



Research article

Dynamic competition and stability analysis of dual-track battery recycling systems under low-carbon transition

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Abstract: With the rapid development of the electric vehicle industry, the environmental pollution caused by retired batteries has made effective battery recycling increasingly important. The battery recycling market is characterized by the coexistence of whitelist-compliant enterprises and black-market workshops. To analyze their competitive relationship, this study develops a static Bertrand game and a discrete-time dynamic model under bounded rationality. The static analysis focuses on recycling prices, quantities, and research and development (R&D) effort, while the dynamic analysis examines how behavioral adjustment speeds and policy interventions jointly shape system stability. The results indicate that recycling R&D, consumer low-carbon preference, and regulatory pressure affect equilibrium decisions and profits, with some effects depending on technological and consumer characteristics. From a dynamic perspective, moderate adjustment speeds facilitate convergence, whereas excessive adjustments may induce oscillations and chaos. The stability threshold of each adjustment speed depends on the speeds of the other decision variables. Under the examined parameter settings, stronger regulatory pressure on black-market workshops expands the stability region, whereas higher subsidies for whitelist-compliant enterprises may shrink it. The joint policy analysis further shows that jointly increasing the three adjustment speeds reduces the range of subsidy-regulation combinations compatible with steady convergence. These findings provide insights into coordinating regulatory and subsidy policies while accounting for firms' adjustment behavior.

Keywords: battery recycling supply chain; formal-informal competition; static and dynamic game; bounded rationality

Mathematics Subject Classification: 90B06, 91A50, 91A80

1. Introduction

The rapid expansion of the electric vehicle industry is driving the world's first wave of large-scale battery retirement [1,2]. The International Energy Agency forecasts that by 2030, retired electric vehicle batteries globally will reach 1.85 million tons. As the largest electric vehicle market, China's retired battery output during the same period will exceed 1 million tons [3]. Currently, end-of-life batteries pose environmental risks while also holding resource value. Improper disposal may lead to heavy metal and electrolyte leakage, whereas standardized recycling facilitates the reintroduction of valuable metal resources into the supply chain. However, the global battery recycling rate remains below 30%, with China consistently falling short of 25% [4]. The contradiction between rapidly escalating retirement volumes and low effective recycling rates leads to a severe imbalance in the power battery recycling market.

The primary cause of this imbalance is the dominant position held by informal enterprises in the current recycling market [5,6]. Although formal recycling channels offer high recovery rates and low environmental pollution, the high costs of recycling processing often result in formal recyclers offering lower purchase prices than informal channels. This price disadvantage leads to a significant portion of end-of-life batteries being sold not to formal recyclers for proper treatment, but instead to informal workshops for violent dismantling and utilization, causing irreversible environmental pollution [7]. To address this, China, the EU, and others are actively implementing the 'whitelist' system to strengthen market access regulatory thresholds while raising consumer environmental awareness, ensuring end-of-life batteries are recycled properly. However, due to the persistent cost disadvantage of formal channels, many informal workshops circumvent the 'whitelist' system through various means, allowing retired batteries to enter non-compliant channels. Consequently, over 40% of end-of-life power batteries still flow into informal channels, which starkly reflects that the core of the current market competition between whitelist-compliant enterprises and black-market workshops lies in the significant asymmetry in recycling costs between the two sides [8].

Under this supply chain competition structure between whitelist-compliant enterprises and black-market workshops, consumers' choices for selling retired batteries depend on the pricing decisions of these two types of recyclers. The recycling prices offered by these recyclers are strictly constrained by their respective costs. Governments tend to enhance the competitive edge of whitelist-compliant enterprises through subsidy policies and regulatory measures that encourage batteries to flow through compliant recycling channels. However, black-market workshops leverage their cost advantages to raise acquisition offers, exerting a more direct influence on the distribution ratio of end-of-life batteries between formal and informal channels [9]. Furthermore, whitelist-compliant enterprises' research and development (R&D) investments in recycling technologies may reduce recycling costs and strengthen their low-carbon advantages, while informal recyclers face increasing regulatory exposure as their recycling scale expands. Although formal-informal recycling competition has received increasing attention, how technological investment, consumer low-carbon preference, government incentives, and regulatory pressure jointly reshape competition between the two channels remains insufficiently understood. This paper therefore systematically analyzes the strategic decision-making behaviors and key influencing parameters of these two recycler types, with particular attention to the asymmetric policy environment faced by formal and informal recyclers.

Although existing literature explores the strategic decisions of stakeholders in battery recycling supply chains from various perspectives, most studies are confined to static game analysis. However, static equilibrium analysis cannot fully explain the persistent coexistence of formal and informal recycling channels or capture the evolutionary instability caused by differences in decision adjustment behaviors. In actual supply chain environments, corporate decisions are often dynamic and continuously adjusted based on market outcomes, exhibiting distinct evolutionary characteristics [10,11]. Furthermore, many studies assume firms make perfectly rational decisions and that outcomes can be promptly optimized, whereas decision-makers in reality exhibit bounded rationality [12]. Discrete-time bounded-rationality models have been widely used to characterize such adjustment processes. Nevertheless, limited attention has been paid to how competitive asymmetry and policy interventions jointly affect the dynamic stability of dual-track battery recycling systems. To address this gap, this paper develops a discrete-time dynamic game framework incorporating asymmetric competition and heterogeneous adjustment speeds, and examines how regulatory pressure and subsidies jointly shape stability regions and long-term market dynamics.

Based on this, this paper examines static competition and dynamic stability in a dual-track battery recycling market comprising a whitelist-compliant recycler and a black-market workshop, with particular attention to their asymmetric competitive conditions and behavioral adjustment processes. Specifically, this study addresses three questions: (1) How do R&D costs, regulatory pressure, consumer low-carbon preference, and technological cost-reduction efficiency affect equilibrium decisions and profits, and under what conditions do these effects differ between the two recycling channels? (2) How do the adjustment speeds of the two recyclers' prices and the compliant recycler's R&D effort jointly affect stability boundaries and transitions between steady, periodic, and complex dynamic states? (3) How do regulatory pressure and subsidies, individually and jointly, affect system stability under different adjustment-speed configurations? By addressing these questions, this study provides insights into the dynamic consequences of asymmetric competition and the coordination of regulatory and subsidy policies in dual-track battery recycling markets, thereby informing policy design that supports compliant recycling while maintaining market stability.

The remainder of this paper is organized as follows. Section 2 briefly reviews the relevant literature. Section 3 constructs a static game model and a discrete dynamic analysis. Section 4 presents numerical simulations under both static game and dynamic analysis frameworks. Section 5 summarizes the main findings and provides managerial and policy insights.

2. Literature Review

This study is closely related to three streams of literature: competition in battery recycling markets, consumer low-carbon preferences in supply chains, and dynamic games under bounded rationality. Accordingly, we review the relevant literature from these three perspectives.

2.1. Competition in battery recycling markets

With the rapid proliferation of electric vehicles, a large number of batteries are approaching the end of their service life. Currently, the battery recycling market features multiple types of recyclers, including vehicle manufacturers, battery suppliers, and third-party recycling platforms. The increasingly competitive battery recycling market has prompted many scholars to focus on competition among

heterogeneous recyclers or different channels. Consequently, pricing strategies, recycling volumes, and profit distribution in multi-player recycling markets have become key research topics. Xia et al. [13] concluded that the cooperative recycling pattern yields optimal economic benefits, while the third-party recycling pattern demonstrates superior environmental outcomes. Yu et al. [7] constructed a differential game model for a dual-channel closed-loop supply chain, finding that full cooperation maximizes recycling rates while increasing profits for all participants. Xu and Tan [14] demonstrated that under Extended Producer Responsibility policies, subsidies for manufacturers effectively boosts recycling rates and fosters a win-win scenario for multiple supply chain stakeholders. Beyond channel competition, government policies also significantly influence the competitive landscape of battery recycling markets. Cai et al. [15] found that government subsidies exert a significant positive impact on battery recycling supply chains, with one-time subsidies and capability-oriented subsidies yielding differentiated effects at different thresholds. Zhao et al. [5] recommended increased government subsidies, mandatory manufacturer responsibility, and enhanced supply chain coordination to boost profitability. Zhang et al. [16] emphasized that hybrid subsidy strategies enhance demand and recycling volumes more effectively than single subsidies, maximizing overall supply chain profits. In addition to competition among compliant recycling channels, recent studies have increasingly examined competition between formal and informal recyclers [1,17,18], highlighting the roles of recycling prices, cost differences, and government policies. However, relatively limited attention has been paid to how regulatory pressure and technological investment jointly shape competition between the two channels. Therefore, this study further examines formal-informal recycling competition by considering asymmetric costs, regulatory pressure, recycling R&D, and consumer low-carbon preference.

