

Article

Empirical Analysis of Renewable Energy Subsidy Policies on Regional Employment and Growth

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Abstract

Against the global backdrop of carbon peaking and carbon neutrality goals, renewable energy subsidy policies worldwide are shifting from universal, tariff-based schemes toward targeted, market-oriented mechanisms. However, existing research remains divided on the incentive effects of subsidies on firm investment and the risk of resource misallocation, and few studies have established a clear micro-macro linkage between firm-level subsidy receipts and regional employment and growth outcomes. Taking China's 2016 renewable energy subsidy reform—characterized by competitive project bidding and green certificate trading—as a quasi-natural experiment, this study constructs a two-layer panel dataset covering 286 A-share listed renewable energy firms (2010–2023, 2412 firm-year observations) and 30 provincial-level regions in China (2010–2023, 420 region-year observations). Employing difference-in-differences (DID), triple difference-in-differences (DDD), mediation effect models, and threshold regression, combined with instrumental variables and placebo tests to address endogeneity, we empirically examine how subsidy policies transmit from firm behavior to regional employment and economic growth. The results indicate that the 2016 reform significantly boosted regional employment (elasticity = 0.035, $p < 0.01$) and economic growth (elasticity = 0.031, $p < 0.05$) in treated provinces. At the firm level, subsidy intensity exhibits an inverted U-shaped relationship with investment efficiency, with an estimated inflection point at 8.3% of operating revenue within the sample. Mechanism analysis shows that easing financing constraints, stimulating technological innovation, and reducing operational risk serve as core transmission channels, with the strongest contribution from financing constraint alleviation. Heterogeneity analysis further finds larger effects for private firms, high-tech enterprises, and coastal regions. This study develops a nonlinear analytical framework of “subsidy intensity–firm behavior–regional outcomes”, identifies context-specific boundaries of subsidy effectiveness, and provides integrated micro-macro empirical evidence for optimizing subsidy policies and advancing the global energy transition.



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Keywords: renewable energy subsidies; regional employment; economic growth; energy transition policy; subsidy intensity; micro-macro transmission

1. Introduction

1.1. Practical Background

The global drive toward decarbonization has transformed energy systems and policy instruments over the past two decades. Renewable generation capacity has scaled rapidly:

wind and solar installed capacity worldwide rose from under 200 GW in 2005 to over 3000 GW by 2023, a shift that has pushed governments to reconsider how to accelerate deployment while containing fiscal costs and market distortions [1]. This rapid expansion of wind energy, in particular, has been linked to reduced ecological footprints and improved environmental sustainability alongside economic development [2]. Early subsidy regimes—characterized by broad feed-in tariffs, flat production premiums, and blanket investment tax credits—prioritized rapid scale-up and investor certainty. These universal instruments delivered predictable cashflows and catalyzed nascent industries, but they also produced significant fiscal burdens and rent-seeking when technology costs fell faster than designs anticipated [3]. As unit costs of wind and solar declined by 85% and 90%, respectively, between 2010 and 2023, policymakers began to question the efficiency and equity of one-size-fits-all transfers and moved toward more targeted, market-oriented mechanisms [4].

China, as the world's largest renewable energy market, implemented a landmark subsidy reform in 2016. The reform replaced the nationwide fixed feed-in tariff system with competitive bidding for new projects and introduced a green certificate trading mechanism to complement direct fiscal transfers [5]. This policy shift provides an ideal quasi-natural experiment to evaluate the economic impacts of different subsidy designs. While existing studies have examined either firm-level investment responses or aggregate regional outcomes, few have established a clear micro-macro linkage that explains how subsidies to individual firms translate into regional employment and growth [6]. This gap is particularly critical for policymakers who need to design policies that balance industrial development, job creation, and fiscal sustainability (See Figure 1).

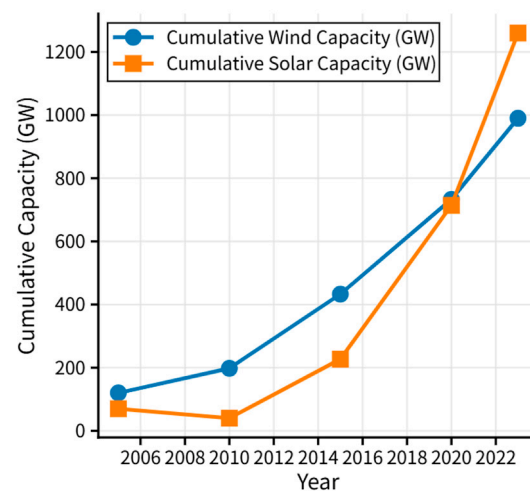


Figure 1. Changes in global cumulative installed capacity of wind and solar power from 2005 to 2023.

The contemporary policy evolution emphasizes three operational imperatives: market discipline, fiscal sustainability, and social acceptability (see Table 1). Technically, the welfare implications of transitioning subsidy design can be formalized by considering a social surplus function $S = CS + PS - B$, where CS is consumer surplus, PS is producer surplus, and B denotes budgetary transfers. Moving to targeted instruments typically reduces B for a given installed capacity while maintaining or increasing CS and efficient PS, thus improving S [7]. Against this backdrop, evaluating how these evolving subsidy designs affect regional employment and growth requires careful disaggregation: different instruments alter capital intensity, local content, and investment timing—each of which shapes labor demand and productivity paths at the regional level.

Table 1. Comparative features of universal and targeted subsidy regimes.

Feature	Universal Subsidies	Targeted Subsidies
Allocation method	Administrative rates	Competitive auctions
Cost exposure	High fiscal risk	Lower, market-determined
Incentive precision	Low	High
Technological neutrality	Often low	Often higher
Adaptability to grid needs	Poor	Better
Rent-seeking risk	High	Lower

Source: Author compilation based on IEA (2021) [4] and Chinese Energy Policy Research Institute (2022) [5].

