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Subsidy Phase-Out, Innovation, and Policy Design: Evidence from China's Photovoltaic Industry

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Data availability statement

The data supporting the findings of this study were obtained from the CSMAR Database and can be accessed through the CSMAR data platform at https://data.csmar.com/. Access to the original data is subject to the licensing and subscription requirements of CSMAR. Therefore, the authors are unable to publicly deposit or redistribute the raw data. Information on data processing and variable construction is available from the corresponding author upon reasonable request.

Author Contributions

***Runjie Fan**: Writing–original draft, Conceptualization, Formal analysis, Methodology, Validation, Visualization. **Hao Liu**: Writing–original draft, Data curation, Formal analysis, Visualization. **Le Zhang**: Writing–review and editing, Validation.*

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Competing interests

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This article does not contain any studies with human participants performed by any of the authors.

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Abstract: This study examines the impact of subsidy phase-out policies on firm-level research and development (R&D) investment in the new energy sector. A sequential game-theoretic model is developed to analyze strategic interactions between government and firms, and its implications are empirically tested using a propensity score matching difference-in-differences approach based on Chinese listed manufacturing firms from 2016 to 2021. The results show that subsidy phase-out policies significantly reduce firms' R&D investment. This negative effect operates primarily by deteriorating firms' operating performance. The impact is more pronounced for non–state-owned firms, high-growth firms, and firms located in central regions. The theoretical analysis further reveals that subsidy efficiency, market expansion effects, and firms' subsidy capture rates exhibit diminishing marginal returns. Excessive subsidies also redirect fiscal resources toward consumers with weaker low-carbon preferences. Based on these findings, this study proposes an integrated subsidy phase-out mechanism incorporating the phase-out rate, critical trigger thresholds, and the phase-out period. The mechanism is designed to prevent market contraction, ensure that policy exit is synchronized with the growth of endogenous market forces, and ultimately facilitate the transition of the new energy industry from policy-driven to market-driven development.

Keywords: New energy industry; Subsidy phase-out; Policy effects; Research and development investment; Mechanism design; Photovoltaic industry

1. Introduction

The energy transition and climate action are now widely recognized as a global consensus. Within this context, the new energy industry is regarded as essential to energy structure optimization and low-carbon development, thereby attracting increasing international attention (Li et al., 2025c). Technological innovation is generally considered the primary driver of energy system transformation (Tan and Gan, 2025). However, rapid technological iteration and large-scale commercialization often rely on policy support, particularly during early development stages, to overcome high costs and achieve economies of scale (Lee et al., 2024). Since the introduction of policies aimed at actively developing the new energy industry around 2000, China has implemented a series of subsidy programs covering sectors such as new energy vehicles (NEVs), photovoltaic

(PV) power generation, and biomass power generation. Under these policy incentives, China's new energy industry experienced rapid growth. As reported in *the BP Statistical Review of World Energy 2024*, China has become the largest contributor to global renewable energy expansion, accounting for 57% of newly added global wind and solar power capacity. The development of China's new energy sector provides empirical support for prior studies, confirming that subsidy policies initially generated positive effects on corporate financial performance (Zhang and Chiu, 2023), research and development (R&D) investment (Duan et al., 2024), production efficiency (Lu et al., 2022), and industrial expansion (Wang et al., 2023).

However, the long-term viability of subsidies as a transitional policy tool has been increasingly questioned (Liu and Gai, 2025). Excessive subsidies may not further promote the growth of the new energy industry and may instead create dual pressures, namely fiscal unsustainability and market distortions (Xu, 2024). On one hand, prolonged and large-scale subsidies place substantial pressure on public finances (Aryanpur et al., 2022). Estimates suggest that China's total renewable energy subsidy demand from 2013 to 2025 will amount to approximately 3 trillion RMB. This financial burden has resulted in significant payment arrears, with accumulated unpaid subsidies reaching approximately 400 billion RMB by the end of 2021. On the other hand, subsidy policies may give rise to moral hazard and market inefficiency (Li et al., 2024). Some firms may prioritize capacity expansion to obtain subsidies, rather than improving their core technological competitiveness. This behavior leads to low-capacity utilization (Lin and Xie, 2023), as well as inefficient energy consumption and resource waste (van den Bergh et al., 2024). Consequently, scholars argue that the new energy industry should shift from a policy-driven model to a market-driven one (Brown et al., 2019). This shift requires the development of an industrial ecosystem with endogenous dynamism and sustainable innovative capacity. This goal can be achieved through cost optimization (Hao et al., 2014), R&D incentives (Ma et al., 2017), and demand-side stimulation (Fan and Dong, 2018). Against this backdrop, it is particularly urgent to examine the policy effects of subsidy phase-out and to design a rational exit mechanism.

In recent years, extensive research has been conducted to examine the effects of subsidy phase-out policies. In the field of NEVs, Sheldon et al. (2023) found that the subsidy discontinuation in 2017 led nearly half of U.S. new car buyers with below-median incomes to forgo plug-in electric vehicles. Wang et al. (2025b) observed that phase-out policies incentivized firms to increase R&D investment, while simultaneously reducing symbolic innovation activities. Yao et al. (2025) reported that three subsidy phase-outs in China adversely affected firms throughout the NEV industrial chain. Moreover, two of these phase-outs were found to cause sales declines in national NEV pilot cities. Hao et al. (2025) further differentiated vehicles by driving range and revealed that China's range-

linked phase-out policy significantly reduced sales of low-range models, but increased sales of high-range models. In the field of renewable power generation, Chen and Wang (2022) indicated that subsidy phase-outs might prompt firms to adopt more passive strategies, while encouraging greater household participation in distributed PV projects. Liu et al. (2024) found that announcements of subsidy phase-outs initially triggered a pronounced rebound in total electricity consumption; however, this effect weakened as policy implementation progressed. Additionally, Lin and Zhang (2025) demonstrated that subsidy phase-out policies significantly improved total factor productivity among PV firms.

In summary, research indicates that the impacts of subsidy phase-out policies exhibit significant industrial heterogeneity and segment-level variation (Ding et al., 2023). On one hand, the phase-out has been shown to stimulate innovation and improve industrial efficiency (Xu et al., 2022). On other hand, it may result in short-term market disruptions (Wang et al., 2019), increase financial pressure on firms (Liu et al., 2022), and potentially reduce emission mitigation benefits (Xie et al., 2021). Consequently, the design and identification of post-phase-out policies have become a central research focus. For NEVs, proposed measures include strengthened charging infrastructure (Li et al., 2025a), restrictions on internal combustion engine vehicle production and scrappage incentives (Du et al., 2024), the use of social media for market promotion (Fan et al., 2020), the introduction of carbon trading mechanisms (Guo et al., 2024), and additional non-subsidy incentives (Wang et al., 2024), all aimed at mitigating market fluctuations. For renewable power generation, financial leasing has been demonstrated to substitute for government subsidies, thereby supporting investment continuity during the phase-out period (Xie and Lin, 2025). However, research on the phase-out mechanism itself remains limited, particularly due to the absence of systematic transition pathways for the new energy industry. Although exploratory studies exist, such as multi-agent modeling for optimal phase-out timing in regional cleaning subsidies (Li et al., 2025b) and differentiated phase-out schemes for Plug-in Hybrid Electric Vehicles (Shao et al., 2022), these efforts remain preliminary and have not yet produced a unified analytical framework.

The core objective of subsidy phase-out policy design is to shift the development of the new energy industry from a policy-driven model to an innovation-driven model, thereby stimulating endogenous and sustainable growth (Zhang and Wang, 2023). Specifically, market competition pressure is introduced through the gradual reduction of subsidies under phase-out policies. As a result, firms are compelled to reallocate resources from basic capacity expansion to more competitive R&D activities, with the aim of improving innovation efficiency and quality (Xu et al., 2022). However, if the phase-out pace is excessively rapid or the policy mechanism is poorly designed, R&D investment may be reduced due to short-term profit pressures (Shi and Lin, 2023).

Therefore, accurate identification of the net impact of phase-out policies on R&D investment in the new energy sector is crucial for policy design and optimization.