2.2. *Consumer preference in supply chains*

Beyond competition among enterprises, consumers' environmental preferences are playing an increasingly significant role in battery recycling. A growing body of literature incorporates consumer sensitivity to environmental performance or emissions reduction into model studies, examining how consumer behavioral preferences influence corporate decisions regarding pricing, recycling efforts, and technology adoption. Xiao et al. [19] demonstrated that a consumer-driven recycling model offers innovative enterprises both environmental and economic advantages by enhancing flexibility and adaptability while simultaneously maximizing profits, reducing costs, and improving operational efficiency. Ma et al. [20] found that integrating blockchain technology into power battery closed-loop supply chains strengthens consumer trust and, through heightened sensitivity to secondary-use performance, drives higher design standards and greater recycling participation, thereby improving profitability across all chain segments. Wu [21] showed that intensified channel competition in battery recycling weakens supply chain profitability and recycling rates, whereas growing consumer environmental awareness exerts a significant positive influence on both outcomes. Moreover, some scholars also examined the impact of corporate information disclosure or environmental, social, and governance (ESG) practices on supply chains. Zhao et al. [22] found that consumer price sensitivity toward recycling is a critical enabler and that integrating ESG improvements into closed-loop supply chains can meaningfully advance sustainability. Yang et al. [23] demonstrated that high consumer attention to remanufactured product information disclosure, combined with low blockchain transaction fees, enables blockchain technology to raise retail prices for both new and remanufactured products and improve social welfare. Existing studies generally confirm that consumer environmental preferences

can significantly affect recycling decisions and supply chain performance. However, relatively limited attention has been paid to how consumer low-carbon preference interacts with the technological characteristics of compliant recyclers and further reshapes competition between formal and informal recycling channels. Therefore, this study incorporates consumer low-carbon preference into the recycling quantity of the whitelist-compliant recycler and examines its interaction with recycling R&D and cost-reduction effects.

2.3. Dynamic game and bounded rationality

By allowing decision variables to evolve over time, dynamic games provide a more realistic description of firms' long-term strategic behavior. Differential games, typically grounded in full rationality and perfect foresight, model firms as intertemporal profit optimizers who solve optimal control problems over continuous time. Wang et al. [24] employed a differential game framework to examine equity structures in supply chains, showing that unilateral shareholding increases costs and investment as equity stakes rise, whereas cross-shareholding achieves more balanced cost sharing with lower equity ratios. Wang et al. [25] developed a differential game model for a three-tier integrated circuit supply chain, demonstrating that centralized decision-making yields the highest level of collaborative innovation. Moreover, evolutionary game theory relaxes the assumption of perfectly rational decision-makers by modeling agents with bounded rationality, serving as a crucial tool for scholars to conduct dynamic analyses of decision-making behavior. Zhu and He [26] constructed a stochastic evolutionary game model, finding that enhancing data standardization and reducing random disturbance intensity can accelerate the system's evolution toward an ideal state, while equalizing the distribution of benefits is more conducive to tripartite coordination. Xia et al. [27] built a three-party evolutionary game model and proposed that supporting policies should be implemented alongside the EU Battery Regulation to guide the system toward an ideal steady state. Discrete-time nonlinear dynamic systems incorporate bounded rationality by allowing decision-makers to adjust their strategies in each period according to local marginal profit signals, and have therefore been widely applied to analyze the dynamic evolution of competitive decisions. Ahmed et al. [28] developed a heterogeneous duopoly model and found that faster decision adjustment can drive the system from stability to periodic oscillations and chaos. Based on bounded rationality, Liu et al. [29] established a dynamic green competition model employing a gradient adjustment mechanism and found that increasing the adjustment rate within a specific range can mitigate the system's chaotic behavior. Existing studies have also examined how environmental and policy parameters affect the dynamic stability of competitive systems. Xi and Zhang [30] showed that environmental policy parameters can significantly alter system stability in competing green supply chains, while Bao et al. [31] investigated the long-term dynamic behavior of parallel supply chains under government subsidies. However, limited attention has been paid to how regulatory pressure and subsidies jointly shape the dynamic stability of formal-informal competition in battery recycling markets. Thus, this study examines how heterogeneous adjustment speeds and the individual and joint effects of these policy instruments influence system stability and long-term market dynamics.

2.4. Research gap and contributions

Although existing literature has extensively explored competition in battery recycling supply chains, several research gaps remain. First, although competition between formal and informal recyclers has received increasing attention, limited research has examined how regulatory pressure, recycling R&D, and consumer low-carbon preference jointly affect their competitive decisions. Second, the joint effects of heterogeneous price and R&D adjustment speeds on stability boundaries and transitions between dynamic states in dual-track recycling systems remain insufficiently understood. Third, although bounded-rational dynamic games have been widely applied to supply chain competition, limited attention has been paid to how regulatory pressure and subsidies individually and jointly affect system stability under different adjustment-speed configurations.

To address these gaps, this study develops an analytical framework for competition and stability in a dual-track battery recycling system. First, we model competition between a whitelist-compliant recycler and a black-market workshop by incorporating asymmetric costs, recycling R&D, and consumer low-carbon preference, and identify their conditional effects on equilibrium decisions and profits. Second, we extend the static game to a discrete-time nonlinear dynamic system under bounded rationality and characterize how heterogeneous adjustment speeds jointly shape local stability boundaries and the distribution of steady, periodic, and complex dynamic states. Third, we examine the individual and joint effects of regulatory pressure and subsidies on dynamic stability, identifying how the stability implications of policy combinations vary across different adjustment-speed configurations.

3. Problem definition and model analysis

In this section, our paper presents a game theory model constructed based on several realistic assumptions regarding market structure, consumer behavior, and corporate technological decisions. The model aims to conduct an in-depth analysis of the key economic and environmental characteristics of the power battery recycling market.

Hypothesis 1: The battery recycling market consists of two heterogeneous recyclers: a black-market workshop and a whitelist-compliant enterprise. The black-market recycler relies on rudimentary and violent dismantling methods to extract valuable components, which leads to severe environmental pollution but requires only limited technological investment. In contrast, the whitelist-compliant enterprise adopts standardized and advanced metallurgical recycling technologies that significantly reduce environmental emissions at the cost of substantial R&D investment [32,33]. For analytical convenience, the black-market workshop and the whitelist-compliant enterprise are denoted by recyclers R_1 and R_2 , respectively. Both recyclers operate in the same market and engage in a non-cooperative game under complete information.

Hypothesis 2: Consumers exhibit low-carbon behavioral preferences, implying that higher carbon emissions reduce their willingness to recycle end-of-life batteries. Let p denote the market price of a new battery, and let P_1 and P_2 represent the recycling prices offered by recyclers R_1 and R_2 , respectively, where $P_1, P_2 > 0$, consistent with observed market practices. Recycler R_2 employs environmentally friendly recycling technologies that enable remanufacturing or repurposing of retired batteries with minimal pollution, whereas recycler R_1 generates severe environmental externalities while incurring relatively low technological costs. Accordingly, the unit recycling costs are assumed to be C_1 for recycler R_1 and $C_2 - \sigma e$ for recycler R_2 , where $C_2 > C_1 > 0$ [34]. The parameter e denotes the recycling

R&D effort of the whitelist-compliant enterprise, which improves the environmental performance of recycling while reducing its unit recycling cost. The parameter σ captures the cost-reduction efficiency of recycling R&D. Referring to the study of Long et al. [35] and Jian et al. [36], the R&D investment cost is assumed to be a quadratic function $\frac{\mu e^2}{2}$, with μ representing the R&D cost parameter.

Hypothesis 3: The recycling quantity of each recycler is jointly influenced by its own recycling price, the competitor's recycling price, and consumers' preferences for low-carbon recycling. Specifically, similar to the research of Lin et al. [37] and Gao et al. [38], the recycling quantities of recyclers R_1 and R_2 are given by $Q_1 = \alpha + \beta P_1 - \gamma P_2$ and $Q_2 = \alpha + \beta P_2 - \gamma P_1 + \eta e$, respectively. Here, $\alpha (\alpha \geq 0)$ denotes the baseline recycling quantity, $\beta > 0$ measures consumers' sensitivity to the recycler's own recycling price, and $\gamma > 0$ captures the substitution effect induced by the rival's recycling price, with $\beta > \gamma$. The parameter $\eta (\eta > 0)$ reflects consumers' environmental preference, indicating that stronger emission-reduction efforts by the whitelist-compliant enterprise increase its recycling quantity.

Hypothesis 4: Whitelist-compliant recyclers generally possess more advanced processing technologies and are therefore able to recover a higher residual value from collected batteries than informal recyclers. Accordingly, the residual values per unit of collected batteries are denoted by $k_2 p$ for the whitelist-compliant recycler and $k_1 p$ for the informal recycler, where $p > 0$ and $k_2 > k_1 > 0$ [39]. To encourage batteries to flow through regulated recycling channels, the government provides the whitelist-compliant recycler with a per-unit collection subsidy t . Thus, the total subsidy received by the whitelist-compliant recycler is tQ_2 [40]. In contrast, the informal recycler faces increasing regulatory exposure as its collection scale expands. A larger informal collection quantity makes its activities more visible to regulators and entails greater inspection, concealment, coordination, and expected penalty costs. We therefore represent the scale-dependent regulatory cost of the informal recycler by $\frac{\xi}{2} Q_1^2$, where $\xi > 0$ measures the intensity of regulatory pressure.

For the descriptions of the following models, Table 1 gives the main notations used in our research.

Based on the above assumptions, the benefit functions for recycled batteries from the whitelist-compliant enterprise and the black-market workshop are respectively

$$\pi_1 = \underbrace{(k_1 p - C_1 - P_1)Q_1}_{\text{Recycling revenue}} - \underbrace{\frac{\xi}{2} Q_1^2}_{\text{Regulatory cost}}, \quad (3.1)$$

$$\pi_2 = \underbrace{(k_2 p - C_2 - P_2 + \sigma e)Q_2}_{\text{Recycling revenue}} + \underbrace{tQ_2}_{\text{Government subsidy}} - \underbrace{\frac{\mu}{2} e^2}_{\text{R\&D cost}}. \quad (3.2)$$

As shown in Eqs. (3.1) and (3.2), the profit structures of the black-market workshop and the whitelist-compliant enterprise differ substantially. The black-market workshop's profit consists of its recycling revenue minus the scale-dependent expected regulatory cost. By contrast, the whitelist-compliant enterprise's profit consists of its recycling revenue and the government subsidy minus its recycling R&D cost. According to the functions of both parties' benefits, our study will analyze the game both from static and dynamic perspectives, both grounded in the scenario where the parties are engaged in a Bertrand game.