1.2. Theoretical Debates and Research Gaps

Debates on the economic consequences of renewable energy subsidies center on competing theoretical predictions and the empirical difficulties of isolating causal channels. One strand argues for straightforward Keynesian-style expansionary effects: subsidies lower the effective capital cost of renewable projects, stimulate investment, and directly create jobs in construction, manufacturing, and installation [8]. Another contends that crowding-out and allocative distortions may dominate; subsidies financed by taxation or public debt can suppress private consumption and non-energy investment, while price distortions may favor capital-intensive technologies that generate fewer long-term jobs per unit of output [9]. A critical unresolved issue is non-linearity: the marginal effect of an additional dollar of subsidy likely depends on existing subsidy intensity, regional absorptive capacity, and the maturity of local supply chains [10].

Mechanism quantification is another significant gap. While theory lists plausible channels—direct jobs in renewable installations, indirect jobs through upstream suppliers, induced demand from higher local incomes, and productivity gains via technological spillovers—few studies decompose total effects into these constituent parts with robust identification [11]. Most existing research either focuses exclusively on firm-level outcomes or uses aggregate regional data without establishing the causal link between micro-level subsidy receipts and macro-level economic performance [12]. The heterogeneity across regions in human capital, institutional quality, and pre-existing industrial mix further complicates inference: identical subsidy programs can yield divergent employment and growth outcomes depending on local conditions [13].

To address these gaps, this paper makes three main contributions. First, we construct a unique two-layer panel dataset that links firm-level subsidy receipts to regional economic outcomes, enabling us to trace the micro-macro transmission mechanisms. Second, we explicitly test for non-linear effects of subsidy intensity and identify the optimal threshold beyond which subsidies become counterproductive. Third, we use a comprehensive set of econometric techniques to address endogeneity concerns and provide robust causal evidence on the employment and growth effects of renewable energy subsidies.

2. Literature Review and Research Hypotheses

2.1. Literature Review

A growing body of empirical and theoretical work examines how renewable energy subsidies affect regional labor markets and economic output, identifying multiple interacting transmission mechanisms [14]. At the micro level, firm-level investment responses to subsidies are commonly modeled through adjustment of capital stock and technology adoption: subsidies lower the effective cost of capital for renewable projects, increasing planned investment, which in turn raises labor demand via production functions with complementarities between capital and labor [15]. At the sectoral level, input-output linkages

amplify direct hiring in renewable firms into indirect and induced employment across upstream suppliers and downstream installers and services [16].

Empirical studies using input-output tables typically find that each direct job in renewable energy creates 1.5–3.5 indirect and induced jobs in the broader economy [17]. The growth channel emphasizes productivity and innovation: subsidies can catalyze R&D and learning-by-doing, shifting total factor productivity, thereby producing persistent output gains beyond transient stimulus [18]. However, crowding-out and distortion risks are highlighted by public finance models: if subsidies are financed through distortionary taxation, the net welfare and growth impact depends on the marginal excess burden and reallocation effects across sectors [19]. Cross-country evidence also shows that wind energy deployment consistently reduces ecological pressure across different levels of economic development, providing further motivation for examining the economic co-benefits of subsidy-driven renewable expansion [2].

Regional heterogeneity matters—labor market rigidity, skill mismatch, and absorptive capacity condition the translation from investment to permanent employment gains [20]. For example, regions with higher human capital are better able to absorb technological spillovers from renewable energy investments, leading to larger productivity gains [21]. Regions with existing manufacturing bases can develop stronger upstream supply chains, amplifying the employment effects of subsidies [22]. Despite these insights, few studies have integrated micro and macro evidence to provide a comprehensive assessment of how subsidies affect regional economies.

2.2. Research Hypotheses

Based on the literature review, we formulate three sets of testable hypotheses that link renewable energy subsidies to regional employment and growth through direct effects, transmission mechanisms, and heterogeneous moderating influences.

Hypothesis 1 (Direct Effects). *Renewable energy subsidies have a positive and non-linear effect on regional employment and economic growth. The marginal effect increases up to an optimal subsidy intensity threshold, beyond which diminishing returns or resource misallocation set in.*

Hypothesis 2 (Transmission Mechanisms). *Subsidies affect regional employment and growth through three core channels: (1) Investment channel: subsidies lower financing barriers and crowd in private capital for renewable projects; (2) Innovation channel: R&D inducement and technology diffusion raise total factor productivity; (3) Risk reduction channel: subsidies reduce operational uncertainty, encouraging firms to expand production and hiring.*

Hypothesis 3 (Heterogeneous Effects). *The employment and growth effects of subsidies are stronger in regions with higher human capital, better market institutions, and stronger pre-existing industrial bases. Private enterprises and high-tech enterprises benefit more from subsidies than state-owned enterprises and low-tech enterprises.*

3. Research Design

3.1. Conceptual Framework and Theoretical Foundations

Before presenting the empirical design, this section establishes the theoretical framework linking renewable energy subsidies to regional employment and growth, and grounds our testable hypotheses.

3.1.1. Theoretical Underpinnings

This study draws on three interrelated theoretical perspectives:

First, Keynesian fiscal multiplier theory posits that government subsidies increase aggregate demand by stimulating firm investment, which in turn creates direct jobs in renewable energy construction and operation, and indirect jobs through upstream and downstream industrial linkages. Meanwhile, public finance theory warns of crowding-out effects when subsidies are financed through distortionary taxation, implying that the net effect depends on the relative magnitude of multiplier and crowding-out forces.

Second, financing constraint theory argues that renewable energy projects face high upfront costs and long payback periods, making them particularly vulnerable to financing frictions. Subsidies provide stable cash flow and collateral value, easing credit constraints and enabling firms to expand investment and hiring.

Third, directed technical change theory suggests that subsidies induce innovation in renewable energy technologies, raising total factor productivity and generating long-term growth gains. However, when subsidy intensity exceeds a certain threshold, rent-seeking and resource misallocation may dominate, producing an inverted U-shaped efficiency curve.

