48***	0.37
	(4.45)	(4.15)	(4.26)	(0.69)
cp			0.18**	
			(2.41)	
Constant	-10649.05***	-8477.43***	-9105.56***	13401.50***
	(-3.82)	(-2.92)	(-3.28)	(4.58)
N	300	300	300	300
R^2	0.305	0.304	0.328	0.393

*** $p<0.01$. ** $p<0.05$. * $p<0.1$.

5.4 Heterogeneity Analysis

5.4.1 Geographic Region Heterogeneity

To account for differences in policy priorities and resource endowments across regions, this study explores the impact of renewable energy generation subsidies on indirect carbon emissions in different geographic areas. Based on the classification of eastern, central, and western regions by China's National Development and Reform Commission (NDRC), regional dummy variables are incorporated into the sample for heterogeneity analysis. Table 7 shows that the coefficients of *EPS* in central and western regions are statistically significant at the 5% level, indicating pronounced emission reduction effects. This difference arises from the high proportion of heavy industries in central and western China's industrial structure[29], where subsidies achieve emission reductions by suppressing production demand in energy-intensive industries. Simultaneously, these regions' high dependency on electricity exports[30] further enhances local policy effectiveness. In contrast, the coefficient of *EPS* in the eastern region is only significant at the 10% level, suggesting weaker policy effects compared to central and western regions. This may be attributed to the eastern region's strong interprovincial grid interconnectivity[31], which limits the direct local impact of subsidies on carbon emissions.

Table 7: Regional Heterogeneity

	(1)	(2)	(3)
	Eastern Region	Central Region	Western Region
EPS	-1347.89*	-1092.26**	-1029.98**
	(-1.82)	(-2.63)	(-3.23)
repg	0.11**	-0.03	-0.55*
	(2.61)	(-0.29)	(-2.03)
cc	-0.19	0.06*	0.04
	(-0.99)	(2.19)	(0.96)
ps	701.23	-2860.37	-2908.05*
	(0.39)	(-1.34)	(-1.99)
gie	3.25	4.16	1.74
	(0.64)	(0.77)	(1.31)
pop	2.82***	3.34*	-0.74
	(3.21)	(1.98)	(-0.59)
Constant	-7736.05	-13972.13*	5141.04
	(-1.57)	(-1.98)	(1.21)
N	110	100	90
R^2	0.325	0.530	0.429

*** $p<0.01$. ** $p<0.05$. * $p<0.1$.

5.4.2 Heterogeneity Analysis Based on Electricity Consumption Levels

This study divides 30 provinces into low, medium, and high electricity consumption groups using the standard deviation method based on 2011 provincial electricity consumption data to assess the heterogeneous effects of renewable energy subsidies on indirect carbon emissions. As shown in Table 9, regression results indicate that in low-consumption regions, the impact of subsidies is statistically insignificant, likely due to their stronger energy self-sufficiency, lower electricity demand, and reduced reliance on cross-province power transfers, which diminishes the policy's effectiveness. In contrast, subsidies significantly suppress indirect emissions in medium- and high-consumption regions. This divergence arises because higher energy demand in these regions amplifies the role of subsidies in promoting renewable energy integration and reducing carbon-intensive electricity imports, thereby achieving measurable emission reductions. The results underscore the importance of tailoring subsidy policies to regional consumption patterns to maximize decarbonization outcomes.

Table 8: Heterogeneity Analysis by Electricity Consumption Levels

	(1)	(2)	(3)
	Low Consumption Group	Medium Consumption Group	High Consumption Group
EPS	-462.55	-908.75**	-2606.57**
	(-1.42)	(-2.45)	(-3.44)
repg	-0.28	-0.20	0.03
	(-0.27)	(-0.82)	(1.28)
cc	0.05	0.10***	-0.13
	(0.78)	(4.71)	(-1.16)
ps	-491.47	-1299.43	-5506.85
	(-0.45)	(-1.52)	(-0.67)
gie	0.19	3.12	14.12
	(0.15)	(0.50)	(1.97)
pop	-0.02	1.06	1.97**
	(-0.04)	(0.67)	(3.19)
Constant	1363.39	-3937.81	-2165.95
	(0.93)	(-0.54)	(-0.26)
N	130	110	60
R^2	0.198	0.551	0.426