Table 1. Main notations.

Variables	Descriptions
$P_1(P_2)$	Recycling prices for recycler 1(2)
e	Recycling R&D effort of recycler 2
Parameters	Descriptions
R_1	Recycler 1 (black-market workshop)
R_2	Recycler 2 (whitelist-compliant enterprise)
$C_1(C_2)$	Unit recycling cost of recycler 1(2)
$Q_1(Q_2)$	Recycling quantity of recycler 1(2)
$\pi_1(\pi_2)$	Profit of recycler 1(2)
p	Price of unit new battery
α	Baseline recycling quantity
β	Parameter of price preference
γ	Parameter of substitute product price preference
η	Consumer low-carbon preference parameter
μ	Cost parameter of recycling technology R&D
σ	Efficiency of unit cost reduction through recycling technology R&D
ξ	Regulatory intensity parameter for the informal recycler
$k_1(k_2)$	Residual value ratio of unit recycled product
t	Unit subsidy for recycler 2's recycling quantity
$\theta_1, \theta_2, \theta_3$	Adjustment parameter of P_1, P_2, e

3.1. Static game

When both parties share the same market-determined sequence, the whitelist-compliant enterprise will make decisions regarding its product recycling price P_2 and recycling technology R&D effort e , while the black-market workshop will solely determine the recycling price P_1 . Since the profit function for the whitelist-compliant enterprise contains two core variables, P_2 and e , our study first calculates the Hessian matrix of π_2 with respect to P_2 and e , which is denoted as $\begin{bmatrix} -2\beta & -\eta + \beta\sigma \\ -\eta + \beta\sigma & -\mu + 2\eta\sigma \end{bmatrix}$. Thereby, when $\mu > \frac{(\eta + \beta\sigma)^2}{2\beta}$, the Hessian matrix is negative, and there is an extreme value. Furthermore, letting $\frac{\partial \pi_1}{\partial P_1} = 0$, $\frac{\partial \pi_2}{\partial P_2} = 0$, and $\frac{\partial \pi_2}{\partial e} = 0$, the game equilibrium can be calculated as

$$P_1 = \frac{\gamma(1 + \beta\xi)(\beta\mu - \eta^2 - \beta\eta\sigma)A_2 - \alpha(1 + \beta\xi)A_3 + \beta A_1 A_4}{M}, \quad (3.3)$$

$$P_2 = \frac{\beta(2 + \beta\xi)(\beta\mu - \eta^2 - \beta\eta\sigma)A_2 - (\alpha A_5 - \beta\gamma A_1)[\mu - \sigma(\eta + \beta\sigma)]}{M}, \quad (3.4)$$

$$e = \frac{(A_2 A_6 + \alpha A_5 - \beta\gamma A_1)(\eta + \beta\sigma)}{M}. \quad (3.5)$$

Among the equations, $M = (4\beta^2 - \gamma^2 + 2\beta^3\xi - \beta\gamma^2\xi)\mu - (\eta + \beta\sigma)[\eta(\beta^2\xi + 2\beta) + \sigma(\beta^3\xi + 2\beta^2 - \gamma^2 - \beta\gamma^2\xi)]$, $A_1 = k_1p - C_1$, $A_2 = k_2p - C_2 + t$, $A_3 = (2\beta + \gamma)\mu - \eta^2 - (2\beta + \gamma)\eta\sigma - \beta^2\sigma^2 - \beta\gamma\sigma^2$, $A_4 = 2\beta\mu - (\eta + \beta\sigma)^2$, $A_5 = \gamma + \beta^2\xi + \beta(2 + \gamma\xi)$, $A_6 = 2\beta^2 - \gamma^2 + \beta^3\xi - \beta\gamma^2\xi$, and $A_7 = (2\beta^2 - \gamma^2)(\mu - \eta\sigma) - \beta^3\sigma^2 - \beta(\eta^2 - \gamma^2\sigma^2)$.

To facilitate the analysis, we assume that $\mu_1 = \frac{(\eta+\beta\sigma)^2}{2\beta}$ and $\mu_2 = \frac{(\eta+\beta\sigma)[\eta(\beta^2\xi+2\beta)+\sigma(\beta^3\xi+2\beta^2-\gamma^2-\beta\gamma^2\xi)]}{4\beta^2-\gamma^2+2\beta^3\xi-\beta\gamma^2\xi}$. For the equilibrium result to be economically meaningful, the condition $M > 0$ must be satisfied, and thus we conclude that $\mu_2 > 0$. Given that $\mu_2 - \mu_1 = \frac{\gamma^2(1+\beta\xi)(\eta^2-\beta^2\sigma^2)}{2\beta(4\beta^2-\gamma^2+2\beta^3\xi-\beta\gamma^2\xi)}$, it can be obtained that $\mu > \begin{cases} \mu_1, & \eta \leq \beta\sigma \\ \mu_2, & \eta > \beta\sigma \end{cases}$.

Consequently, the equilibrium result of recycling quantity and recyclers' profits are

$$Q_1 = \frac{\beta[A_1A_7 + \alpha A_3 - \gamma(\beta\mu - \eta^2 - \beta\eta\sigma)A_2]}{M}, \quad (3.6)$$

$$Q_2 = \frac{\beta\mu(A_2A_6 + \alpha A_5 - \beta\gamma A_1)}{M}, \quad (3.7)$$

$$\pi_1 = \frac{\beta(2 + \beta\xi)[A_1A_7 + \alpha A_3 - \gamma(\beta\mu - \eta^2 - \beta\eta\sigma)A_2]^2}{2M^2}, \quad (3.8)$$

$$\pi_2 = \frac{\mu(A_2A_6 + \alpha A_5 - \beta\gamma A_1)^2 A_4}{2M^2}. \quad (3.9)$$

It is obvious that $A_1, A_2, A_4, A_5, A_6 > 0$. Further, we assume that $\mu_3 = \frac{(\eta+\beta\sigma)[\eta+(\beta+\gamma)\sigma]}{2\beta+\gamma}$ and $\mu_4 = \frac{\beta\eta^2+2\beta^2\eta\sigma-\gamma^2\eta\sigma+\beta^3\sigma^2-\beta\gamma^2\sigma^2}{2\beta^2-\gamma^2}$, then it is obtained that $\mu_3 - \mu_1 = -\frac{\gamma(\eta^2-\beta^2\sigma^2)}{2\beta(2\beta+\gamma)}$, $\mu_3 - \mu_2 = -\frac{\gamma A_5(\eta^2-\beta^2\sigma^2)}{(2\beta+\gamma)(4\beta^2-\gamma^2+2\beta^3\xi-\beta\gamma^2\xi)}$, $\mu_4 - \mu_1 = \frac{\gamma^2(\eta^2-\beta^2\sigma^2)}{4\beta^3-2\beta\gamma^2}$, and $\mu_4 - \mu_2 = \frac{\beta\gamma^2(\eta^2-\beta^2\sigma^2)}{(2\beta^2-\gamma^2)(4\beta^2-\gamma^2+2\beta^3\xi-\beta\gamma^2\xi)}$. Thus, when $\eta \geq \beta\sigma$, we can obtain that $\mu_3 \leq \mu_1, \mu_2$ and then $A_3 > 0$. When $\eta < \beta\sigma$, we can obtain that $\mu_3 > \mu_1, \mu_2$, thus $A_3 < 0$ if $\mu \in (\mu_1, \mu_3)$ and $A_3 \geq 0$ if $\mu \in [\mu_3, +\infty)$. On the contrary, when $\eta \leq \beta\sigma$, we can obtain that $\mu_4 \leq \mu_1, \mu_2$ and then $A_7 > 0$. When $\eta > \beta\sigma$, we can obtain that $A_7 < 0$ if $\mu \in (\mu_2, \mu_4)$ and $A_7 \geq 0$ if $\mu \in [\mu_4, +\infty)$.

In the regulated battery recycling market, the whitelist-compliant enterprise and the black-market workshop engage in Bertrand competition. Based on the static equilibrium, we focus on four key parameters: the formal recycler's R&D cost parameter μ , the informal recycler's regulatory cost parameter ξ , the effectiveness of the formal recycling effort in attracting consumers η , and the effectiveness of R&D effort in reducing unit recycling costs σ . **Propositions 1–4** examine how these parameters affect the equilibrium recycling prices, recycling quantities, formal recycling R&D effort, and the profits of both recyclers. The detailed proofs of **Propositions 1–4** are provided in the Supplementary Material. The effects identified in these propositions depend critically on the relative magnitude of η and $\beta\sigma$. Parameter η captures the demand expansion effect of the recycling R&D effort by attracting used batteries to the formal recycling channel, while $\beta\sigma$ reflects the cost reduction effect, where σ measures the reduction in unit recycling cost generated by the recycling R&D effort and β captures the response of recycling quantity to recycling price. Accordingly, when $\eta > \beta\sigma$, the demand-expansion effect dominates; when $\eta < \beta\sigma$, the cost-reduction effect dominates.