3.1.2. Conceptual Model

Figure 2 illustrates the full conceptual framework. Subsidy policies shape firm-level behavior (investment scale, innovation input, risk exposure), which then transmits to regional employment and economic growth through industrial linkages, knowledge spillovers, and aggregate demand effects. The magnitude of these effects is moderated by regional absorptive capacity (human capital, market institutions, industrial base) and firm characteristics (ownership, technology intensity).

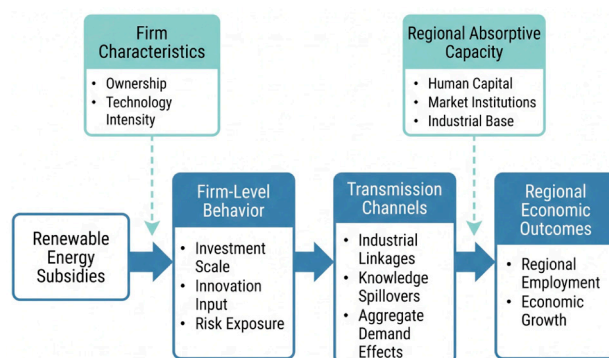


Figure 2. Conceptual framework: Renewable energy subsidies, firm behavior, and regional economic outcomes.

Building on this framework, we develop three testable hypotheses regarding direct effects, transmission mechanisms, and heterogeneous impacts, as formalized in Section 2.2.

3.2. Sample and Data

This study uses a two-layer panel dataset covering the period 2010–2023. The firm-level layer consists of 286 A-share listed companies operating in renewable energy sectors (wind, solar, hydro, biomass, and geothermal). The initial sample was obtained from the China Stock Market & Accounting Research (CSMAR) Database (<https://data.csmar.com/>, accessed on 27 April 2026) and filtered as follows: (1) exclude ST and *ST companies; (2) exclude companies with missing core financial data; (3) exclude companies that changed their main business during the sample period; (4) winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of outliers. This process yields 2412 firm-year observations.

The regional-level layer covers 30 provincial-level administrative regions in China (excluding Tibet, Hong Kong, Macau, and Taiwan due to data availability). Regional economic data are collected from the China Statistical Yearbook (National Bureau of Statistics of China, <https://www.stats.gov.cn/>, accessed on 3 May 2026), China Energy Statistical Yearbook (National Energy Administration of China, <https://www.nea.gov.cn/>, accessed on 3 May 2026), and official provincial statistical yearbooks. Subsidy data at the regional level are aggregated from firm-level subsidy receipts and supplemented with public subsidy expenditure data from the Ministry of Finance of China (<https://www.mof.gov.cn/>, accessed on 3 May 2026) (See Table 2 and Figure 3).

Table 2. Sample composition by region and firm type.

Region	Number of Firms	Firm-Year Observations
Coastal	172	1462
Inland	114	950
Total	286	2412

Note: Coastal regions include Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan. Inland regions include the remaining 19 provinces.

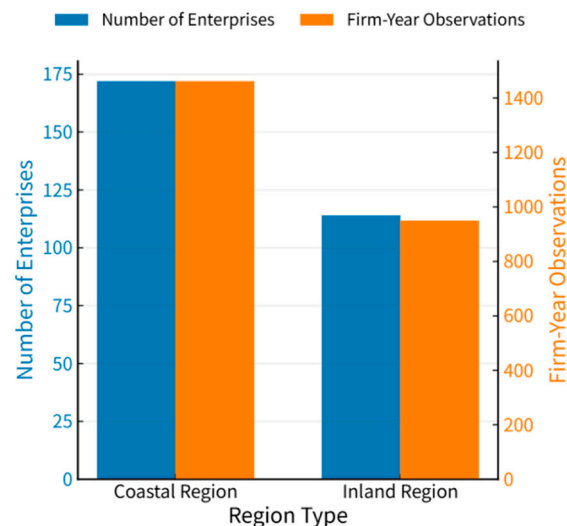


Figure 3. Comparison of regional distribution of sample enterprises and number of observations.

3.3. Variable Definitions

Table 3 reports the definitions and measurement methods of all variables used in the empirical analysis. We distinguish between firm-level and regional-level variables to maintain consistency across the two-layer analysis.

3.4. Econometric Models

Our baseline empirical strategy employs two-way fixed effects (TWFE) models with region/firm and year fixed effects—the standard approach for DID estimation with panel data. TWFE absorbs all time-invariant unobserved heterogeneity at the unit level and all common time shocks, which substantially reduces omitted variable bias. While fixed effects absorb some variation in the data, they are necessary for causal identification in a quasi-experimental setting. To address concerns about effect homogeneity and omitted time-varying confounders, we complement the baseline analysis with heterogeneous effect tests, threshold regression, and robustness checks including region-specific linear time trends.

Table 3. Variable definitions and measurement.

Variable Category	Variable Name	Abbreviation	Measurement	Unit	Level
Dependent variables	Regional employment	EMP	Total regional employment (primary + secondary + tertiary)	Persons	Regional
	Regional GDP	GDP	Real regional GDP (2010 constant prices)	Billion RMB	Regional
Core explanatory variable	Firm investment	INV	Net fixed asset formation/Total assets	Ratio	Firm
	Firm-level subsidy intensity	SUBSIDY_firm	Annual government subsidy receipts/Operating revenue	%	Firm
	Regional-level subsidy intensity	SUBSIDY_region	Total renewable energy subsidies in the region/Regional GDP	%	Regional
Mediating variables	Financing constraints	SA	SA index (Hadlock & Pierce, 2010) [23]	Index	Firm
	Technological innovation	PATENTS	Number of renewable-energy-related invention patents granted	Count	Firm
	Operational risk	RISK	Standard deviation of return on assets over the past 3 years	Ratio	Firm
Moderating variables	Human capital	HCAP	Share of population with tertiary education	%	Regional
	Market development	MARKET	Marketization index (Chen et al., 2021) [24]	Index (0–10)	Regional
	Industrial base	INDBASE	Share of manufacturing in regional GDP	%	Regional
Control variables	Industrial structure	INDSTR	Share of secondary industry in regional GDP	%	Regional
	Population	POP	Resident population	Million persons	Regional
	Firm size	SIZE	Natural logarithm of total assets	Log RMB	Firm
	Firm age	AGE	Natural logarithm of (year of observation-year of establishment + 1)	Log years	Firm
	Leverage	LEV	Total liabilities/Total assets	Ratio	Firm