The evolution of China's PV industry provides a representative case for examining the relationship between subsidy phase-out policies and corporate R&D investment. China, as the world's largest producer of PV equipment, initially relied on subsidy policies to support the rapid expansion of PV power generation capacity. The introduction of the 2018 "531 New Policy" marked a critical turning point in industrial policy. By accelerating the phase-out of PV subsidies, the policy focus was shifted from construction support to operational support. As a result, firms were compelled to move from scale-based competition to innovation-driven competition. This shift provides a useful lens for examining the interaction between subsidy phase-out policies and corporate innovation. Although existing studies have noted the effects of subsidy phase-outs, empirical evidence on their impact on innovative performance in the PV industry remains limited. Some studies confirm that government subsidies promote innovation in the PV industry (Xu et al., 2022). Other studies examine the underlying mechanisms (Zhang and Wang, 2023). However, the effects of subsidy phase-out policies are not simply the inverse of subsidy effects. Such policies may generate both crowding-in and crowding-out effects on innovation. Therefore, their net impact must be empirically identified and evaluated.

Therefore, this study develops an analytical framework integrating both theoretical deduction and empirical testing. First, a sequential game model is developed to analyze the strategic interactions between the government and firms. Then, using data from listed companies in China's PV industry, the Propensity Score Matching-Difference-in-Differences (PSM-DID) method is used to estimate the net effect of the phase-out policy. Finally, combining insights from the model and empirical results, the necessity of the subsidy phase-out is examined, and a phase-out mechanism is designed.

This study makes three contributions:

(1) At the theoretical level, the negative impact of subsidy phase-outs on corporate innovation is revealed. Furthermore, the transmission mechanisms and the heterogeneity of this effect are examined. This offers a new perspective for understanding fluctuations in corporate R&D investment during policy transitions.

(2) Methodologically, a dynamic game theory model is combined with empirical testing. The game model captures anticipatory effects of policy adjustments, while the PSM-DID method effectively estimates the net causal effect of the policy intervention. This hybrid methodology enhances the findings, integrating the theoretical rigor of game theory with the real-world explanatory power of empirical analysis. It introduces an innovation for policy evaluation.

(3) Regarding policy implications, the necessity of the subsidy phase-out and potential phase-out pathways is examined. By extending the game theory model and analyzing factors such as diminishing marginal returns of subsidies, the study clarifies why a phase-out is necessary. A practical phase-out mechanism for the new energy industry is subsequently designed, focusing on the phase-out rate, critical triggers for starting the phase-out, and its duration. This offers a practical approach for balancing effective market forces and capable government intervention.

The structure of this paper is outlined as follows. Section 2 presents a sequential game model that involves the government and firms. Based on the derived equilibrium solutions, hypotheses are developed. Section 3 provides a detailed description of the data sources and the specification of the econometric model. Section 4 presents empirical results, including baseline regression, placebo tests, mechanism analysis, and heterogeneity analysis. Section 5 examines the necessity of the subsidy phase-out and the design of the phase-out policy. Section 6 presents a discussion of the findings. The final section concludes with a summary of policy implications and study limitations.

2. Theoretical model and research hypotheses

2.1. Model description

This section develops a sequential game model in which the government acts as the leader and the new energy firm as the follower. The government formulates subsidy policies with the aim of maximizing social welfare, while the new energy firm determines its production and innovation strategies based on the goal of maximizing its own profit. The model considers a representative new energy firm in the market[①]. Two scenarios are considered: the baseline scenario where the subsidy continues (the SC mode), and the counterfactual scenario where the subsidy is phased out (the SP mode). The specific assumptions of the model are as follows:

Assumption 1: Referring to the work of Wang et al. (2020), the demand q for new energy products depends on the product's sales price p $(p > 0)$ and the technological innovation level (hereafter referred to as innovation level) t $(t > 0)$, and is given by $q = \alpha - \beta p + \gamma t$, where α $(\alpha > 0)$ is the market capacity for new energy products, β $(\beta > 0)$ is the price elasticity coefficient, and γ $(\gamma > 0)$ represents the marginal effect of innovation on demand, reflecting consumer preference for low-carbon attributes. It is assumed that $\alpha \gg max\{\beta, \gamma\}$.

Assumption 2: The new energy firm incurs R&D investment and determines the innovation level t. The R&D investment function is expressed as $C(t) = \delta t^2/2$, where $\delta(\delta > 0)$ is the cost

[①] Of course, an oligopoly market model based on Cournot competition has also been developed. The results indicate that the intensity of market competition moderates the strength of the subsidy phase-out effect, but does not affect the direction of the impact of subsidy phase-out on firm R&D investment. Therefore, due to the purpose of the theoretical model and space constraints, only a simplified baseline model is retained in the main text to illustrate the core impact of subsidy phase-out.

elasticity of innovation. Additionally, the unit cost of production for each new energy product is c.

Assumption 3: Following the framework of Chen and 'Ulya (2019), social welfare U consists of consumer surplus (CS), producer surplus (π), and the ecological improvements resulting from new energy products (E). Thus, $U = CS + PS + E$. Based on the approach of Sinayi and Rasti-Barzoki (2018), consumer surplus is expressed as $CS = \int_{p_{market}}^{p_{max}} q\, dp = \int_{p_1}^{\frac{\alpha+t\gamma}{\beta}} \alpha - \beta p + \gamma t\, dp = \frac{(\alpha - p\beta + t\gamma)^2}{2\beta}$, where p_{market} and p_{max} are the market equilibrium price and the maximum price for new energy products, respectively. The ecological improvement effect is assumed to be a linear function of the innovation level and sales, expressed as $E = \mu t q$, where $\mu(\mu > 0)$ denotes the marginal environmental benefit per unit of product.

Assumption 4: Considering the design of innovation-oriented subsidy policies, it is assumed that if a firm's product passes the review, the government provides a unit subsidy $h(h > 0)$ based on its innovation level, with the total subsidy amount being ht. Due to budget constraints, the total subsidy has an upper limit M, such that: $ht \leq M$.

Assumption 5: To ensure the validity of the research results, it is assumed that $\beta\delta - \gamma^2 > 0$.

2.2. Model construction and solution

2.2.1 Baseline model: Subsidy continues (SC Mode)

In the case where the government provides innovation subsidies based on the innovation level of new energy products, the firm aims to maximize its profit π^{SC}. The decision function is expressed as:

$$\max_{p,t} \pi^{SC^*} = (p - c)q - \frac{\delta t^2}{2} + ht \tag{1}$$

The government, which aims to maximize social welfare U^{SC}, determines the subsidy intensity h. The decision function is given by:

$$\max_{h} U^{SC^*} = CS + \pi^{SC} + E = \frac{(\alpha - p\beta + t\gamma)^2}{2\beta} + (p - c)q - \frac{\delta t^2}{2} + ht + \mu t q$$

$$s.t.\, ht \leq M \tag{2}$$

This is formulated as a sequential game in which the government acts as the leader and the new energy firm as the follower. The firm maximizes profit as in equation (1), and the government maximizes social welfare as in equation (2). The equilibrium is solved by backward induction. The Hessian matrix is negative definite, and $\pi^{SC}(p, t)$ has a maximum value. The firm chooses the optimal p and t based on the subsidy intensity h set by the government. By solving the first-order conditions $\partial\pi^{SC}/\partial p = 0$ and $\partial\pi^{SC}/\partial t = 0$, the reaction functions are derived as:

$$p^{SC} = \frac{\alpha\delta + c\beta\delta - h\gamma - c\gamma^2}{2\beta\delta - \gamma^2} \tag{3}$$

$$t^{SC} = \frac{\alpha\gamma + 2h\beta - c\beta\gamma}{2\beta\delta - \gamma^2} \tag{4}$$

Substituting equations (3) and (4) into the government's decision equation (2) yields $U^{SC'}(h) = \frac{2h\beta(4\beta\delta + 4\beta\gamma\mu - \gamma^2) + 2(\alpha - c\beta)(3\beta\gamma\delta + \beta\gamma^2\mu + 2\beta^2\delta\mu - \gamma^3)}{2(2\beta\delta - \gamma^2)^2}$ and $U^{SC''}(h) = \frac{\beta(4\beta\delta + 4\beta\gamma\mu - \gamma^2)}{(2\beta\delta - \gamma^2)^2} > 0$. Setting $U'(h) = 0$ yields $h = -\frac{(\alpha - c\beta)(+3\beta\gamma\delta + \beta\gamma^2\mu + 2\beta^2\delta\mu - \gamma^3)}{\beta(4\beta\delta + 4\beta\gamma\mu - \gamma^2)} < 0$. Thus, social welfare increases with the subsidy intensity h. When the budget constraint is binding (i.e., $ht = M$), the optimal subsidy intensity is given by:

$$h^{SC^*} = \frac{\sqrt{(\alpha - c\beta)^2\gamma^2 + 8M\beta(2\beta\delta - \gamma^2)} - (\alpha - c\beta)\gamma}{4\beta} \tag{5}$$

Substituting equation (5) into equations (3) and (4) provides the equilibrium price, innovation level, output, and other variables (*see Supplementary Table S1*).