Proposition 1. *At the static equilibrium, e and Q_2 decrease as parameter μ increases. When $\eta > \beta\sigma$, P_1 and P_2 increase, whereas Q_1 and π_1 decrease as parameter μ increases. The effect of parameter μ on π_2 depends on the relative magnitude of η and $\beta\sigma$. When $\eta \geq \beta\sigma$, π_2 decreases as parameter μ increases; when $\eta < \beta\sigma$, π_2 increases for $\mu_1 < \mu < \mu_5$ and decreases for $\mu > \mu_5$.*

Proposition 1 shows how recycling R&D parameter μ affects market outcomes. A higher value of μ increases the marginal cost of emission reduction and reduces the optimal recycling R&D effort e . The decline in e directly weakens the demand expansion driven by consumers' low-carbon preference and

indirectly reduces Q_2 through cost effects. Therefore, e and Q_2 exhibit a robust monotonic response to μ , while the impact of μ on other market outcomes depends on the interaction between demand-expansion effects and cost-reduction effects. When the demand-expansion effect dominates, the reduction in e substantially weakens the attractiveness of compliant recycling, resulting in higher equilibrium recycling prices P_1 and P_2 and lower Q_1 and π_1 . Thus, deterioration in the R&D efficiency of the whitelist-compliant recycler does not necessarily benefit the black-market workshop, but may instead suppress recycling activities in both channels. However, for the whitelist-compliant recycler, the impact of μ on its profits is also influenced by other factors. When the demand-expansion effect dominates, the loss of competitive advantage exceeds the savings in R&D expenditure, and thus π_2 decreases with μ . When the cost-reduction effect dominates and μ remains below μ_5 , however, the savings in R&D expenditure outweigh the losses in demand and cost-reduction benefits, causing π_2 to increase. Once μ exceeds μ_5 , further reductions in e substantially weaken the competitive advantage of compliant recycling, and π_2 declines accordingly. These results indicate that the benefits of recycling R&D depend not only on technological efficiency but also on the strength of consumers' environmental preferences.

Proposition 2. *At the static equilibrium, e , Q_2 , and π_2 increase, whereas P_1 decreases as parameter ξ increases. The effect of parameter ξ on P_2 , Q_1 , and π_1 depends on the relative magnitude of η and $\beta\sigma$. When $\eta \leq \beta\sigma$, Q_1 and π_1 decrease as parameter ξ increases; when $\eta > \beta\sigma$, Q_1 increases for $\mu_2 < \mu < \mu_4$ and decreases for $\mu > \mu_4$ while π_1 increases for $\mu_2 < \mu < \mu_7$ and decreases for $\mu > \mu_7$. When $\eta \geq \beta\sigma$, P_2 decreases as parameter ξ increases; when $\eta < \beta\sigma$, P_2 increases for $\mu_1 < \mu < \mu_6$ and decreases for $\mu > \mu_6$.*

Proposition 2 shows how the regulatory parameter ξ affects market outcomes. A higher value of ξ increases the regulatory cost faced by the black-market workshop and weakens its competitive advantage. As the competitive pressure from informal recycling decreases, the whitelist-compliant recycler has stronger incentives to increase its recycling R&D effort e , leading to higher Q_2 and π_2 . At the same time, P_1 decreases, indicating that stronger regulation limits the ability of the black-market workshop to attract used batteries through high recycling prices. When the cost-reduction effect dominates, stronger regulation also reduces Q_1 and π_1 , showing that the regulatory cost effectively suppresses informal recycling. However, when the demand-expansion effect dominates and μ is relatively small, Q_1 and π_1 may instead increase with ξ . This occurs because stronger regulation not only directly raises the cost of informal recycling but also changes the equilibrium recycling decisions and prices of both recyclers. The resulting strategic response may temporarily outweigh the direct regulatory effect. Once μ exceeds the respective thresholds, these effects are reversed, and stronger regulation reduces Q_1 and π_1 . The response of P_2 also changes with the relative strength of the demand-expansion and cost-reduction effects. These results indicate that stronger regulation generally benefits compliant recycling, while its effect on black-market workshops depends on recycling technology and consumers' environmental preferences.

Proposition 3. *At the static equilibrium, e and Q_2 increase as parameter η increases. The effect of parameter η on P_1 , P_2 , Q_1 , π_1 , and π_2 depends on the relative magnitude of η and $\beta\sigma$. When $\eta \geq \beta\sigma$, P_1 and P_2 decrease while Q_1 and π_1 increase as parameter η increases; when $\eta < \beta\sigma$, P_1 and P_2 increase while Q_1 and π_1 decrease for $\mu_1 < \mu < \mu_8$. These effects are reversed when $\mu > \mu_8$. When $\eta \geq \beta\sigma$, π_2 increases with parameter η ; when $\eta < \beta\sigma$, π_2 decreases for $\mu_1 < \mu < \mu_9$ and increases for $\mu > \mu_9$.*

Proposition 3 shows how consumers' low-carbon preference parameter η affects market outcomes.

A higher η indicates a stronger consumer preference for low-carbon recycling, which increases the return from emission reduction and encourages the whitelist-compliant recycler to increase e . The increase in e further expands Q_2 . When the demand-expansion effect dominates, a higher η expands the recycling market, resulting in lower equilibrium recycling prices P_1 and P_2 and higher Q_1 and π_1 . Meanwhile, π_2 also increases because the benefit from market expansion outweighs the additional R&D expenditure associated with a higher e . This result suggests that stronger consumer environmental preference does not simply shift used batteries from the informal channel to the formal channel, but may benefit both recyclers through market expansion. When the cost-reduction effect dominates, however, these effects further depend on μ . When μ is relatively small, a higher η increases P_1 and P_2 but reduces Q_1 and π_1 , while these effects are reversed once μ exceeds μ_8 . Similarly, π_2 decreases with η for $\mu_1 < \mu < \mu_9$ because the additional R&D expenditure outweighs the benefit from stronger consumer preference, but increases once $\mu > \mu_9$. Thus, the market effects of stronger environmental preference depend on the recycling R&D effort.

Proposition 4. *At the static equilibrium, e and Q_2 increase as parameter σ increases. When $\eta \leq \beta\sigma$, P_1 and P_2 increase while Q_1 and π_1 decrease as parameter σ increases; when $\eta > \beta\sigma$, P_1 and P_2 decrease while Q_1 and π_1 increase for $\mu_2 < \mu < \mu_{10}$. These effects are reversed when $\mu > \mu_{10}$. The effect of σ on π_2 is parameter-dependent and cannot be determined unambiguously in the general case.*

Proposition 4 shows how the cost reduction parameter σ affects market outcomes. A higher value of σ improves the ability of the recycling R&D effort to reduce recycling costs, encouraging the whitelist-compliant recycler to increase e and further expanding Q_2 . When the cost-reduction effect dominates, a higher σ strengthens the cost advantage of compliant recycling, resulting in higher equilibrium recycling prices P_1 and P_2 and lower Q_1 and π_1 . This indicates that improved recycling technology can strengthen the competitive position of the whitelist-compliant recycler and reduce the market space of the black-market workshop. When the demand-expansion effect dominates, however, the competitive effect of σ further depends on μ . When μ is relatively small, a higher σ reduces P_1 and P_2 and increases Q_1 and π_1 , suggesting that technological improvement in compliant recycling may also benefit the informal channel through market expansion. Once μ exceeds μ_{10} , these effects are reversed as the high R&D cost weakens the benefits generated by technological improvement. The effect of σ on π_2 cannot be determined unambiguously because changes in σ simultaneously affect its recycling price, recycling quantity, recycling R&D effort, and R&D expenditure. This relationship is therefore further examined through numerical analysis.

3.2. Dynamic game

The static numerical analysis above characterizes how key parameters affect equilibrium outcomes in the static game. However, these results are obtained when decision-makers can instantaneously adjust their strategies to the equilibrium levels. In practice, recycling prices, quantities, and environmental efforts are typically updated gradually through bounded rational adjustments based on past outcomes [41]. Motivated by this consideration, we further investigate the dynamic stability of the system by introducing an adjustment mechanism within the parameter region where the static equilibrium is economically meaningful.

Over time, the recycling price P_1 of the black-market workshop, the recycling price P_2 , and the recycling R&D effort e of the whitelist-compliant enterprise are continuously adjusted according to

their respective marginal profit signals. Decisions in each period are revised based on the outcomes of the previous period. Accordingly, the adjustment directions are determined by the first-order partial derivatives of the profit functions with respect to the corresponding decision variables, given by $\frac{\partial \pi_1}{\partial P_1} = \beta A_1 - 2P_1\beta + \gamma P_2 - \beta^2\xi P_1 + \beta\gamma\xi P_2 - \alpha(1 + \beta\xi)$, $\frac{\partial \pi_2}{\partial P_2} = -\alpha + \beta(A_2 - 2P_2 + \sigma e) - \eta e + \gamma P_1$, and $\frac{\partial \pi_2}{\partial e} = -\mu e + \sigma(\alpha + \beta P_2 - \gamma P_1 + \eta e) + \eta(A_2 - P_2 + \sigma e)$. Let θ_1 , θ_2 , and θ_3 denote the adjustment speeds of P_1 , P_2 , and e , respectively, with $\theta_1, \theta_2, \theta_3 > 0$. Referring to the research of Ahmed et al. [28] and Liu et al. [29], the nonlinear dynamic system governing the evolution of P_1 , P_2 , and e can therefore be expressed as follows:

$$\begin{cases} P_1(t+1) = P_1(t) + \theta_1 P_1(t) \frac{\partial \pi_1}{\partial P_1}, \\ P_2(t+1) = P_2(t) + \theta_2 P_2(t) \frac{\partial \pi_2}{\partial P_2}, \\ e(t+1) = e(t) + \theta_3 e(t) \frac{\partial \pi_2}{\partial e}. \end{cases} \quad (3.10)$$

From an economic perspective, neither the black-market workshop nor the whitelist-compliant enterprise will set their recycling prices to 0. Thereby boundary solutions with $P_1 = 0$ or $P_2 = 0$ are excluded from consideration [28]. Under this restriction, the dynamic system (Eq. 10) admits two economically meaningful equilibrium points: equilibrium E^0 , in which the whitelist-compliant enterprise exerts zero recycling R&D effort, and equilibrium E^* , in which all strategic variables are strictly positive. Specifically, these equilibria are defined as $E^0 = \{\frac{\partial \pi_1}{\partial P_1} = 0, \frac{\partial \pi_2}{\partial P_2} = 0, e = 0\}$ and $E^* = \{\frac{\partial \pi_1}{\partial P_1} = 0, \frac{\partial \pi_2}{\partial P_2} = 0, \frac{\partial \pi_2}{\partial e} = 0\}$. Furthermore, by analyzing the equilibrium point and local stability, we obtain **Propositions 5-6**.