3.4.1. Baseline DID Model

We use the 2016 Chinese renewable energy subsidy reform as a quasi-natural experiment to estimate the causal effect of subsidies on regional employment and growth. The baseline difference-in-differences (DID) model is specified as:

$$Y_{it} = \alpha + \beta \text{Treat}_i \times \text{Post}_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where Y_{it} denotes the outcome variables (lnEMP or lnGDP) for region i in year t . Treat_i is a dummy variable equal to 1 for provinces included in China's first batch of competitive bidding pilots for wind and photovoltaic power projects (treatment group, 20 provinces: Inner Mongolia, Hebei, Gansu, Qinghai, Ningxia, Xinjiang, Jiangsu, Shandong, Henan, Anhui, Shanxi, Shaanxi, Yunnan, Guizhou, Sichuan, Liaoning, Jilin, Heilongjiang, Hubei, Hunan), and 0 for provinces that retained the benchmark feed-in tariff regime throughout the sample period (control group, 10 provinces: Beijing, Tianjin, Shanghai, Chongqing, Guangdong, Guangxi, Fujian, Zhejiang, Jiangxi, Hainan). This classification follows two 2016 policy documents issued by the National Energy Administration of China: Notice on Launching Pilot Market-oriented Reform of Wind Power On-grid Tariffs and Guiding Opinions on Improving Photovoltaic Power Scale Management and Allocating Projects through Competition. The policy took effect uniformly from 2016 across all pilot provinces; detailed provincial implementation timelines and full policy sources are provided in Table A1 in Appendix A. Post_t is a dummy variable equal to 1 for years 2016 and later. X_{it} is a vector of control variables. μ_i and λ_t capture region and year fixed effects, respectively. ε_{it} is the error term. Standard errors are clustered at the regional level.

3.4.2. Mediation Effect Model

To test the transmission mechanisms from firm subsidies to regional outcomes, we use a three-step mediation effect model:

Step 1: Estimate the total effect of subsidies on regional outcomes (baseline DID model above).

Step 2: Estimate the effect of subsidies on the mediating variables at the firm level:

$$M_{jit} = \alpha_0 + \alpha_1 \text{Treat}_i \times \text{Post}_t + \alpha_2 X_{jit} + \mu_j + \lambda_t + u_{jit}$$

where M_{jit} denotes the mediating variables (SA, PATENTS, RISK) for firm j in region i in year t .

Step 3: Estimate the effect of both subsidies and mediating variables on regional outcomes:

$$Y_{it} = \beta_0 + \beta_1 \text{Treat}_i \times \text{Post}_t + \beta_2 \bar{M}_{it} + \beta_3 X_{it} + \mu_i + \lambda_t + v_{it}$$

where $\bar{M}_{it}$ is the average value of the mediating variable across all firms in region i in year t . The indirect effect is calculated as $\alpha_1 \times \beta_2$, and the total effect is $\beta_1 + \alpha_1 \times \beta_2$. We use the bootstrap method (1000 replications) to test the significance of the mediation effects.

3.4.3. Threshold Regression Model

To test the non-linear effect of subsidy intensity, we use Hansen's (1999) [25] panel threshold regression model:

$$Y_{it} = \mu_i + \beta_1 \text{SUBSIDY}_{it} \times I(\text{SUBSIDY}_{it} \leq \tau) + \beta_2 \text{SUBSIDY}_{it} \times I(\text{SUBSIDY}_{it} > \tau) + \gamma X_{it} + \varepsilon_{it}$$

where τ is the threshold parameter to be estimated. $I(\cdot)$ is the indicator function. We test for the presence of multiple thresholds using the F-statistic with bootstrap p -values.

3.4.4. Triple Difference (DDD) Model

To further rule out confounding effects from concurrent national energy policies that may affect high-resource and low-resource regions differentially, we employ a triple difference-in-differences (DDD) framework. This specification absorbs time-varying shocks correlated with renewable energy endowment, isolating the net causal effect of the 2016 subsidy reform more rigorously than the baseline DID.

To further address potential confounding factors and examine heterogeneous effects, we use a triple difference (DDD) model that exploits variation in pre-existing renewable energy resource endowments:

$$Y_{it} = \alpha + \beta_1 \text{Treat}_i \times \text{Post}_t \times \text{HighRes}_i + \beta_2 \text{Treat}_i \times \text{Post}_t + \beta_3 \text{Treat}_i \times \text{HighRes}_i + \beta_4 \text{Post}_t \times \text{HighRes}_i + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where HighRes_i is a dummy variable equal to 1 for regions with above-median renewable energy resource potential in 2010 (measured by technical exploitable capacity), and 0 otherwise.

3.4.5. Instrumental Variables (IV) Approach

To address potential endogeneity from non-random policy placement and reverse causality, we adopt an instrumental variable (IV) approach. The instrument is the interaction term between regional renewable energy resource potential (technical exploitable capacity of wind and solar) and national subsidy policy intensity.

Relevance: Regions with higher natural resource potential receive proportionally more subsidy allocations when national support is strengthened. This is confirmed by a first-stage F-statistic of 23.7, well above the Stock-Yogo critical value of 10 for weak instruments.