2.2.2 Subsidy phase-out (SP Mode)

In the absence of subsidies, the firm's profit π^{SP} maximization problem is defined in equation (6).

$$\max_{p,t} \pi^{SP^*} = (p - c)q - \delta t^2/2 \tag{6}$$

In this case, the Hessian matrix is negative definite, and $\pi^{SP}(p, t)$ has a maximum value. The equilibrium solution is obtained by solving the first-order conditions (*see Supplementary Table S1*).

2.3. Model comparison

By comparing the equilibrium solutions of the SC and SP modes, the following propositions are presented (*proof provided in Supplementary 2*).

Proposition 1: Subsidies encourage firms to increase R&D investment, i.e., $\mathrm{C}(t)^{SC^*} > \mathrm{C}(t)^{SP^*}$.

Proposition 1 suggests that subsidies, as a positive incentive tool, can alleviate the financial constraints and externalities that new energy firms face in their innovation activities. Under the SC mode, firms are partially compensated for R&D costs through subsidies, thereby making them more inclined to increase their R&D investment and improve product innovation, thereby enhancing product upgrades and market competitiveness. This conclusion aligns with empirical research on the "crowding-in effect" of subsidies on firm R&D investment (Bajgar and Srholec, 2025).

However, Proposition 1 also implies policy risks. If subsidies are completely phased out, i.e., transitioning from the SC to the SP model, R&D investment may contract significantly due to increased costs. Further, by analyzing the impact of subsidy scale (M) changes on the equilibrium outcomes, Proposition 2 is presented (*proof provided in Supplementary 3*).

Proposition 2: Firm R&D investment decreases as subsidies phase out.

Proposition 2 reveals that the phase-out of subsidies adversely affects firm R&D through budget constraint and expectation adjustment mechanisms. On one hand, the phase-out directly reduces the available funds for R&D, leading to a contraction in innovative activities. On the other hand, the phase-out policy may trigger pessimistic expectations about the industry's future, further dampening firms' long-term innovation incentives.

2.4. Case simulation and hypothesis development

To further validate Proposition 1 and Proposition 2, data from BYD is used. Based on its sales, R&D, and subsidy data, real-world constraints are applied to the parameter settings and subsequent sensitivity analysis. The parameter assignment process based on real-world data is outlined in *Supplementary 4*, and the resulting parameters are provided in Table 1.

Table 1. Parameter assignment results

Parameter	c	β	α	δ	γ	M	μ
Value	17.9	1.4	61.9	1	0.1	170	0.5

Using the parameter values from the above example, the changes in optimal decisions under the SC mode and SP mode as subsidies gradually decrease are analyzed. Let the maximum subsidy amount M be the independent variable, gradually decreasing from 170 to 0. The variation in firm R&D investment $C(t)$ is shown in Figure 1.

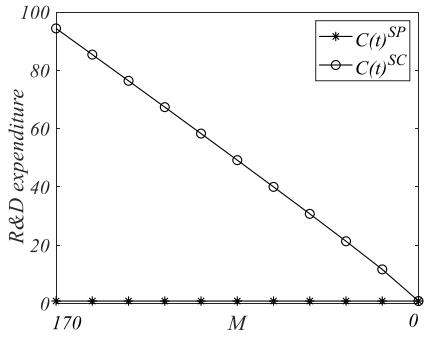


Figure 1. Changes in firm R&D investment with subsidy amount *M* during phase-out

Figure 1 confirms the results derived from Proposition 1 and Proposition 2, leading to the following research hypothesis:

Hypothesis: The implementation of the subsidy phase-out policy will lead new energy firms to reduce their R&D investment.

3. Research design

3.1. Sample selection and data processing

To investigate the impact of the subsidy phase-out policy on R&D investment in new energy firms at the micro level, this study draws on a sample of A-share manufacturing listed companies

on the Shanghai and Shenzhen stock exchanges from 2016 to 2021. The data were sourced from the *iFind* and *CSMAR* databases.

Data for the "PV Equipment" sector within the "Shenwan Industry Classification" of the *iFind* financial data terminal were extracted. Listed companies whose primary products or main business operations included keywords such as "monocrystalline silicon, polysilicon, silicon rods, silicon wafers, PV modules, cell modules, solar PV cells, PV glass, optical films, and PV supports" were identified based on their annual reports. Ultimately, 56 Chinese PV equipment manufacturing firms were selected.

The sample underwent the following data pre-processing steps. First, companies listed in 2018 or later were excluded to ensure a clear comparison between the pre- and post-policy periods of the accelerated subsidy phase-out. Second, ST and *ST firms were removed to avoid distortions arising from abnormal financial conditions. Third, observations from the initial public offering (IPO) year were excluded to eliminate IPO-related distortions in financial indicators. Fourth, observations with substantial missing values in key variables were discarded. Finally, all firm-level continuous variables were winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. The final sample for propensity score matching (PSM) consisted of 14,286 firm-year observations from 2,381 listed firms.

3.2. Variable definitions

(1) Explained variable. Firm R&D investment (RD) is used as the explained variable. R&D intensity is employed as a proxy for R&D investment and is calculated as total R&D expenditure divided by operating revenue.

(2) Core Explanatory variable. The core explanatory variable is the interaction term between the policy shock indicator and the treatment indicator, $Post_t \times Treat_i$. $Post_t$ is a dummy variable that captures the period after the accelerated subsidy phase-out policy and is set to 1 for 2018 and later years, and 0 otherwise. $Treat_i$ is the treatment variable and is set to 1 for PV equipment manufacturing firms and 0 for other firms.

(3) Mechanism variable. Firm operating performance ($JROA$) is included as the mechanism variable. It is measured by the net profit margin on total assets for the current year and is calculated as net profit divided by total assets.

(4) Control variables. To alleviate potential endogeneity arising from omitted variables, several firm-level control variables are included. These variables comprise firm age (Age), measured as the logarithm of the number of years since establishment; firm size ($Size$), measured as the logarithm of total assets; leverage ratio (LEV), measured as total liabilities divided by total assets at year-end; growth ($Growth$), proxied by Tobin's Q, defined as the ratio of market value to

total assets; ownership concentration ($Stcon$), measured as the shareholding ratio of the largest shareholder at year-end; and fixed asset ratio ($Fata$), measured as the ratio of fixed assets to total assets at year-end.

Detailed definitions for all variables in this section are provided in Table 2.

Table 2. Variable definitions

Variable type	Variable name	Symbol	Explanation
Explained variable	R&D investment	RD	Ratio of total R&D expenditure to operating revenue
Core explanatory variable	Policy shock	$Post$	Dummy variable equal to 1 for 2018 and later years, and 0 otherwise
	Treatment group	$Treat$	Dummy variable equal to 1 for PV equipment manufacturing firms, and 0 otherwise
Mechanism variable	Operating performance	$JROA$	Net profit divided by total assets
Control variables	Firm age	Age	Natural logarithm of firm age (years since establishment)
	Firm size	$Size$	Natural logarithm of total assets at year-end
	Leverage ratio	LEV	Total liabilities divided by total assets at year-end
	Growth	$Growth$	Tobin's Q, measured as market value divided by total assets
	Ownership concentration	$Stcon$	Shareholding ratio of the largest shareholder at year-end
	Fixed asset ratio	$Fata$	Fixed assets divided by total assets at year-end

3.3 Identification strategy

In the context of a natural experiment, the Difference-in-Differences (DID) method is used to mitigate the influence of confounding factors. This is achieved by comparing outcome differences before and after a policy shock between a treatment group and a control group. A key requirement of the DID method is the common trend assumption. This assumption requires that, in the absence of the accelerated subsidy phase-out policy, trends in R&D investment for PV equipment manufacturing firms and other manufacturing firms do not exhibit systematic differences over time. However, given industry-specific characteristics and the strategic role of the PV industry, this assumption may be violated.