Proposition 5. *The boundary equilibrium point $E^0(P_1^0, P_2^0, 0)$ of system (Eq. 3.10) is unstable.*

Based on the requirements of dynamic equilibrium, the game equilibrium point can be denoted as $E^0 = (P_1^0, P_2^0, 0)$ when $e = 0$. Here, $P_1^0 = \frac{-\alpha(2\beta+\gamma)(1+\beta\xi)+\beta[2\beta A_1+\gamma(1+\beta\xi)A_2]}{4\beta^2-\gamma^2+2\beta^3\xi-\beta\gamma^2\xi}$ and $P_2^0 = \frac{\beta[\gamma A_1+\beta(2+\beta\xi)A_2]-\alpha[\gamma+\beta^2\xi+\beta(2+\gamma\xi)]}{4\beta^2-\gamma^2+2\beta^3\xi-\beta\gamma^2\xi}$. At this time, the stability of equilibrium point $E^0 = (P_1^0, P_2^0, 0)$ through the Jacobian matrix of the dynamic system (Eq. 3.10), which can be drawn as

$$J(E^0) = \begin{bmatrix} Z_1 & \theta_1\gamma(1+\beta\xi)P_1^0 & 0 \\ \theta_2\gamma P_2^0 & Z_2 & -\theta_2 P_2^0(\eta - \beta\sigma) \\ 0 & 0 & Z_3 \end{bmatrix}. \quad (3.11)$$

Among Eq. (3.11), $Z_1 = 1 + \theta_1 [\beta A_1 - 4\beta P_1^0 + \gamma P_2^0 - 2\beta^2\xi P_1^0 + \beta\gamma\xi P_2^0 - \alpha(1 + \beta\xi)]$, $Z_2 = 1 + \theta_2(-\alpha + \beta A_2 - 4\beta P_2^0 + \gamma P_1^0)$, and $Z_3 = 1 + \theta_3(\eta A_2 - \eta P_2^0 + \alpha\sigma + \beta\sigma P_2^0 - \gamma\sigma P_1^0)$.

According to the stability criterion for equilibrium in the Jury criterion, if the eigenvalues are nonzero and their absolute values are greater 1, then this equilibrium point is unstable [28,42]. Substitute P_1^0 and P_2^0 for Z_3 , and it can be calculated that $A_2 > P_2^0$ and $\alpha + \beta P_2^0 - \gamma P_1^0 > 0$. Since it is easy to verify that the matrix $J(E^0)$ has the eigenvalue $\lambda = |Z_3| > 1$, $J(E^0)$ is an unstable equilibrium point.

Proposition 6. *The interior Nash equilibrium point $E^*(P_1^*, P_2^*, e^*)$ is locally asymptotically stable if and only if the Jury stability conditions are satisfied.*

The Jacobian matrix of equilibrium point $E^*(P_1^*, P_2^*, e^*)$ is

$$J(E^*) = \begin{bmatrix} Z_4 & \theta_1\gamma(1 + \beta\xi)P_1^* & 0 \\ \theta_2\gamma P_2^* & Z_5 & -\theta_2P_2^*(\eta - \beta\sigma) \\ -\theta_3\gamma\sigma e^* & -\theta_3e^*(\eta - \beta\sigma) & Z_6 \end{bmatrix}. \quad (3.12)$$

Among Eq. (3.12), $Z_4 = 1 + \theta_1[\beta A_1 - 4\beta P_1^* + \gamma P_2^* - 2\beta^2\xi P_1^* + \beta\gamma\xi P_2^* - \alpha(1 + \beta\xi)]$, $Z_5 = 1 + \theta_2[-\alpha + \beta(A_2 - 4P_2^* + \sigma e^*) - \eta e^* + \gamma P_1^*]$, and $Z_6 = 1 + \theta_3[-2\mu e^* + \eta(A_2 - P_2^*) + \sigma(\alpha + \beta P_2^* - \gamma P_1^* + 4\eta e^*)]$.

Because the characteristic polynomial is of third order and analytical eigenvalues are intractable, Jury's stability criterion is employed to derive necessary and sufficient conditions for local stability.

Based on Jacobian matrix $J(E) = \begin{bmatrix} J_{11} & J_{12} & J_{13} \\ J_{21} & J_{22} & J_{23} \\ J_{31} & J_{32} & J_{33} \end{bmatrix}$, the characteristic polynomial representation of

Jury's criterion is $f(\lambda) = |\lambda E - J| = \lambda^3 + U_2\lambda^2 + U_1\lambda + U_0$. Here, $U_0 = J_{13}J_{22}J_{31} - J_{12}J_{23}J_{31} - J_{13}J_{21}J_{32} + J_{11}J_{23}J_{32} + J_{12}J_{21}J_{33} - J_{11}J_{22}J_{33}$, $U_1 = -J_{12}J_{21} + J_{11}J_{22} - J_{13}J_{31} - J_{23}J_{32} + J_{11}J_{33} + J_{22}J_{33}$, and $U_2 = -(J_{11} + J_{22} + J_{33})$.

According to the stability criterion for equilibrium in the Jury criterion, the necessary and sufficient condition for the local stability of Nash equilibrium $J(E^*)$ is

$$\begin{cases} f(1) = 1 + U_2 + U_1 + U_0 > 0, \\ f(-1) = -1 + U_2 - U_1 + U_0 < 0, \\ |U_0| < 1, \\ |U_0^2 - 1| > |U_0U_2 - U_1|. \end{cases} \quad (3.13)$$

4. Numerical simulation

To further illustrate the analytical results in the previous section, numerical simulations in this section serve two primary objectives. First, based on the results derived from the static equilibrium, we visualize the impact of key parameters on equilibrium outcomes from a static game perspective. Second, by embedding the static equilibrium outcomes into a dynamic adjustment process, we further examine the stability properties of the dynamic system and trace the evolutionary paths of strategic decisions over time. By combining static and dynamic numerical results, this study aims to provide deep insights into how technological conditions, environmental regulation, consumer low-carbon preferences, and strategic competition interact in the recycling market.

4.1. Static game perspective

In this part, we will examine the effects of key parameters on the equilibrium decisions of recyclers R_1 and R_2 . According to **Propositions 1–4**, the effects of R&D cost parameter μ , regulatory intensity parameter ξ , consumer low-carbon preference parameter η , and R&D cost-reduction parameter σ depend not only on the relative magnitude of η and $\beta\sigma$, but also, for some equilibrium outcomes, on several threshold conditions. Therefore, the numerical analysis focuses on these four parameters to illustrate both the comparative-static results and representative threshold effects. Since some threshold values vary with the parameters under consideration, representative values of μ located in different threshold

intervals are selected when necessary. Accordingly, drawing on previous research and incorporating practical characteristics, the benchmark parameter values used in the numerical simulation are set as follows: $\alpha = 10$, $\beta = 1.6$, $\gamma = 1$, $t = 3$, $p = 120$, $k_1 = 0.25$, $k_2 = 0.40$, $C_1 = 10$, and $C_2 = 30$ [43–45].

4.1.1. Impacts of μ on equilibrium results

To examine the impact of R&D cost parameter μ , we consider two cases according to the relative magnitude of η and $\beta\sigma$. Specifically, $\eta = 1.5$ and $\eta = 2.5$ represent the cases of $\eta < \beta\sigma$ and $\eta > \beta\sigma$, respectively, while $\sigma = 1.5$ and $\xi = 0.2$ are fixed. Since the feasible range of μ varies with η , we set $7 \leq \mu \leq 30$ for $\eta = 1.5$ and $9 \leq \mu \leq 30$ for $\eta = 2.5$. The results are shown in Figure 1.