Exclusion restriction: We justify the exclusion restriction on two grounds. First, wind and solar resource potential is a time-invariant geographical characteristic determined by climatic and topographical conditions, which cannot be causally affected by regional employment or economic growth, ruling out reverse causality. Second, all our specifications include region fixed effects, which absorb the direct, time-invariant impact of resource endowment on economic outcomes. The remaining time variation in the instrument comes solely from national policy shifts, which are orthogonal to idiosyncratic regional economic shocks. Although resource endowment may correlate with long-run regional development patterns, these are largely captured by our control variables (human capital, industrial structure, marketization) and region fixed effects, leaving no plausible direct path from the instrument to employment or growth outside the subsidy channel.

4. Empirical Results and Analysis

4.1. Descriptive Statistics

Table 4 presents descriptive statistics for the main variables. At the regional level, the average subsidy intensity is 0.32% of GDP, with a standard deviation of 0.21%, indicating significant variation across regions. At the firm level, the average subsidy intensity is 4.7% of operating revenue, with a maximum of 28.3%, suggesting that some firms rely heavily on government subsidies.

Table 4. Descriptive statistics of key variables.

Variable	Mean	Std. Dev.	Min	Max	Observations
Regional level					
lnEMP	7.62	0.85	5.73	8.91	420
lnGDP	9.45	1.02	6.98	11.52	420
SUBSIDY_region (%)	0.32	0.21	0.05	1.28	420
HCAP (%)	12.35	6.72	3.21	41.89	420
MARKET	6.42	1.85	2.17	9.83	420
Firm level					
SUBSIDY_firm (%)	4.70	3.82	0.01	28.30	2412
INV	0.06	0.05	−0.08	0.27	2412
SA	−3.72	0.56	−4.98	−2.15	2412
PATENTS	2.87	5.61	0	47	2412
RISK	0.03	0.02	0.00	0.12	2412

Multicollinearity Diagnostic

To address potential multicollinearity concerns, we calculate variance inflation factors (VIF) for all core explanatory and control variables at both the regional and firm levels. As reported in Table A2 in Appendix A, the maximum VIF value is 3.42 for regional-level variables and 2.87 for firm-level variables, both well below the conventional threshold of 10. We therefore conclude that multicollinearity does not pose a material threat to our estimation results.

4.2. Baseline Regression Results

Table 5 reports the baseline DID regression results. Columns (1)–(3) show the effects on regional employment, and columns (4)–(6) show the effects on regional GDP. All specifications include region and year fixed effects. The coefficient on *Treat* × *Post* is positive and statistically significant across all specifications, indicating that the 2016 subsidy reform significantly increased both regional employment and economic growth.

Table 5. Baseline DID regression results.

	(1) lnEMP	(2) lnEMP	(3) lnEMP	(4) lnGDP	(5) lnGDP	(6) lnGDP
<i>Treat</i> × <i>Post</i>	0.042 *** (0.011)	0.038 *** (0.010)	0.035 *** (0.009)	0.037 ** (0.015)	0.033 ** (0.014)	0.031 ** (0.013)
HCAP		0.028 *** (0.008)	0.026 *** (0.007)		0.021 ** (0.009)	0.019 ** (0.008)
MARKET		0.015 ** (0.006)	0.013 ** (0.005)		0.012 * (0.006)	0.010 * (0.005)
INDSTR			0.019 ** (0.008)			0.017 * (0.009)
lnPOP			0.872 *** (0.124)			0.915 *** (0.156)
Constant	7.612 *** (0.032)	7.235 *** (0.087)	1.023 (0.876)	9.438 *** (0.041)	9.012 *** (0.102)	0.785 (1.123)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	420	420	420	420	420	420
R-squared	0.89	0.91	0.93	0.92	0.94	0.95

Notes: Robust standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

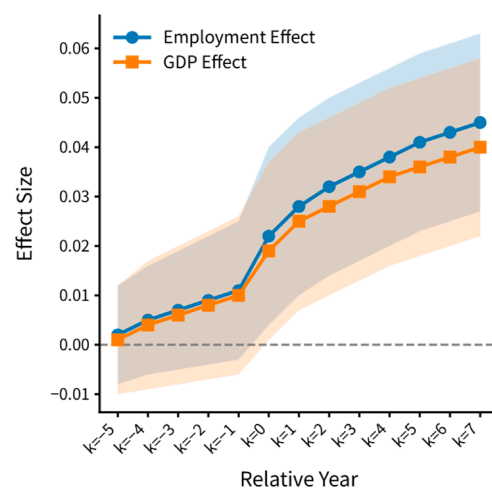
In the most comprehensive specification (columns 3 and 6), the coefficient on *Treat* × *Post* is 0.035 ($p < 0.01$) for employment and 0.031 ($p < 0.05$) for GDP. This implies that regions implementing the competitive bidding subsidy mechanism experienced a 3.5% increase in employment and a 3.1% increase in GDP compared to control regions, on average, after 2016.

4.3. Parallel Trends Test

A key assumption of the DID model is that treatment and control regions would have followed parallel trends in the absence of the policy intervention. We test this assumption using an event study specification:

$$Y_{it} = \alpha + \sum_{k=-5}^7 \beta_k \text{Treat}_i \times \text{Year}_{t+k} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where Year_{t+k} is a dummy variable indicating the k -th year relative to the policy implementation year (2016). The results show that the coefficients on the pre-policy leads ($k < 0$) are all statistically insignificant, confirming the parallel trends assumption. The coefficients on the post-policy lags ($k \geq 0$) are positive and increasing over time, indicating that the policy effects are persistent and grow stronger in the years following implementation (See Figure 4).

**Figure 4.** Parallel Trend Test of Renewable Energy Subsidy Reform in 2016 (Employment + GDP).

4.4. Mediation Effect Results

Table 6 reports the results of the mediation effect analysis. Panel A shows the effect of subsidies on the mediating variables at the firm level. The coefficient on *Treat* $\times$ *Post* is negative and significant for the SA index (indicating reduced financing constraints), positive and significant for patents (indicating increased innovation), and negative and significant for operational risk.