The PSM-DID method proposed by Heckman et al. (1997) helps restore the common trend assumption by improving comparability between groups. Therefore, the PSM-DID approach is adopted to evaluate the impact of the accelerated subsidy phase-out policy on R&D investment in PV equipment manufacturing firms. In practice, DID is suited to panel data, whereas PSM is designed for cross-sectional data. Given the long-time span of the sample, directly converting panel data into cross-sectional data may lead to self-matching bias. To address this issue, a yearly matching strategy is employed. This approach allows time fixed effects (FEs) to be better controlled and enables an analysis of dynamic treatment effects. DID estimation is then conducted based on the matched samples.

To test Hypothesis 1, the baseline DID specification is presented in equation (7),

$$RD_{i,t} = \alpha + \beta_1 Post_t \times Treat_i + \gamma Control_{i,t} + Trend_j + \lambda_i + \eta_t + \varepsilon_{i,t} \quad (7)$$

where i, j, and t denote firm, industry, and year, respectively. RD is the dependent variable, representing the R&D investment of listed firm i in year t. $Post$ and $Treat$ denote the policy shock variable and the treatment indicators. $Control$ denotes a vector of firm-level characteristics, including Age, $Size$, LEV, $Growth$, $Fata$, and $JROA$. Industry-specific cyclical trends are included to capture sectoral fluctuations in innovation activity. Firm and year FEs are represented by λ_i and η_t, respectively, and $\varepsilon_{i,t}$ is the error term.

The coefficient of interest, β_1, captures the average effect of the accelerated subsidy phase-out policy on R&D investment in the PV industry. Standard errors are clustered at the firm level to address serial correlation. Based on the hypothesis, β_1 is expected to be significantly negative.

3.4 Propensity score matching and descriptive statistics

Following the identification strategy, PV equipment manufacturing firms are defined as the treatment group, while other manufacturing firms serve as the control group. Propensity scores are estimated using a Logit model. Caliper matching is applied, and the common support condition is imposed. Balance tests (*Supplementary Tables S3 and S4*) show no significant differences in matching variables between the two groups across years. This result indicates that the balance requirements are satisfied. In addition, kernel density plots of the propensity scores (*Supplementary Figures S1 and S2*) indicate that the yearly PSM approach effectively reduces sample selection bias.

After matching, no significant differences in key firm characteristics are observed between the PV and non-PV groups. Observations with missing values for core variables are then removed. The final matched sample consists of 453 firm-year observations. Descriptive statistics for the main variables are reported in Table 3.

Table 3. Descriptive statistics for key variables

Variable	Observations	Mean	Standard deviation	Min	Max
RD	453	4.1685	2.6046	0.09	21.11
Age	453	2.7909	0.2994	2.1972	3.4340
$Size$	453	8.9529	1.2709	6.2683	11.8958
LEV	453	0.4804	0.1783	0.0647	0.9079
$Growth$	453	2.2436	1.5482	0.8697	8.8351
$Stcon$	453	33.3769	13.8636	8.99	70.049
$Fata$	453	0.2560	0.1457	0.0164	0.6028
$JROA$	453	0.0365	0.0668	-0.2662	0.2260

4. Results

4.1. Baseline regression analysis

Equation (7) is used to estimate the baseline effects. Columns (1) and (2) of Table 4 report the results based on the sample constructed using yearly PSM. Column (1) shows that, with industry FE, firm FE, and year FE included, the coefficient on the interaction term is negative and significant at the 10% level. After further controlling for firm-level covariates, the interaction term in column (2) remains negative and becomes significant at the 5% level.

Based on column (2) and in conjunction with Table 3, the economic significance of the estimated coefficient is illustrated. Relative to non-PV firms, the accelerated subsidy phase-out policy is associated with a reduction of 1.2842 in R&D investment for PV firms. This magnitude is equivalent to 49.31% of one standard deviation over the sample period (1.2842 / 2.6046). Overall, the results indicate that the accelerated subsidy phase-out policy has a statistically and economically significant negative effect on R&D investment in PV firms, thereby supporting the hypothesis.

Table 4. Baseline regression results, excluding early phase-out effects and shortening the time window

	(1) RD	(2) RD	(3) RD	(4) RD	(5) RD
Post1×Treat	-1.1010* (-1.6507)	-1.2842** (-2.2567)	-1.6355* (-1.9592)	-0.9909* (-1.8781)	-1.8012* (-1.7152)
Post2016×Treat			-0.6446 (-0.8247)		
Post2017×Treat				0.6446 (0.8247)	
Control variables	N	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	453	453	453	453	273
Adj. R^2	0.9326	0.9326	0.9326	0.9326	0.9099

Notes: Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The same notation applies to all subsequent tables.

4.2. Robustness tests

4.2.1 Placebo test

To alleviate concerns about the influence of unobservable factors on the baseline results, placebo tests are conducted by randomly assigning treatment status and policy implementation years. A Monte Carlo simulation is conducted 500 times, and the distribution of the estimated coefficients is plotted. As shown in Figure 2, the baseline estimate (–1.2842) lies far from the mean of the placebo estimates (–0.00013) and falls outside two standard deviations of the simulated distribution. This result indicates that the negative effect of the accelerated subsidy phase-out policy on firm R&D investment is unlikely to be driven by unobserved confounding factors.

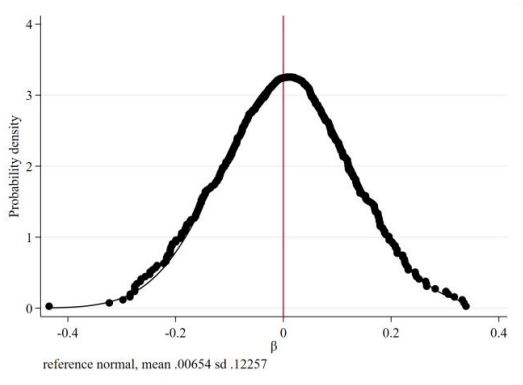


Figure 2. Placebo test results

4.2.2 Assessing the impact of omitted variables

The potential influence of omitted variables is further examined. First, the coefficient β_F is estimated using a limited set of controls. Then, the coefficient β_R is obtained using the full set of controls. The ratio is computed as $\text{Ratio} = \beta_F/|\beta_R - \beta_F|$. A larger ratio implies a lower likelihood that omitted variables substantially bias the estimated results. When the ratio exceeds one, the bias from omitted variables can be considered negligible.

Table 5. Assessment of omitted variable bias

	Limited set of controls	Full set of controls	Ratio
Group 1	Only industry FE, firm FE, and year FE (-1.1010)	All control variables (-1.2842)	6.0098
Group 2	Only firm FE and year FE (-1.0739)	All control variables (-1.2842)	5.1065

Table 5 reports ratio values of 6.0098 and 5.1065 for the two specifications. Both values are well above one, indicating that omitted variables do not materially affect the baseline estimates.

4.2.3 Excluding early phase-out effects and shortening the time window

As discussed in the policy background, benchmark feed-in tariffs for PV power generation were also reduced in 2016 and 2017. To mitigate their potential influence, dummy variables for 2016 and 2017 are constructed and interacted with the treatment indicator. The results, reported in columns (3) and (4) of Table 4, show that the coefficient on Post × Treat remains significantly negative, whereas the coefficients on Post2016 × Treat and Post2017 × Treat are not statistically significant. This suggests that tariff adjustments in 2016 and 2017 do not drive baseline findings.