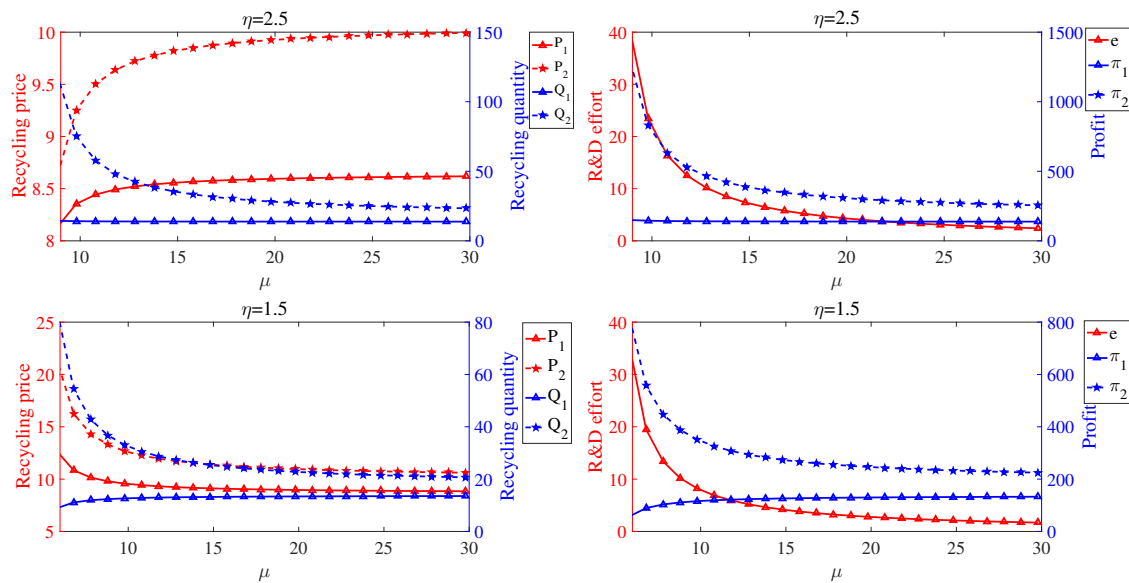


Figure 1. Impacts of parameter μ on game results.

Figure 1 shows the impact of recycling technology R&D cost parameter μ under the cases of $\eta < \beta\sigma$ and $\eta > \beta\sigma$. Consistent with **Proposition 1**, an increase in μ reduces e and Q_2 in both cases, indicating that higher R&D costs directly weaken the R&D incentive of recycler R_2 . In contrast, the effects on recycling prices P_i , quantity Q_1 , and profits π_i depend on the relative strength of the demand-expansion and cost-reduction effects. When $\eta > \beta\sigma$, the demand-expansion effect dominates. Higher μ reduces R&D effort of recycler R_2 and weakens the demand generated by its low-carbon advantage, resulting in higher recycling prices but lower recycling quantities and profits of both recyclers. When $\eta < \beta\sigma$, the cost-reduction effect dominates. Higher μ weakens the technological cost advantage of recycler R_2 , leading to lower P_1 and P_2 , while part of the recycling quantity shifts toward recycler R_1 , and thus Q_1 and π_1 increase. Although **Proposition 1** identifies a threshold effect of μ on π_2 when $\eta < \beta\sigma$, Figure 1 focuses on the overall comparative-static pattern over the economically feasible range of μ . More importantly, the numerical results reveal a clear difference in the magnitude of these effects. Changes in μ have substantial effects on e , Q_2 , and π_2 , whereas Q_1 and π_1 change only slightly, especially when $\eta > \beta\sigma$. This is because μ directly affects the R&D activities of recycler R_2 , while recycler R_1 is affected only indirectly through competition for recycling quantities. Therefore, changes in R&D costs are mainly absorbed by the compliant recycling channel rather than being fully transmitted to the informal recycler.

4.1.2. Impacts of ξ on equilibrium results

To examine the impact of regulatory intensity parameter ξ , we focus on the case of $\eta < \beta\sigma$, with $\eta = 1$ and $\sigma = 1.5$. According to **Proposition 2**, the effects of ξ on several equilibrium outcomes are robust, whereas some effects depend on μ . Therefore, $\mu = 30$ and $\mu = 4.5$ are selected to represent different R&D cost conditions, with $0.1 \leq \xi \leq 0.5$. The results are shown in Figure 2.

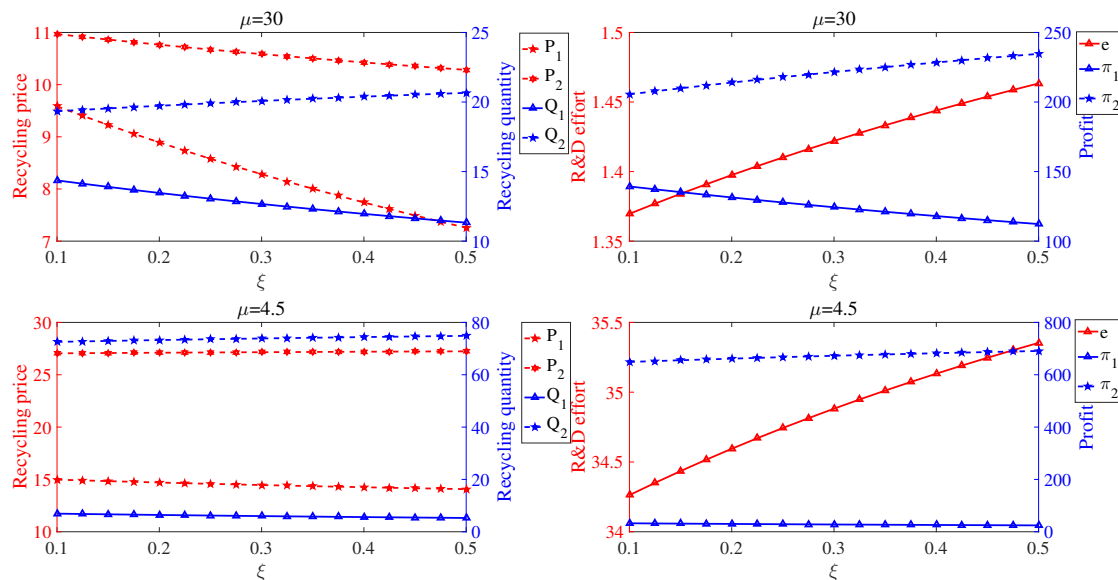


Figure 2. Impacts of parameter ξ on game results.

Figure 2 shows the impact of regulatory intensity parameter ξ when $\eta < \beta\sigma$ under different R&D cost conditions. Consistent with **Proposition 2**, an increase in ξ reduces P_1 but increases e , Q_2 , and π_2 for both $\mu = 30$ and $\mu = 4.5$, indicating that stronger regulation weakens the competitive position of recycler R_1 and benefits the compliant recycling channel. When $\mu = 30$, the effects of ξ exhibit clear and stable monotonic patterns. In particular, P_1 and P_2 decrease, while Q_2 , e , and π_2 increase as ξ increases. Stronger regulation raises the operating burden of the black-market workshop, allowing recycler R_2 to strengthen its recycling advantage and R&D effort. When $\mu = 4.5$, the robust effects on P_1 , Q_2 , e , and π_2 remain unchanged, whereas P_2 shows a different response, confirming that the effect of regulation on the pricing decision of recycler R_2 depends on R&D cost conditions. Moreover, Q_1 and π_1 decrease more noticeably when $\mu = 30$, whereas their changes remain relatively small when $\mu = 4.5$. This suggests that the impact of stronger regulation on the informal recycler also depends on R&D cost conditions, while the compliant recycler consistently benefits from stronger regulation. Overall, Figure 2 indicates that regulatory intensity has a stable positive effect on the development of the compliant recycling channel, but its influence on market pricing is conditioned by recycler R_2 's R&D efficiency.

4.1.3. Impacts of η on equilibrium results

To examine the impact of consumer low-carbon preference parameter η , we focus on the case of $\eta < \beta\sigma$, where several effects depend on the threshold conditions of μ . In contrast, when $\eta \geq \beta\sigma$, the directions of these effects are clearly determined in **Proposition 3**. Therefore, $\sigma = 1.5$ and $\xi = 0.2$

are fixed, and $\mu = 30$ and $\mu = 5$ are selected to represent different different R&D cost conditions, with $0.5 \leq \eta \leq 1.2$. The results are shown in Figure 3.

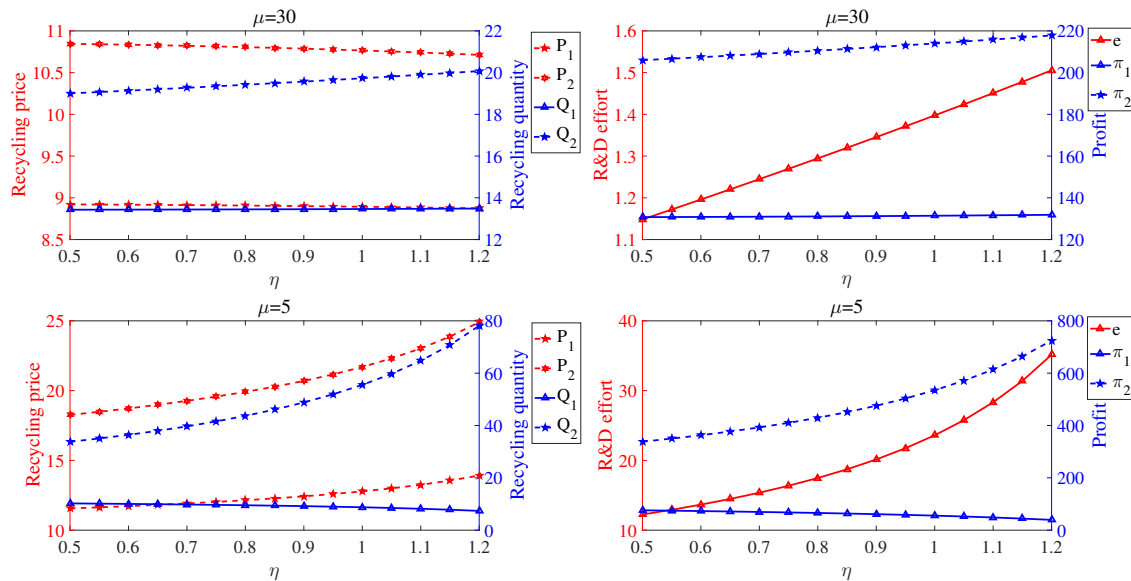


Figure 3. Impacts of parameter η on game results.