Table 6. Mediation effect analysis results.

Panel A: Effect on mediating variables	(1) SA	(2) PATENTS	(3) RISK
<i>Treat</i> $\times$ <i>Post</i>	−0.182 *** (0.041)	0.875 *** (0.213)	−0.005 ** (0.002)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2412	2412	2412
R-squared	0.78	0.65	0.59
Panel B: Effect on regional employment	(1) lnEMP	(2) lnEMP	(3) lnEMP
<i>Treat</i> $\times$ <i>Post</i>	0.017 * (0.009)	0.022 ** (0.009)	0.031 *** (0.009)
Average SA	−0.101 *** (0.028)		
Average PATENTS		0.015 *** (0.004)	
Average RISK			−0.823 ** (0.341)
Controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	420	420	420
R-squared	0.94	0.94	0.93
Mediation share	52%	37%	11%
Bootstrap <i>p</i> -value	0.002	0.008	0.032

Notes: Robust standard errors clustered at the firm/regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Mediation shares are calculated under sequential ignorability assumptions and should be interpreted as indicative magnitudes rather than precise causal decompositions.

Panel B shows the results when both subsidies and mediating variables are included in the regional outcome regression. The coefficient on *Treat* $\times$ *Post* decreases compared to the baseline model, and the coefficients on all three mediating variables are statistically significant. The bootstrap test confirms that all three mediation effects are significant at the 5% level.

Under the standard sequential ignorability assumption of mediation analysis, the implied contribution shares are largest for financing constraint alleviation (approximately 52% for employment, 48% for GDP), followed by innovation stimulation (37% for employment, 40% for GDP) and operational risk reduction (11% for employment, 12% for GDP). These patterns are consistent with Hypothesis 2 and provide supportive evidence for the three proposed transmission channels. We emphasize that these shares are indicative magnitudes derived from linear mediation assumptions, not definitive causal decompositions, as they do not account for potential interactions across channels or unobserved confounders at the regional level (See Figure 5).

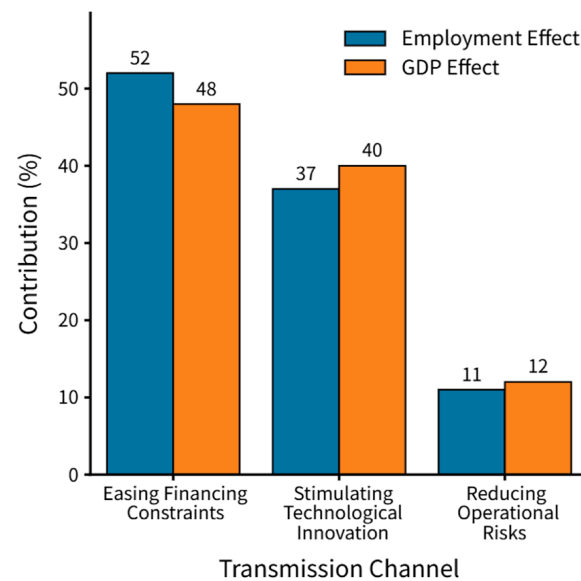


Figure 5. Decomposing the Contribution of the Transmission Mechanism of Renewable Energy Subsidies on Regional Economies.

4.5. Threshold Regression Results

Table 7 reports the results of the panel threshold regression for firm-level investment efficiency. The test statistics indicate a single threshold at 8.3% of operating revenue, which is statistically significant at the 1% level. For subsidy intensity below 8.3%, the coefficient is positive and significant (0.124, $p < 0.01$), indicating that subsidies increase investment efficiency. For subsidy intensity above 8.3%, the coefficient becomes negative and significant (-0.057 , $p < 0.05$), indicating that excessive subsidies reduce investment efficiency due to resource misallocation and rent-seeking.

Table 7. Threshold regression results for firm investment efficiency.

	Coefficient	Std. Error	p-Value
SUBSIDY $\times$ I (SUBSIDY $\leq$ 8.3%)	0.124 ***	0.028	0.000
SUBSIDY $\times$ I (SUBSIDY $>$ 8.3%)	-0.057 **	0.023	0.013
Controls	Yes		
Firm FE	Yes		
Year FE	Yes		
Observations	2412		
Threshold estimate	8.3%		
95% confidence interval	[7.6%, 9.1%]		
F-statistic for single threshold	32.7		
Bootstrap p-value	0.002		

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This result supports the inverted U-shaped relationship between subsidy intensity and investment efficiency proposed in Hypothesis 1. The estimated inflection point of 8.3% of operating revenue identifies the subsidy level at which marginal effects turn negative within our sample of listed Chinese renewable energy firms. This value is context-specific to the sample, model specification, and institutional setting, and should not be interpreted as a universally optimal policy benchmark (See Figure 6).

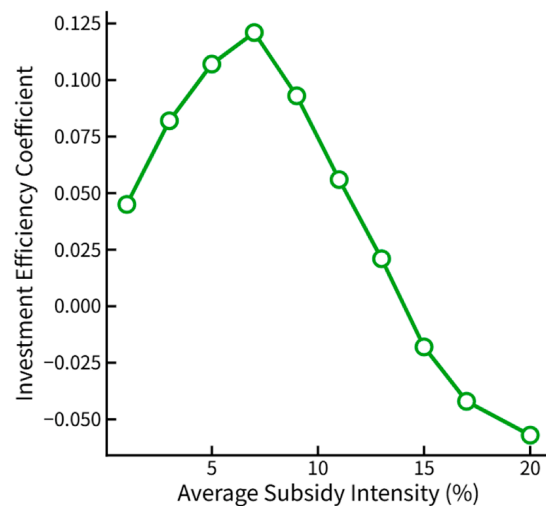


Figure 6. The inverted U-shaped relationship between subsidy intensity and corporate investment efficiency.