To further reduce the influence of other contemporaneous policies, the sample period is restricted to 2017–2020. Column (5) of Table 4 shows that the interaction term remains significantly negative, further supporting the robustness of the baseline results.

4.2.4 Alternative fixed effects and adjusted clustered standard errors

The baseline regressions control for firm FE and year FE. Although most firms do not change their province or industry, such changes may occur in some cases. Ignoring province- or industry-specific heterogeneity may therefore omit relevant factors and lead to biased or inconsistent

estimates. To address this concern, industry–year FE and province–year FE are incorporated while retaining firm FE and year FE.

Columns (1) and (2) of Table 6 show that neither the magnitude nor the statistical significance of the interaction term changes materially. This stability indicates that the main conclusions are robust to alternative FE specifications.

Table 6. Alternative fixed effects, adjusted clustered standard errors, and mechanism analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	RD	RD	RD	RD	JROA	JROA
Post1×Treat	-2.6425***	-2.2717***	-1.2842**	-1.2842**	-0.0172	-0.0432**
	(-3.1229)	(-7.0826)	(-2.2536)	(-2.4680)	(-0.8931)	(-2.3054)
Control variables	Y	Y	Y	Y	N	Y
Individual FE	N	Y	Y	Y	Y	Y
Industry–year FE	Y	N	N	N	N	N
Province–year FE	N	Y	N	N	N	N
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	453	453	453	453	463	463
Adj. R^2	0.8992	0.9266	0.9323	0.9323	0.7521	0.7990

To further address potential spatial autocorrelation in firm R&D investment, standard errors are re-clustered at the industry level and the province level, respectively. The results reported in columns (3) and (4) of Table 6 show that, relative to the baseline regressions, the statistical significance of the interaction term remains unchanged. This finding further supports the robustness of the estimated results.

4.3. Why does R&D investment decline?

To uncover the mechanism through which the subsidy phase-out policy affects firm R&D investment, a mechanism analysis is performed from the perspective of operating performance. A subsidy phase-out directly compresses firms' disposable resources through budget constraint effects and expectation adjustment effects. Operating performance, as a core indicator of financial health, captures changes in internal liquidity under policy shocks. If the phase-out policy significantly deteriorates operating performance, firms are likely to face tighter financing constraints and greater profit pressure. Under such conditions, long-term investments such as R&D are more likely to be reduced. Therefore, examining the impact of the phase-out policy on operating performance offers a more systematic and coherent explanation for changes in R&D investment. To examine the operating performance channel, equation (8) is estimated.

$$JROA_{i,t} = \alpha + \beta_2 Post_t \times Treat_i + \gamma Control_{i,t} + Trend_j + \lambda_i + \eta_t + \varepsilon_{i,t} \quad (8)$$

where the dependent variable is $JROA$, which measures the operating performance of listed

firms. All other variables are defined and measured consistently with the baseline specification in equation (7). The coefficient β_2 captures the net effect of the subsidy phase-out policy on operating performance. Its sign and statistical significance indicate whether operating performance serves as an effective transmission channel.

Columns (5) and (6) of Table 6 show that, after the inclusion of control variables, the interaction term is significantly negative at the 5% level and economically meaningful. The estimated effect accounts for 62.70% of one standard deviation over the sample period. These results indicate that the subsidy phase-out policy is associated with a deterioration in firm operating performance, which in turn indirectly suppresses R&D investment.

4.4. Heterogeneity analysis

4.4.1 Ownership heterogeneity

Firms are classified into state-owned firms (SOEs) and non–state-owned firms (non-SOEs) based on ownership structure. The heterogeneous effects of the accelerated subsidy phase-out policy on R&D investment in PV firms across ownership types are reported in columns (1) and (2) of Table 7. For SOEs, the coefficient on the interaction term is 0.1285. Although positive, it is not statistically significant. In contrast, for non-SOEs, the interaction coefficient is –1.4122 and is significant at the 10% level.

To formally assess the difference between these two coefficients, a Fisher combination test is applied to the grouped samples. The results indicate that the difference between non-SOEs and SOEs is significantly negative at the 1% level. This finding suggests that the negative impact of the accelerated subsidy phase-out policy on R&D investment is primarily concentrated among non–state-owned PV firms.

Table 7. Ownership and life-cycle heterogeneity

	(1) SOEs RD	(2) non-SOEs RD	(3) growth RD	(4) non-growth RD
Post×Treat	0.1285	-1.4122*	-4.4721***	-1.0710**
	(0.1088)	(-1.8101)	(-3.4029)	(-1.9926)
0–1 Intergroup differences	-1.541***		3.401***	
Control variables	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	94	359	262	191
Adj. R^2	0.9775	0.9166	0.9396	0.9677

4.4.2 Life-cycle heterogeneity

Firm growth is proxied by the growth rate of operating revenue, which captures the stage of firm development. In general, firms with an operating revenue growth rate exceeding 10% are considered to exhibit strong growth potential and are classified as growth firms. Based on this criterion, firms are divided into growth and non-growth groups to examine whether the subsidy phase-out policy has heterogeneous effects across life-cycle stages.

Columns (3) and (4) of Table 7 show that the interaction term is significantly negative for both growth and non-growth firms, at the 1% and 5% levels, respectively. Moreover, the between-group difference is significantly negative at the 1% level. This result suggests that the accelerated subsidy phase-out policy is associated with a stronger negative effect on R&D investment among growth firms.

4.4.3 Regional heterogeneity

Firms are further classified according to their geographic location into eastern (East), central (Cen), and western (West) regions. Table 8 reports the estimation results for these three regional subsamples. The interaction coefficients are negative across all regions. Compared with other regions, firms in the eastern region exhibit larger coefficient magnitudes and higher levels of statistical significance.

The between-group difference tests provide additional insights. The difference between the western region and other regions is significantly positive at the 1% level. In contrast, the difference between the central region and other regions is significantly negative at the 1% level, whereas the difference between the eastern region and other regions is not statistically significant. These findings suggest that the negative effect of the accelerated PV subsidy phase-out policy on R&D investment is strongest for firms in the central region. The effect is weakest in the western region and may even be positive.

Table 8. Regional heterogeneity

	(1) East RD	(2) non-East RD	(3) Cen RD	(4) non-Cen RD	(5) West RD	(6) non-West RD
Post×Treat	-2.0204***	-1.3436*	-0.9183	-1.2650*	4.8641***	-1.5686***
	(-3.0303)	(-1.7631)	(-0.7145)	(-1.9173)	(10.9110)	(-2.6258)
0–1 Intergroup differences	0.677		-0.347*		-6.433***	
Control variables	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

N	324	129	64	389	65	388
Adj. R^2	0.9375	0.9615	0.9534	0.9331	0.9979	0.9301

5. Necessity of the subsidy phase-out policy and mechanism design

5.1. Why a subsidy phase-out is necessary

5.1.1 Subsidy efficiency

Evaluating subsidy efficiency helps assess whether fiscal spending effectively stimulates endogenous market dynamics. Subsidy efficiency is defined as the increment in innovation attributable to government subsidies. This metric helps explain why a phase-out policy is required. Subsidy efficiency is defined in equation (9).

$$\theta^{SC} = \frac{t^{SC^*} - t^{SP^*}}{M} = \frac{\sqrt{(\alpha - c\beta)^2\gamma^2 + 8M\beta(2\beta\delta - \gamma^2)} - (\alpha - c\beta)\gamma}{2M(2\beta\delta - \gamma^2)} \tag{9}$$

Taking the partial derivative of θ^{SC} with respect to the subsidy cap M leads to Proposition 3 (*proof provided in Supplementary 6*).

Proposition 3: Subsidy efficiency in the new energy industry exhibits diminishing marginal returns.

Proposition 3 implies that initial subsidies can substantially enhance innovation outcomes. However, as subsidies expand, the innovation gain per unit of fiscal input declines. Given China's tight fiscal conditions in both the present and near future, characterized by rising budgetary pressure and fiscal risks, improving the efficiency of resource allocation becomes imperative. Hence, a gradual subsidy phase-out is warranted for mature segments of the new energy industry.