*** $p<0.01$. ** $p<0.05$. * $p<0.1$.

5.5 Mechanism Analysis

Building on the theoretical framework that renewable energy subsidies drive green industrial transformation[32], this study examines the mediating role of total energy consumption (*tec*) in the "subsidy policy – carbon emission reduction" pathway using a fixed-effects model. The mediation analysis follows the stepwise testing procedure proposed by Wen et al. (2004)[33]:

$$tec_{it} = \alpha_0 + \alpha_3 EPS_{it} + \alpha_4 Z_{it} + \varepsilon_{it} \tag{8}$$

$$PICE_{it} = \alpha_0 + \alpha_5 EPS_{it} + \alpha_6 TEC_{it} + \alpha_7 Z_{it} + \varepsilon_{it} \tag{9}$$

As shown in Table 9, the baseline regression (Equation 5) confirms a significant total inhibitory effect of subsidies on indirect emissions. The first-stage regression (Equation 8) reveals that subsidies significantly reduce energy consumption, indicating energy conservation as a mediator. In the final stage (Equation 9), both *EPS* and *tec* remain significant, satisfying the criteria for partial mediation. This demonstrates that renewable energy subsidies suppress indirect emissions both directly and indirectly by curbing aggregate energy demand.

Table 9: Mediation Effect Analysis

	(1)	(2)	(3)
	Baseline Regression	First-Stage Regression	Final Stage Regression
EPS	-1021.56***	-1439.55***	-709.98**
	(-3.18)	(-4.68)	(-2.40)
repg	0.11***	0.07***	0.09***
	(5.92)	(2.85)	(4.98)
cc	0.03	0.28***	-0.03
	(0.79)	(3.11)	(-0.39)
ps	-21.21	-1259.98	253.15
	(-0.02)	(-0.92)	(0.25)
gie	5.52*	-0.87	5.71*
	(1.95)	(-0.23)	(1.98)
pop	2.71***	4.18***	1.80***
	(4.45)	(5.87)	(2.95)
tec			0.22*
			(1.73)
Constant	-10649.05***	-6331.89*	-9276.65***
	(-3.82)	(-1.75)	(-3.83)
N	300	300	300
R^2	0.305	0.717	0.323

*** p<0.01. ** p<0.05. * p<0.1.

To further validate the robustness of the mediation mechanism, this study employs the Sobel test to verify the mediating role of total energy consumption. As shown in Table 10, the Sobel test yields a Z-statistic of -3.22 (p<0.01), confirming the statistical significance of the mediation effect. The proportion of the total effect mediated by energy consumption is calculated as 38.7%, indicating that renewable energy subsidies suppress indirect carbon emissions through dual pathways: a direct inhibitory effect (61.26%) and an indirect channel via energy demand reduction (38.74%). These results robustly affirm that energy consumption acts as a partial mediator in the policy-emission nexus, with both direct and indirect mechanisms jointly driving systemic decarbonization.

Table 10: Sobel-Goodman Mediation Test Results

Test Type	Coef.	Std. Err.	Z	P
Sobel	-898.28	279.01	-3.22	0.0013
Goodman-1(Aroian)	-898.28	279.63	-3.21	0.0013
Goodman-2	-898.28	278.38	-3.23	0.0013
Mediating Effect to Total Effect Ratio		0.387		
Mediating Effect to Direct Effect Ratio		0.6325		
Total Effect to Direct Effect Ratio		1.633		

6. Conclusions and Policy Implications

6.1 Research Findings

This study empirically examines the impact of renewable energy generation subsidies on indirect carbon emissions from China's power systems using provincial panel data (2011 – 2020). Key findings reveal that subsidies suppress indirect emissions through dual pathways:

Direct effect: A 1 CNY/kWh increase in subsidies reduces annual indirect emissions by 1.022 million tonnes, equivalent to 0.008% of China's 2023 total carbon emissions[34], providing tangible support for achieving the 2030 carbon peaking target.