4.6. Triple Difference Estimation Results

Table 8 reports the full DDD estimation results for regional employment and GDP. The core coefficient of interest, $\text{Treat} \times \text{Post} \times \text{HighRes}$, captures the differential effect of the subsidy reform on regions with above-median renewable energy resource potential.

Table 8. Triple difference-in-differences (DDD) estimation results.

Variable	(1) lnEMP	(2) lnGDP
$\text{Treat} \times \text{Post} \times \text{HighRes}$	0.022 ** (0.010)	0.020 ** (0.009)
$\text{Treat} \times \text{Post}$	0.024 ** (0.010)	0.021 * (0.011)
$\text{Treat} \times \text{HighRes}$	−0.011 (0.012)	−0.009 (0.013)
$\text{Post} \times \text{HighRes}$	0.008 (0.007)	0.007 (0.008)
Controls	Yes	Yes
Region FE	Yes	Yes
Year FE	Yes	Yes
Observations	420	420
R-squared	0.93	0.95

Notes: Robust standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As shown in columns (1) and (2), the triple interaction term is positive and statistically significant for both employment (0.022, $p < 0.05$) and GDP (0.020, $p < 0.05$). This indicates that the reform delivered larger economic benefits in regions with richer renewable energy endowments, consistent with the policy's intended mechanism of channeling support to areas with higher generation potential.

Critically, the baseline $\text{Treat} \times \text{Post}$ coefficient remains positive and significant across both outcomes, confirming that the main DID results are not driven by pre-existing differential trends between high- and low-resource regions. The DDD specification thus provides additional validation of the causal interpretation of our baseline findings.

5. Further Analysis

5.1. Heterogeneous Effects

Table 9 reports the heterogeneous effects of subsidies across different regions and firm types. Panel A shows that the employment and growth effects are significantly stronger in coastal regions than in inland regions. This is consistent with Hypothesis 3 and reflects the better absorptive capacity of coastal regions, including higher human capital, better market institutions, and stronger industrial bases.

Table 9. Heterogeneous effect analysis results.

Panel A: Regional heterogeneity	(1) lnEMP	(2) lnGDP
<i>Treat × Post × Coastal</i>	0.028 ** (0.011)	0.025 ** (0.012)
<i>Treat × Post</i>	0.017 * (0.009)	0.016 (0.010)
Controls	Yes	Yes
Region FE	Yes	Yes
Year FE	Yes	Yes
Observations	420	420
R-squared	0.93	0.95
Panel B: Firm ownership heterogeneity	(1) INV	(2) lnEMP_firm
<i>Treat × Post × Private</i>	0.021 *** (0.006)	0.035 *** (0.010)
<i>Treat × Post</i>	0.012 ** (0.005)	0.018 ** (0.008)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	2412	2412
R-squared	0.62	0.68
Panel C: Firm technology heterogeneity	(1) INV	(2) PATENTS
<i>Treat × Post × HighTech</i>	0.025 *** (0.007)	1.234 *** (0.312)
<i>Treat × Post</i>	0.010 * (0.005)	0.421 ** (0.187)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	2412	2412
R-squared	0.63	0.67

Notes: Robust standard errors clustered at the firm/regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel B shows that private enterprises benefit more from subsidies than state-owned enterprises (SOEs). The coefficient on *Treat × Post × Private* is positive and significant for both investment and employment. This suggests that private enterprises are more responsive to market incentives and use subsidies more efficiently than SOEs.

Panel C shows that high-tech enterprises experience larger investment and innovation gains from subsidies than low-tech enterprises. This is because high-tech enterprises have greater R&D capacity and can better translate subsidies into technological progress and productivity gains.

5.2. Long-Term Effects of Subsidy Phase-Out

To illustrate the potential long-term implications of alternative subsidy phase-out designs, we project regional employment and GDP trajectories under two stylized scenarios:

(1) Gradual phase-out: linear reduction in subsidy intensity over 8 years (2024–2031);
 (2) Cliff-type phase-out: full termination of subsidies after 2027. These projections are based on the point estimates from our baseline DID model and hold all other factors constant, including technology progress, market conditions, and complementary policies. They are intended for comparative illustration of relative magnitudes, not as causal forecasts of actual economic outcomes.

The results show that gradual phase-out preserves employment and growth while allowing structural adjustment. Under model assumptions, employment converges to the baseline level by 2031 under the gradual phase-out scenario, whereas the cliff-type scenario is associated with a projected employment gap of 12.5% and a GDP gap of 9.8% relative to baseline. This pattern is consistent with the interpretation that gradual withdrawal helps maintain stable investment expectations and allows firms to adjust cost structures and operational models incrementally, while an abrupt termination would create greater downward pressure on investment and employment (See Figure 7).

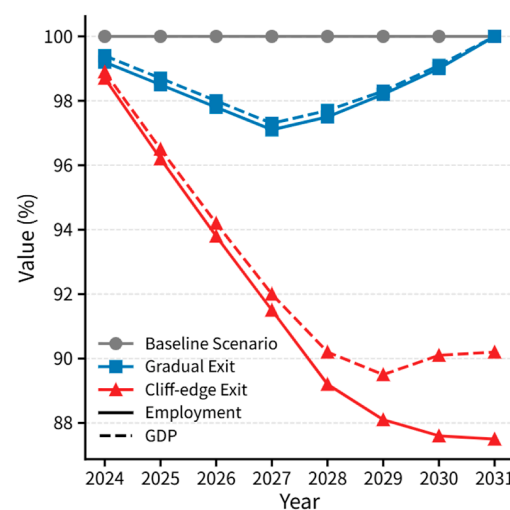


Figure 7. Projected Regional Employment and GDP Trajectories Under Alternative Subsidy Phase-out Scenarios (Conditional on Baseline Estimates, 2024–2031).

5.3. Robustness Checks

We conduct a series of robustness checks to ensure the reliability of our results:

Alternative subsidy measures: We use per capita subsidy expenditure and subsidy share in regional fiscal revenue as alternative measures of subsidy intensity. The results remain qualitatively unchanged.