5.1.2 Strength of the market expansion effect

Assessing the market expansion effect helps distinguish short-term, policy-driven growth from endogenous and sustainable market development. The strength of the market expansion effect is defined in equation (10).

$$\tau^{SC} = \frac{q^{SC^*} - q^{SP^*}}{M} = \frac{\gamma\sqrt{(\alpha - c\beta)^2\gamma^2 + 8M\beta(-\gamma^2 + 2\beta\delta)} - (\alpha - c\beta)\gamma^2}{4M(2\beta\delta - \gamma^2)} \tag{10}$$

Taking the partial derivative of τ^{SC} with respect to M, which positively determines subsidy intensity, leads to Proposition 4 (*proof provided in Supplementary 7*).

Proposition 4: The market expansion effect of subsidies in the new energy industry follows a pattern of diminishing marginal returns.

Proposition 4 implies that although stronger subsidies increase total sales, the market growth generated per unit of fiscal input gradually declines. As industries mature, markets approach

saturation, and subsidies become less effective in attracting new consumers. Policymakers should therefore closely monitor the growth rates of subsidy expenditures and product sales, evaluate market shares, and consider macroeconomic conditions to identify an appropriate timing for subsidy phase-out.

5.1.3 Subsidy capture by producers and consumers

Subsidies benefit both firms and consumers through enhanced product innovation. Let the firm subsidy capture rate be defined as $\omega^{SC} = \frac{\Delta\pi}{M} = \frac{-(\alpha-c\beta)^2\gamma^2+4M\beta(2\beta\delta-\gamma^2)+(\alpha-c\beta)\gamma\sqrt{(\alpha-c\beta)^2\gamma^2+8M\beta(2\beta\delta-\gamma^2)}}{8M\beta(2\beta\delta-\gamma^2)}$. while consumer subsidy capture is defined as $\mathrm{M}-\Delta\mathrm{p}$, with the corresponding capture rate denoted by $\varepsilon^{SC} = \frac{\mathrm{M}-\Delta\mathrm{p}}{M} = \frac{(\alpha-c\beta)\gamma^2+4M\beta(2\beta\delta-\gamma^2)-\gamma\sqrt{(\alpha-c\beta)^2\gamma^2+8M\beta(2\beta\delta-\gamma^2)}}{4M\beta(2\beta\delta-\gamma^2)}$. Taking the partial derivatives of ω^{SC} and ε^{SC} with respect to M leads to Proposition 5 (a). Moreover, consumers' demand for higher innovation levels in new energy products continues to increase. This trend is captured in the model by an increase in the coefficient γ, which reflects the impact of innovation on sales volume. The effect of γ on optimal decisions is formalized in Proposition 5(b) (*proof provided in Supplementary 8*).

Proposition 5: (a) The firm subsidy capture rate exhibits diminishing marginal returns. (b) The consumer subsidy capture rate increases with subsidy size but decreases as consumers' low-carbon awareness rises.

Proposition 5 indicates that as consumer preferences for innovative and low-carbon products strengthen, the primary beneficiaries of subsidies gradually shift from producers to consumers. When consumers are willing to pay higher innovation premiums, each unit of subsidy generates smaller marginal welfare gains. As a result, subsidy efficiency declines on both the production and consumption sides. A timely subsidy phase-out therefore allows fiscal resources to be reallocated toward more efficient uses.

5.2. Design of the subsidy phase-out mechanism

The preceding analysis suggests that subsidies should be phased out at an appropriate stage of industry development. However, a poorly designed or abrupt phase-out may trigger industrial disruptions and may even offset the benefits accumulated during earlier subsidy periods. This section analyzes effective subsidy phase-out mechanisms from multiple dimensions, including the phase-out rate, critical trigger points, and the phase-out period, with the objective of maximizing overall subsidy effectiveness.

5.2.1 Design of the phase-out rate

To prevent a contraction in market capacity during the subsidy phase-out, the phase-out rate must remain below a critical threshold. Suppose that consumers' preference for innovation increases from γ to $\gamma + \Delta\gamma$. The government then sets a subsidy phase-out rate $r(0 \le r \le 1)$, where a higher value of r indicates a larger phase-out magnitude. After the phase-out, the remaining subsidy is given by $M_p = (1 - r)M$, where the subscript p denotes the phase-out scenario. After the implementation of the phase-out policy, market demand for new energy products should not fall below the pre–phase-out level. Formally, the condition $q_p^{SC^*}|_{\gamma+\Delta\gamma,M_P} \ge q^{SC^*}|_{\gamma,M}$ should hold. From this condition, Proposition 6 is derived (*proof provided in Supplementary 9*).

Proposition 6: To avoid market deterioration after the subsidy phase-out, the phase-out rate r^{SC} should satisfy $\frac{\{2M(2\beta\delta-\gamma^2)+(\alpha-c\beta)\left[(\alpha-c\beta)\delta+\sqrt{(\alpha-c\beta)^2\delta^2+4M\delta(2\beta\delta-\gamma^2)}\right]\}\nabla\gamma(2\gamma+\nabla\gamma)}{2M(2\beta\delta-\gamma^2)^2}$.

Proposition 6 indicates that a faster phase-out is not necessarily preferable. The pace of subsidy phase-out must be aligned with endogenous demand growth. If subsidies are reduced too sharply or too rapidly, exceeding this critical rate, market demand may decline even in the presence of rising consumer environmental awareness. This proposition thus provides policymakers with an explicit upper bound for the phase-out rate and emphasizes that subsidy phase-out policies should follow a gradual and orderly path. Such an approach helps ensure a smooth transition from policy-driven growth to market-driven development.

5.2.2 Design of the phase-out critical trigger points

From a long-term sustainability perspective, fiscal subsidies are inherently transitional policy instruments. In contrast, consumers' endogenous demand for new energy products constitutes the primary driver of firm production and innovation. Subsidies and consumer low-carbon awareness exhibit strong complementarity in promoting corporate innovation (Liu et al., 2025). Rising consumer awareness strengthens market preferences and induces firms to increase R&D investment in green technologies.

Accordingly, policy design must dynamically respond to changes in consumer awareness. As low-carbon preferences intensify, market forces gradually substitute for subsidies. The phase-out mechanism should be aligned with this transition to avoid efficiency losses. To this end, two benchmark models without consumer low-carbon preferences are constructed: a subsidy-continuation model (NC) and a subsidy phase-out model (NP). These models are compared with the SC and SP models that incorporate consumer preferences. This framework allows the substitution and complementarity between subsidies and consumer awareness to be quantified and provides a basis for identifying critical trigger points for subsidy phase-out.

(1) No consumer low-carbon preference with continued subsidies (NC mode)

Market demand without consumer low-carbon preferences is specified in equation (11).

$$q = \alpha - \beta p \tag{11}$$

The firm's profit maximization problems under the NC modes are given in equation (12).

$$\max_{p,t} \pi^{NC^*} = (p - c)(\alpha - \beta p) - \frac{\delta t^2}{2} + ht \tag{12}$$

The government maximizes social welfare subject to a budget constraint:

$$\max_{h} U^{NC^*} = \frac{(\alpha - p\beta)^2}{2\beta} + (p - c)q - \frac{\delta t^2}{2} + ht + \mu tq$$

$$s.t.\, ht \leq M \tag{13}$$

Solving backward induction, the Hessian matrix of $\pi^{NC}(p,t)$ is $H = \begin{bmatrix} -2\beta & 0 \\ 0 & -\delta \end{bmatrix}$, which implies that $\pi^{NC}(p,t)$ attains a maximum. Solving $\partial \pi^{NC}/\partial p = 0$ and $\partial \pi^{NC}/\partial t = 0$, and substituting the resulting expressions into equation (13), yields $U^{NC'}(h) = \frac{8h\beta + 4\beta\mu(\alpha - c\beta)}{8\beta\delta}$ and $U^{NC''}(h) = \frac{1}{\delta} > 0$. Therefore, social welfare is maximized when the subsidy reaches its upper bound, that is, when $h^{NC^*} = \sqrt{M\delta}$. The remaining equilibrium outcomes under this model are reported in *Supplementary Table S1*.