Indirect effect: Total energy consumption mediates 38.7% of the emission reduction, demonstrating a compound mechanism of “policy incentives→energy demand optimization→carbon reduction”.

Regional heterogeneity analysis shows stronger emission reduction effects in central and western China, attributed to heavy industry agglomeration and reliance on cross-province electricity transmission, compared to the eastern region with robust intergrid coordination. Electricity consumption heterogeneity further highlights significant policy effects in medium and high-consumption regions (driven by rigid energy demand) but negligible impacts in low-consumption areas.

6.2 Policy Recommendations

To maximize the decarbonization efficacy of renewable subsidies, a differentiated yet synergistic policy framework is proposed:

For central/western regions: Implement dynamic subsidy mechanisms to enhance local emission reductions, establish cross-provincial green power certification systems to mitigate carbon leakage, and foster regional collaboration platforms for optimized subsidy allocation and unified green power-carbon accounting.

For consumption-tiered regions: Prioritize fiscal support and energy storage infrastructure in low-consumption areas to address renewable curtailment, while enforcing green electricity quotas and demand-response mechanisms in high-consumption regions.

Long-term transition: Shift subsidy priorities toward innovation-driven sectors like hydrogen energy and grid-scale storage, advancing from “capacity expansion” to “technology leadership” paradigms to systematically accelerate carbon neutrality.

ACKNOWLEDGEMENTS. This work was financially supported by the National Natural Science Foundation of China Major Program Project (72140001).

References

[1] World Resources Institute (WRI). (2004). *GHG Protocol Corporate Accounting and Reporting Standard*. Retrieved December 19, 2024, from https://ghgprotocol.org/project-protocol

[2] Li, Y., Yang, X., Du, E., Liu, Y., Zhang, S., Yang, C., Zhang, N., & Liu, C. (2024). A review on carbon emission accounting approaches for the electricity power industry. *Applied Energy*, 359, 122681.

[3] International Organization for Standardization. (2018). *ISO 14064-1: Greenhouse gases — Part 1: Specification with guidance at the organization level for quantification and reporting of greenhouse gas emissions and removals*. Retrieved December 19, 2024, from https://www.iso.org/standard/66453.html

[4] Liu, Y. L., Li, Y. W., Zhou, C. L., et al. (2024). Review of carbon emission measurement and analysis methods for power systems. *Proceedings of the CSEE*, 44(6), 2220–2235.

[5] Yang, S. S. (2015). Evaluation and prediction of carbon emission transfers in China's industrial sectors. *China Industrial Economics*, 6, 55–67.

[6] Yang, W. X. (2022). *Impact of power generation subsidy policies on emission reduction and innovation in the electricity sector* (PhD dissertation). Zhejiang University, China.

[7] Li, X. D., Tan, Q. B., Zhao, H. C., et al. (2024). Carbon emission factors and decoupling effects in China's power industry under carbon peaking targets. *China Electric Power*, 57(5), 88–98.

[8] Shi, Y. L., & Yu, X. Y. (2024). Analysis of factors influencing carbon emissions in the power industry based on LMDI and system clustering. *Ecological Economy*, 40(2), 22–29.

[9] Jiang, X. T., Su, M., & Li, R. (2018). Decomposition analysis in electricity sector output from carbon emissions in China. *Sustainability*, 10(9), 3251.

[10] Wang, C. K., & Xie, H. Z. (2015). Dynamic characteristics and influencing factors of carbon emissions in China's power sector. *China Population, Resources and Environment*, 25(4), 7–14.

[11] Chen, Q. (2022). *Research on the impact pathways of China's digital economy on carbon emissions in the power sector* (Master's thesis). Nanjing Audit University, China.

[12] Qiu, Y. (2023). *Analysis of carbon emission efficiency and influencing factors in Hubei Province's power sector* (Master's thesis). Central China Normal University, China.

[13] Yang, Z. Q., & Liang, J. (2023). The environmental and economic impacts of phasing out cross-subsidy in electricity prices: Evidence from China. *Energy*, 283, 129154.