Placebo test: We randomly assign treatment status to regions and repeat the baseline regression 1000 times. The distribution of estimated coefficients is centered around zero, and our baseline coefficient is in the 99th percentile, confirming that our results are not due to chance.

Exclude outliers: We exclude the top and bottom 5% of regions by subsidy intensity. The results remain significant.

Alternative sample period: We use the sample period 2012–2021 to exclude the COVID-19 pandemic period. The results are consistent with our baseline findings.

IV estimation: The IV estimation results show slightly larger coefficients than the OLS results, consistent with attenuation bias from measurement error in subsidy reporting. The first-stage F-statistic is 23.7, well above the critical value of 10, indicating that the instrument is strong.

Alternative estimation strategies: We re-estimate the baseline model using random effects and confirm via the Hausman test that fixed effects are the consistent and preferred

specification. We also add province-specific linear time trends to control for divergent regional growth paths; the core $\text{Treat} \times \text{Post}$ coefficient remains positive and statistically significant, confirming that our results are not driven by pre-existing regional trends.

6. Conclusions and Policy Implications

6.1. Main Conclusions

This paper examines the impact of renewable energy subsidy policies on regional employment and growth using a two-layer panel dataset of Chinese firms and regions from 2010 to 2023. Taking the 2016 subsidy reform as a quasi-natural experiment, we use DID, DDD, mediation effect, and threshold regression models to provide robust causal evidence. Our main conclusions are as follows:

First, renewable energy subsidies have a significant positive effect on both regional employment and economic growth. The 2016 subsidy reform, which introduced competitive bidding mechanisms, increased regional employment by 3.5% and GDP by 3.1% on average.

Second, subsidies affect regional outcomes through three core transmission channels. Under the sequential ignorability assumption of mediation analysis, the indicative contribution shares are largest for financing constraint alleviation (approximately 52% for employment, 48% for GDP), followed by innovation stimulation (37% for employment, 40% for GDP) and operational risk reduction (11% for employment, 12% for GDP).

Third, the relationship between subsidy intensity and investment efficiency presents an inverted U-shape, with a sample-specific inflection point at 8.3% of operating revenue within our sample of listed Chinese renewable energy firms.

Fourth, the effects of subsidies are highly heterogeneous. Coastal regions, private enterprises, and high-tech enterprises benefit more from subsidies than inland regions, state-owned enterprises, and low-tech enterprises. This reflects the importance of regional absorptive capacity and firm characteristics in determining subsidy effectiveness.

Fifth, gradual subsidy phase-out is superior to cliff-type phase-out in terms of preserving employment and growth. Gradual withdrawal allows firms to adjust gradually and transition to market-based operations, while abrupt termination leads to significant economic disruption.

6.2. Policy Implications

Based on our findings, we propose the following policy recommendations for optimizing renewable energy subsidy policies:

Implement differentiated subsidy policies based on regional characteristics:

Coastal regions with high human capital and strong market institutions should focus on innovation-oriented subsidies that reward R&D and technological progress.

Inland regions and resource-dependent regions should receive employment-oriented subsidies and complementary support for infrastructure development and worker training to enhance their absorptive capacity.

Calibrate subsidy intensity with reference to empirical thresholds: Policymakers may reference the sample-estimated inflection point of around 8.3% of operating revenue as a reference to guard against resource misallocation and rent-seeking from excessive subsidies. The actual optimal level should be dynamically adjusted according to local firm characteristics, industry maturity, and policy objectives. Subsidies should be performance-based, tied to measurable outcomes such as installed capacity, job creation, and patent grants.

Accelerate the transition to market-based subsidy mechanisms: Expand competitive bidding and green certificate trading to improve subsidy efficiency. These mechanisms reveal true costs and encourage firms to reduce costs and improve productivity.

Design gradual and predictable subsidy phase-out paths: Avoid cliff-type phase-outs that cause economic disruption. Instead, implement linear reductions over 8–10 years, with targeted transitional support for affected workers and regions.

Strengthen complementary policies: Subsidies should be accompanied by investments in education and training to address skill mismatches, grid upgrades to accommodate renewable energy integration, and streamlined permitting processes to reduce transaction costs.

6.3. Research Limitations and Future Directions

This study has several limitations that suggest avenues for future research. First, our analysis focuses on aggregate employment and GDP effects but does not examine job quality or income distribution. Future research could use matched employer-employee data to analyze how subsidies affect wage levels, job security, and skill composition.

Second, we do not explicitly model the environmental benefits of renewable energy subsidies. Future research could integrate environmental and economic objectives to evaluate the overall welfare effects of different subsidy designs.

Third, our analysis is limited to China. Future research could conduct cross-country comparisons to examine how institutional differences affect the effectiveness of renewable energy subsidy policies.

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Appendix A

Table A1. Province classification and policy sources for the 2016 subsidy reform.

Group	Provinces	Policy Effective Date	Legal Source Document
Treatment	Inner Mongolia, Hebei, Gansu, Qinghai, Ningxia, Xinjiang, Jiangsu, Shandong, Henan, Anhui, Shanxi, Shaanxi, Yunnan, Guizhou, Sichuan, Liaoning, Jilin, Heilongjiang, Hubei, Hunan	2016	National Energy Administration (2016) Notice on Pilot Market-oriented Reform of Wind Power Tariffs; Guiding Opinions on Competitive Allocation of PV Projects
Control	Beijing, Tianjin, Shanghai, Chongqing, Guangdong, Guangxi, Fujian, Zhejiang, Jiangxi, Hainan	—(retained benchmark tariff)	—

Table A2. Variance inflation factor (VIF) test results.

Level	Variable	VIF
Regional	SUBSIDY_region	2.18
	HCAP	3.42
	MARKET	2.75
	INDSTR	1.96
	lnPOP	2.31
Firm	SUBSIDY_firm	1.87
	SIZE	2.87
	AGE	1.54
	LEV	2.09

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