(2) No consumer low-carbon preference with subsidy phase-out (NP mode)

When subsidies are fully phased out, demand remains as specified in equation (11). As shown by equation (14), the firm's profit function becomes:

$$\max_{p,t} \pi^{NP^*} = (p - c)(\alpha - \beta p) - \delta t^2/2 \tag{14}$$

At this point, the Hessian matrix of $\pi^{NP}(p,t)$ is $H = \begin{bmatrix} -2\beta & 0 \\ 0 & -\delta \end{bmatrix}$, which implies that $\pi^{NP}(p,t)$ attains a maximum. Solving $\partial \pi^{NP}/\partial p = 0$ and $\partial \pi^{NP}/\partial t = 0$ yields $p^{NP^*} = \frac{\alpha + c\beta}{2\beta}$ and $t^{NP^*} = 0$. The remaining equilibrium outcomes are reported in *Supplementary Table S1*.

More broadly, government subsidies to new energy firms are not designed merely to expand output. Instead, they serve a dual objective. On the one hand, subsidies incentivize frontier technological research and breakthroughs, thereby strengthening long-term industrial competitiveness. On the other hand, they protect reasonable profit margins at specific development stages, sustaining firm survival and reinvestment capacity. Based on these objectives, critical trigger points for subsidy phase-out are identified from two dimensions: promoting technological innovation and preserving reasonable profits. Solving the optimal conditions yields Proposition 7 (*proof provided in Supplementary 10*).

Proposition 7: (a) When $\gamma < \gamma_0$, $t^{SP^*} > t^{NC^*}$; when $\gamma \geq \gamma_0$, $t^{NC^*} > t^{SP^*}$, where $\gamma_0 = \frac{\delta[\sqrt{8M\beta + (\alpha - c\beta)^2} - (\alpha - c\beta)]}{2\sqrt{M\delta}}$ is the innovation threshold. (b) When $\gamma < \gamma_1$, $\pi^{SP^*} > \pi^{NC^*}$; when $\gamma \geq$

γ_1, $\pi^{NC^*} > \pi^{SP^*}$, where $\gamma_1 = \frac{2\beta\sqrt{M\delta}}{\sqrt{2M\beta+(\alpha-c\beta)^2}}$ is the profit threshold.

Proposition 7 illustrates the dynamic interaction and role switching between subsidies and consumer low-carbon awareness in driving the development of the new energy industry. Although both mechanisms enhance innovation and firm profitability, their relative effectiveness is governed by clear threshold values γ_0 and γ_1. These thresholds provide a rigorous basis for policy intervention and orderly subsidy phase-out. Specifically, the phase-out mechanism should be triggered in response to shifts in consumer preferences, initiated at γ_0, and completed before γ_1. This design enables a smooth transition from policy-driven growth to market-driven development.

Figure 3 depicts the subsidy phase-out path implied by the identified critical trigger points. Two incentive mechanisms are examined: government subsidies to new energy firms (the NC mode) and market incentives driven by consumer low-carbon awareness (the SP mode). The phase-out strategy should jointly account for firm innovation performance and profitability.

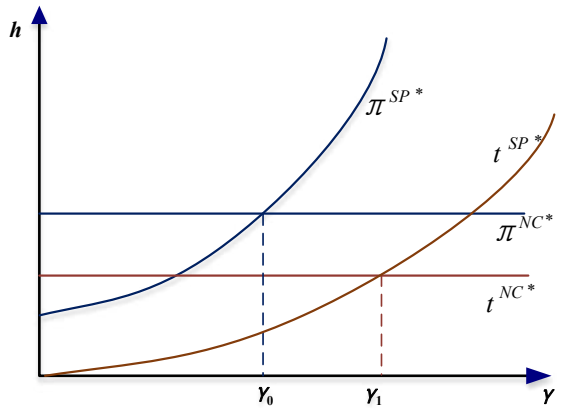


Figure 3. Schematic diagram of the phase-out critical trigger point

As shown in Figure 3, the degree of consumer low-carbon preference γ is the key determinant of subsidy effectiveness. When $\gamma \in [0, \gamma_0]$, subsidies dominate market mechanisms in enhancing both firm profits and innovation outcomes ($\pi^{NC^*} > \pi^{SP^*}$; $t^{NC^*} > t^{SP^*}$). This stage corresponds to the early phase of industry development, during which subsidies are necessary to correct market failures and nurture industry growth. Governments should therefore maintain or moderately increase subsidy intensity.

The threshold γ_0 serves as the trigger point for initiating subsidy phase-out, indicating that policy support should gradually yield to endogenous market forces. When $\gamma \in (\gamma_0, \gamma_1]$, market incentives begin to dominate profit generation ($\pi^{SP^*} > \pi^{NC^*}$), while subsidies remain more effective in stimulating innovation ($t^{NC^*} > t^{SP^*}$). This stage represents a policy–market coexistence stage. Governments should advance the phase-out in a gradual and predictable manner, consistent with fiscal capacity and industrial planning constraints, to allow firms sufficient time for strategic

adjustment.

When consumer awareness strengthens further and reaches γ_1, market mechanisms become at least as effective as subsidies in promoting technological innovation. Thus, γ_1 represents the latest point at which the subsidy phase-out should be completed. When $\gamma \in (\gamma_1, +\infty]$, market mechanisms outperform subsidies in both profit incentives and innovation outcomes ($\pi^{NC^*} < \pi^{SP^*}$; $t^{NC^*} < t^{SP^*}$). Continuing subsidies beyond this stage would result in inefficient fiscal expenditure, increase fiscal burdens, and distort market signals, leading to resource misallocation.

In addition, as established in Proposition 3, subsidy efficiency follows a law of diminishing marginal returns. To ensure the efficient allocation of limited fiscal resources, subsidy efficiency should remain above a minimum acceptable level. Accordingly, let θ_0^{GS} denote the minimum acceptable subsidy efficiency, and M_0^{GS} the corresponding phase-out threshold. When actual subsidy intensity exceeds this threshold, efficiency approaches or falls below the acceptable level, and the phase-out policy should be activated. This reasoning leads to Proposition 8 (*proof provided in Supplementary 11*).

Proposition 8: When $M_0^{GS} < M$, subsidies should be phased out, where $M_0^{GS} = \frac{\beta(2+cp\gamma)-\theta_0^{GS}\alpha\gamma}{\theta_0^{GS^2}(2\beta\delta-\gamma^2)}$.

Proposition 8 establishes a clear trigger mechanism for subsidy phase-out. Subsidies are neither optimal when excessively large nor when excessively prolonged. Once actual subsidy intensity exceeds the critical threshold, fiscal efficiency deteriorates, and the phase-out mechanism should be initiated in a timely manner.

5.2.3 Design of the phase-out period

The phase-out period is determined by the identified critical thresholds. Figure 4 presents a decision tree for determining subsidy phase-out strategies in the new energy industry. As shown in Figure 4, the first step is to assess whether government subsidies remain efficient. When $M_0^{GS} < M$, subsidies should enter the phase-out stage, with M_0^{GS} serving as the critical trigger point, in accordance with Proposition 8.

From the perspective of policy objectives, if the primary goal is to enhance the innovation level of new energy products, Proposition 7 implies that subsidies remain necessary when consumers' low-carbon awareness satisfies $\gamma < \gamma_0$. Once $\gamma \geq \gamma_0$, subsidies can be gradually phased out and eventually fully removed. During this process, the phase-out rate r^{GS} must satisfy the constraint $0 \leq r^{GS} \leq \frac{\Delta\gamma(2\gamma+\Delta\gamma)\delta[(\alpha-c\beta)^2\gamma^2+4M\beta(2\beta\delta-\gamma^2)+(\alpha-c\beta)\gamma\sqrt{(\alpha-c\beta)^2\gamma^2+8M\beta(2\beta\delta-\gamma^2)}]}{2M(\gamma+\Delta\gamma)^2(2\beta\delta-\gamma^2)^2}$ derived in Proposition 6 to ensure market stability. Alternatively, when the policy objective shifts to protecting reasonable profits of new energy firms, subsidies remain efficient when $\gamma < \gamma_1$. Once $\gamma \geq \gamma_1$,

subsidies should also be gradually phased out and eventually fully exited, following the phase-out rate conditions specified in Proposition 5.