Figure 3 shows the impact of consumer low-carbon preference parameter η under different R&D cost conditions. Consistent with **Proposition 3**, an increase in η increases e and Q_2 for both $\mu = 30$ and $\mu = 5$, while the effects on P_1 , P_2 , Q_1 , and π_1 depend on the threshold conditions associated with μ . This conditional effect is particularly evident for P_1 : As η increases, P_1 slightly decreases when $\mu = 30$ but increases when $\mu = 5$. The responses of the other conditional variables are relatively moderate within the considered parameter range. Moreover, Figure 3 shows that increasing η has much stronger effects on Q_2 and π_2 than on Q_1 and π_1 , particularly when $\mu = 5$. A stronger consumer low-carbon preference directly expands the recycling demand for recycler R_2 , which further stimulates its R&D effort and improves its market performance. In contrast, recycler R_1 does not directly benefit from consumer low-carbon preferences and is mainly affected through the competitive interaction with recycler R_2 . Therefore, the effects transmitted to its recycling quantity and profit are relatively limited. These results indicate that stronger consumer low-carbon preferences mainly promote the compliant recycling channel, while their influence on the informal recycling channel is comparatively weak.

4.1.4. Impacts of σ on equilibrium results

To examine the impact of R&D cost-reduction efficiency parameter σ , we focus on the case of $\eta > \beta\sigma$, where several effects are associated with the threshold conditions of μ . Accordingly, $\eta = 3$ and $\xi = 0.2$ are fixed, and $\mu = 15$ and $\mu = 10$ are selected to represent different threshold conditions, with $0.8 \leq \sigma \leq 1.2$. The results are shown in Figure 4.

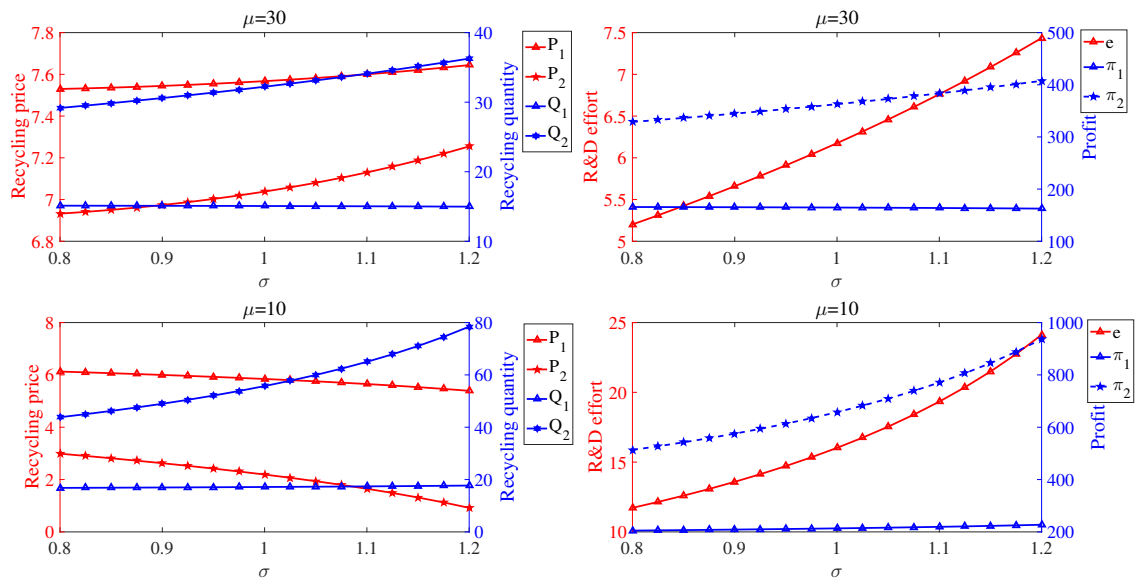


Figure 4. Impacts of parameter σ on game results.

Figure 4 shows the impact of R&D cost-reduction efficiency parameter σ when $\eta > \beta\sigma$ under different R&D cost conditions. Consistent with **Proposition 4**, an increase in σ increases e , Q_2 , and π_2 for both $\mu = 10$ and $\mu = 30$, indicating that a higher cost-reduction efficiency strengthens the technological and market advantages of recycler R_2 . In contrast, the effects on P_1 , P_2 , Q_1 , and π_1 depend on the threshold conditions of μ . This conditional effect is particularly evident in recycling prices. When $\mu = 30$, both P_1 and P_2 increase with σ , whereas they decrease when $\mu = 10$. Higher σ allows recycler R_2 to obtain greater cost savings from a given level of R&D effort, but the resulting pricing response depends on the R&D cost environment. When R&D costs are relatively high, recyclers tend to maintain higher recycling prices as technological efficiency improves; when R&D costs are lower, the stronger cost advantage enables more aggressive price adjustment and market expansion. Although the directions of Q_1 and π_1 also vary with μ , their changes are relatively small in both cases. By comparison, Q_2 , e , and π_2 respond much more strongly to changes in σ . This is because σ directly determines the cost-reduction benefit obtained by recycler R_2 , while its effect on recycler R_1 is transmitted indirectly through market competition. Therefore, improving R&D efficiency mainly strengthens the compliant recycling channel, while its impact on the quantity and profit of the informal recycler remains limited.

Overall, the numerical results in Figures 1–4 are consistent with **Propositions 1–4**, while providing further insights into the magnitude and conditional effects of the key parameters. In particular, μ , ξ , η , and σ exhibit considerably different degrees of influence on equilibrium outcomes, with the R&D effort, recycling quantity, and profit of recycler R_2 generally showing stronger responses than the corresponding market outcomes of recycler R_1 . Moreover, the numerical results illustrate how the effects on recycling prices, quantities, and profits vary across different threshold conditions. These findings complement the analytical results by revealing not only the direction of parameter effects but also their relative magnitude and threshold-dependent differences from a static game perspective. The following analysis further extends the static results to a dynamic setting to examine the stability and evolutionary behavior of the recycling system.

4.2. Dynamic game perspective

The static numerical simulations above elucidate how key parameters influence equilibrium outcomes. In this section, we analyze the local stability region of the static-game equilibrium with respect to the adjustment speeds and investigate how adjustment speeds and policy interventions affect the system's dynamic behavior. By integrating bifurcation diagrams, largest Lyapunov exponents (LLEs), time series, phase portraits, and two-parameter dynamical state diagrams, we further reveal the long-term dynamic characteristics of the battery recycling market and the individual and joint effects of regulatory pressure and subsidies.

4.2.1. Nash equilibrium and local stability

First, we adopt a representative parameter setting consistent with the parameter ranges used in the static analysis: $\alpha = 10$, $\beta = 1.6$, $\gamma = 1$, $\eta = 2.5$, $\mu = 20$, $t = 3$, $\sigma = 1.5$, $p = 120$, $k_1 = 0.25$, $k_2 = 0.4$, $C_1 = 10$, and $C_2 = 30$. Substituting these parameters into the equilibrium solutions yields the Nash equilibrium E^* , which is $(P_1^* = 8.59, P_2^* = 9.92, e^* = 4.29)$. The corresponding recycling quantities and profits are $Q_1^* = 13.82$, $Q_2^* = 28.01$, $\pi_1^* = 138.56$, and $\pi_2^* = 306.42$. Based on the Jury criterion, the local stability region of E^* with respect to the adjustment parameters θ_1 , θ_2 , and θ_3 can then be determined. Figure 5 presents the three-dimensional stability region, while Figure 6 compares stability boundaries in the θ_1 - θ_2 and θ_1 - θ_3 planes under different fixed values of θ_3 and θ_2 , respectively.

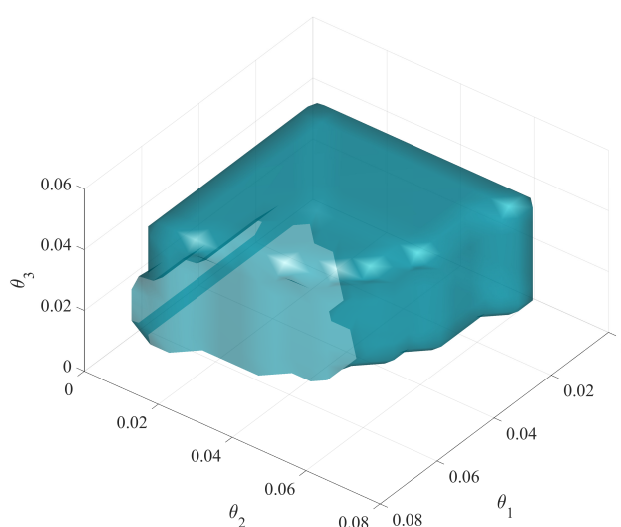


Figure 5. Stability region in the three-dimensional adjustment-speed space.

Figure 5 illustrates the stability region of equilibrium point E^* in the three-dimensional adjustment-speed $(\theta_1, \theta_2, \theta_3)$ space. The results show that the system remains locally stable within a bounded domain where all adjustment speeds are relatively small, and excessively rapid adjustments may destabilize the equilibrium. Additionally, the stable region exhibits a continuous but asymmetric structure, indicating that system stability depends jointly on the adjustment speeds of the three decision variables. Once the adjustment parameters move beyond the stability boundary, the equilibrium E^* loses local stability, and the system may exhibit periodic oscillations, complex fluctuations, or chaotic behavior.