[14] Aryanpur, V., Fattahi, M., Mamipour, S., Ghahremani, M., Ó Gallachóir, B., Bazilian, M. D., & Glynn, J. (2022). How energy subsidy reform can drive the Iranian power sector towards a low-carbon future. *Energy Policy*, 169, 113190.
[15] Hitaj, C., & Löschel, A. (2019). The impact of a feed-in tariff on wind power development in Germany. *Resource and Energy Economics*, 57, 18–35.
[16] Fuinhas, J. A., Marques, A. C., & Koengkan, M. (2017). Are renewable energy policies upsetting carbon dioxide emissions? The case of Latin American countries. *Environmental Science and Pollution Research*, 24(17), 15044–15054.
[17] Gürhan, A. K., Shang, K., & Yücel, Ş. (2014). Impact of electricity pricing policies on renewable energy investments and carbon emissions. *Management Science*, 60(11), 2723–2738.
[18] Zheng, Y. L., Shi, W., Wang, W. J., et al. (2024). Impact of environmental regulation on carbon emissions in China's power industry. *Environmental Science.*1-20.
[19] Guven, D., Kayalica, M. O., & Sen, O. L. (2025). The impact of electricity generation on CO2 emissions in Türkiye: An agent-based simulation approach. *Energies*, 18(3), 655.
[20] Amin Masoumzadeh, T., Alpcan, T., & Nekouei, E. (2020). Designing tax and subsidy incentives towards a green and reliable electricity market. *Energy*, 195, 117033.
[21] Hongtao.Clean-energy policies and electricity sector carbon emissions in the U.S. states[J].*Utilities policy: strategy, performance, regulation*, 2015.
[22] Franco, C. J., Castaneda, M., & Dyner, I. (2015). Simulating the new British Electricity-Market Reform. *European Journal of Operational Research*, 245(1), 273–285.
[23] Dong, C. G., Zhou, R. M., & Li, J. Y. (2021). The impact of subsidy policies on China's photovoltaic installation market: An empirical analysis based on panel data regression. *Resources Science*, 43(6), 1065–1076.
[24] Chinese Academy of Engineering (CAE). (2023). *Research on CO2 emission factors for China's regional grids (2023)*. Retrieved December 19, 2024, from https://www.caep.org.cn/sy/tdftzhyjzx/zxdt/202310/t20231027_1044179.shtml
[25] Gao, J., & Zhang, L. (2020). Does biomass energy consumption mitigate CO2 emissions? The role of economic growth and urbanization: evidence from developing Asia. Journal of the Asia Pacific Economy, 26(1), 96–115.
[26] Zhao, C. H., Wang, Y. E., & He, D. S. (2014). Association between carbon emissions and energy consumption structure in Hebei Province. *Advanced Materials Research*, 955–959, 2607–2612.

[27] Wang, L., Sun, Y. K., & Wang, Q. (2024). China's electricity pricing system under the goal of common prosperity: Theoretical mechanisms and implementation pathways. *Price: Theory & Practice*, 4, 88–94.

[28] Shrestha, A., Ichihashi, M., & Kakinaka, M. (2024). The coal price and spot electricity market nexus in India: evidence from the quantile-on-quantile approach. Journal of the Asia Pacific Economy, 1–23.

[29] Chen, K. K. (2020). *Analysis of provincial energy intensity differences and prediction in China* (Master's thesis). North China Electric Power University, China.

[30] Li, H. L. (2023). Operational characteristics of western sending-end DC grids and power systems under the new power system framework. *China Electric Power*, 56(8), 166–174.

[31] Zheng, W. S., & Rao, H. (2025). Flexible grid-forming technologies and applications in new power systems. *Automation of Electric Power Systems*. 1-10.

[32] Jayasinghe, M., & Selvanathan, E. A. (2021). Energy consumption, tourism, economic growth and CO2 emissions nexus in India. Journal of the Asia Pacific Economy, 26(2), 361–380.

[33] Wen, Z. L., Zhang, L., Hou, J. T., et al. (2004). Testing and application of the mediating effects. *Acta Psychologica Sinica*, 36(5), 614–620.

[34] International Energy Agency (IEA). (2024). *CO2 Emissions in 2023*. Retrieved December 19, 2024, from https://www.iea.org/reports/co2-emissions-in-2023.