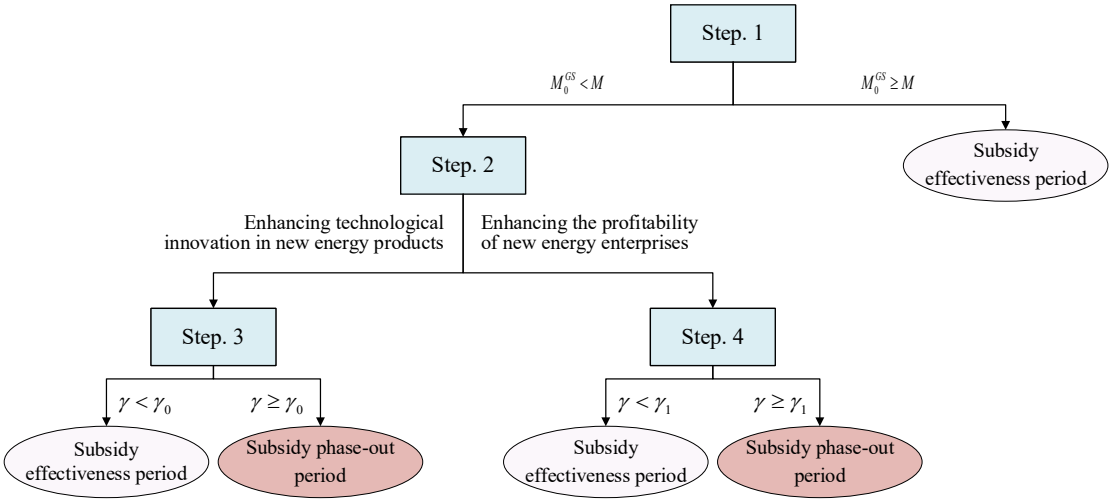


Figure 4. Decision tree for subsidy phase-out strategies in the new energy industry

6. Discussion

First, by integrating theoretical modeling with empirical analysis, this study shows that, at specific stages of development in the new energy industry, subsidy phase-out policies have a negative effect on firm R&D investment. This finding complements the existing literature that emphasizes the innovation-forcing effect of subsidy phase-out (Xu et al., 2022; Wang et al., 2025b). The empirical results indicate that the phase-out policy constrains firms' available funds through the deterioration of operating performance, which leads to a short-term contraction in R&D investment. This conclusion differs from that reported by Xiao and Yang (2025), who find that subsidy phase-out enhances the competitive advantage of PV firms and increases R&D intensity. The discrepancy can be largely attributed to differences in position along the industrial value chain. This study focuses on PV firms in upstream equipment manufacturing segments, which are R&D-intensive and more dependent on subsidies for cash flow. For these firms, subsidy phase-out is more likely to induce financial constraints. In contrast, Xiao and Yang (2025) concentrate on downstream system integration firms, which may benefit from declining component costs after phase-out, thereby expanding profit margins and reallocating resources toward R&D. Therefore, from the perspective of heterogeneity across value-chain segments, this study provides additional insight into understanding the effects of subsidy phase-out policies in the new energy industry.

Second, from a methodological perspective, this study combines a dynamic game-theoretic framework with empirical analysis, offering a novel framework for identifying the net effects of subsidy phase-out policies. Much of the existing literature relies primarily on empirical strategies

(Yao et al., 2025; Lin and Zhang, 2025), which can be vulnerable to omitted-variable bias. By contrast, the sequential game model developed in this study explicitly embeds government budget constraints, consumer low-carbon preferences, and firm R&D decisions within a unified framework. By modeling the sequential order of decisions, the framework captures the interaction between government guidance and firm responses during policy implementation. This framework is particularly suitable for analyzing subsidy phase-out policies in the new energy industry, where hierarchical decision structures and strategic interdependence are pronounced (Wang et al., 2025a). The equilibrium outcomes derived from the model also generate clear ex ante hypotheses for subsequent PSM-DID estimation. This theory-driven and empirically validated hybrid approach helps mitigate policy endogeneity concerns, thereby enhancing both the theoretical rigor and the policy relevance of the conclusions.

Finally, this study extends the policy discussion from the question of whether subsidies should be phased out to how they should be phased out in a systematic and orderly manner. Consistent with concerns about fiscal sustainability raised by Aryanpur et al. (2022), the model-based analysis indicates that subsidy efficiency, market expansion effects, and firm subsidy capture all exhibit diminishing marginal returns. Moreover, consumer subsidy capture decreases as low-carbon awareness increases. These results jointly clarify the economic rationale for subsidy phase-out. Moving beyond existing studies that provide relatively simple discussions of follow-up policies (Shao et al., 2022; Liu et al., 2025b), this study proposes an operational phase-out framework. Specifically, it introduces constraints on the phase-out rate, a dual-threshold mechanism centered on consumer low-carbon preferences, and an explicit phase-out path design. Together, these elements form a coherent and operational phase-out mechanism. The analysis therefore provides concrete guidance on the critical policy questions of when to initiate phase-out and how to implement it, thereby contributing to a smoother transition from policy-driven to market-driven development in the new energy industry.

7. Conclusions and policy implications

Taking China’s PV industry as an empirical case, this study systematically examines the impact of subsidy phase-out policies on firm R&D investment in the new energy industry by integrating theoretical modeling with empirical analysis. The necessity of subsidy phase-out is assessed, and a structured phase-out mechanism is designed. The results show that subsidy phase-out policies significantly suppress firm R&D investment. This effect is transmitted mainly through the deterioration of operating performance, which constrains firms’ internal financial resources. The negative impact is particularly pronounced among non–state-owned firms, growth firms, and firms

located in central regions.

The theoretical model further reveals that subsidy efficiency, the market expansion effect of subsidies, and the subsidy capture rate of new energy firms all follow a pattern of diminishing marginal returns. Moreover, excessive subsidies may redirect fiscal resources toward consumers with weaker low-carbon preferences. These findings provide a clear economic rationale for subsidy phase-out in the new energy industry. Finally, a comprehensive subsidy phase-out mechanism is designed along three dimensions: the phase-out rate, critical trigger points, and the phase-out period. This framework aims to prevent market contraction, ensure that policy exit is aligned with the growth of endogenous market forces, and establish a phased and predictable transition from policy-driven to market-driven development.

Based on these findings, three policy recommendations are proposed.

First, the phase-out path should follow a gradual approach. The phase-out rate should be carefully controlled to avoid sharp market disruptions. Policymakers should be guided by critical thresholds associated with rising consumer low-carbon preferences. As endogenous market momentum strengthens, subsidies should be reduced in stages and in a predictable manner to ease firm adjustment. For example, phase-out schedules can be linked to industry-level technological maturity. Transitional policy instruments, such as tax credits or green finance support, can be introduced at early stages to buffer the negative impact of declining operating performance on innovation activities.

Second, the determination of phase-out thresholds should be dynamically adjusted based on subsidy efficiency and market conditions. Monitoring mechanisms should be strengthened so that phase-out procedures are activated when marginal subsidy benefits decline significantly or when spontaneous consumer demand reaches a critical level. An evaluation system centered on firm innovation capacity and market penetration should be developed to avoid abrupt and uniform exits. Decision-tree tools can be applied to set differentiated phase-out triggers aligned with specific policy objectives.

Third, differentiated supporting policies should be adopted to mitigate the adverse effects of phase-out on vulnerable groups. Targeted support is required for non–state-owned firms, growth firms, and firms in central regions. Instruments such as enhanced R&D tax deductions and intellectual property–backed financing can be used to provide precise relief. At the same time, upgrades in market infrastructure should be accelerated to shift the industry from policy dependence toward demand-driven growth. Market-based mechanisms, including carbon trading and green electricity certificates, should also be coordinated with phase-out policies to form a diversified incentive system and ensure sustained industry development after subsidies are reduced.

Despite clarifying the internal links between phase-out rates, critical thresholds, and firm innovation behavior through analytical modeling and game-theoretic analysis, the proposed framework remains largely conceptual. Parameter calibration and real-world validation are limited. Future research should further focus on empirical parameterization and dynamic optimization, with the aim of transforming the theoretical framework into an operational policy tool.

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