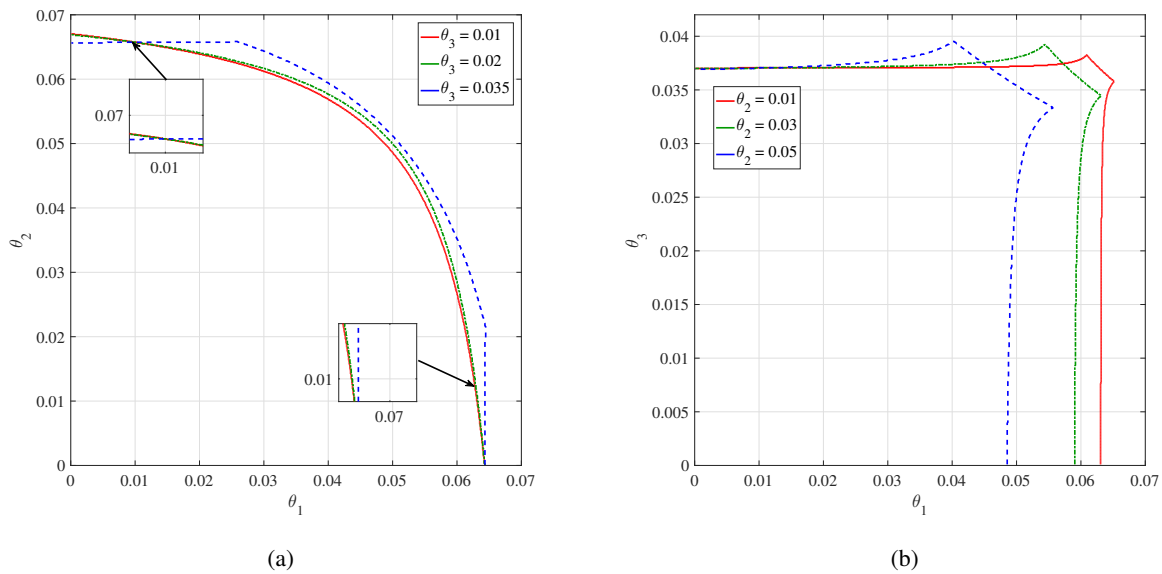


Figure 6. Two-dimensional stability boundaries under different adjustment speeds.

Figure 6 further compares two-dimensional stability boundaries under different adjustment speeds. Within the parameter range examined, changes in θ_3 produce relatively small boundary shifts in the θ_1 - θ_2 plane, whereas changes in θ_2 more noticeably reshape the boundary in the θ_1 - θ_3 plane, particularly at higher values of θ_1 . These results indicate that the admissible range of each adjustment speed depends on the adjustment speeds of the other decision variables.

4.2.2. Bifurcation behavior and Lyapunov exponent

Second, to further examine how changes in adjustment speed affect the dynamic behavior of the system, we fix $\theta_2 = 0.02$ and $\theta_3 = 0.02$ and analyze the impact of θ_1 on the system over the range $0 \leq \theta_1 \leq 0.1$. We employ bifurcation diagrams to reveal the long-term state evolution patterns as the adjustment speed varies, and calculate the LLE to quantitatively identify the onset of chaos, as shown in Figure 7(a)–(c). We further present two-parameter dynamical state diagrams in the θ_1 - θ_2 plane with $\theta_3 = 0.02$ and the θ_1 - θ_3 plane with $\theta_2 = 0.02$, as shown in Figure 7(d)–(e), respectively, to examine the joint effects of adjustment speeds on the distribution of steady, periodic, and complex states, as well as divergent trajectories.

Figure 7(a)–(b) respectively display the bifurcation diagrams of recycling prices and R&D effort as the adjustment parameter θ_1 varies. When θ_1 is sufficiently small, the system converges to a stable equilibrium. Around $\theta_1 \approx 0.06$, the equilibrium loses stability, and prices begin to exhibit periodic fluctuations. As θ_1 increases further, both recycling prices and R&D effort undergo successive bifurcations and increasingly complex fluctuations. At higher adjustment speeds, dense and irregular branches emerge, indicating more complex dynamic behavior. Moreover, the bifurcation structure of e closely resembles that of P_i , with similar critical thresholds, reflecting the coupled responses of pricing and R&D decisions. Figure 7(c) illustrates the corresponding variation in the LLE, providing a quantitative indicator of dynamic stability and chaotic behavior. At low values of θ_1 , the LLE remains negative, consistent with convergence to the stable equilibrium. As θ_1 increases, the LLE

approaches zero at bifurcation thresholds and subsequently fluctuates between negative and positive values, reflecting periodic and chaotic parameter intervals. Positive LLE values indicate sensitivity to initial conditions and support the identification of chaotic dynamics in the corresponding regions. Figure 7(d)–(e) extend this analysis to the θ_1 - θ_2 and θ_1 - θ_3 planes, distinguishing steady states, different periodic states, complex dynamics, and divergence. In Figure 7(d), increasing θ_2 progressively reduces the range of θ_1 compatible with steady convergence. In Figure 7(e), this range changes relatively little at lower values of θ_3 but contracts more noticeably as θ_3 increases. Periodic bands along parts of the steady-state boundaries further illustrate transitions toward more complex dynamics. These results demonstrate that the single-parameter bifurcation threshold is conditional on the other adjustment speeds, highlighting the need to coordinate price and R&D adjustments to maintain market stability.

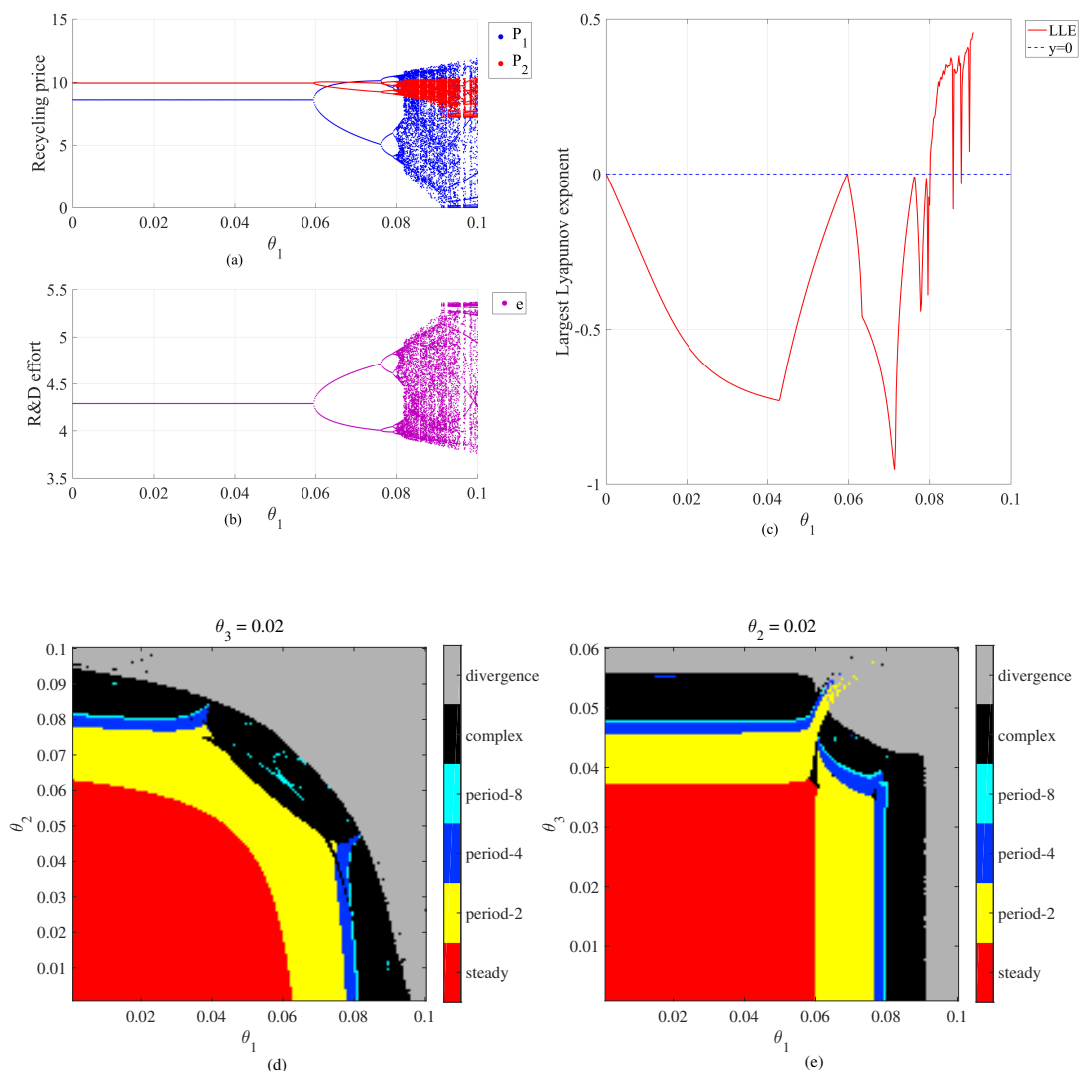


Figure 7. Bifurcation characteristics and dynamical states of the system.

4.2.3. Time series evolution

Then, we further discuss the time series evolution of pricing P_i and R&D effort e under different values of adjustment speed parameter θ_1 . Accordingly, we still set $\theta_2 = \theta_3 = 0.02$. By selecting different values of θ_1 for each state in Figure 7, we examine the time series evolution of P_i and e at $\theta_1 = 0.05$, $\theta_1 = 0.065$, $\theta_1 = 0.08$, and $\theta_1 = 0.085$ as shown in Figure 8.

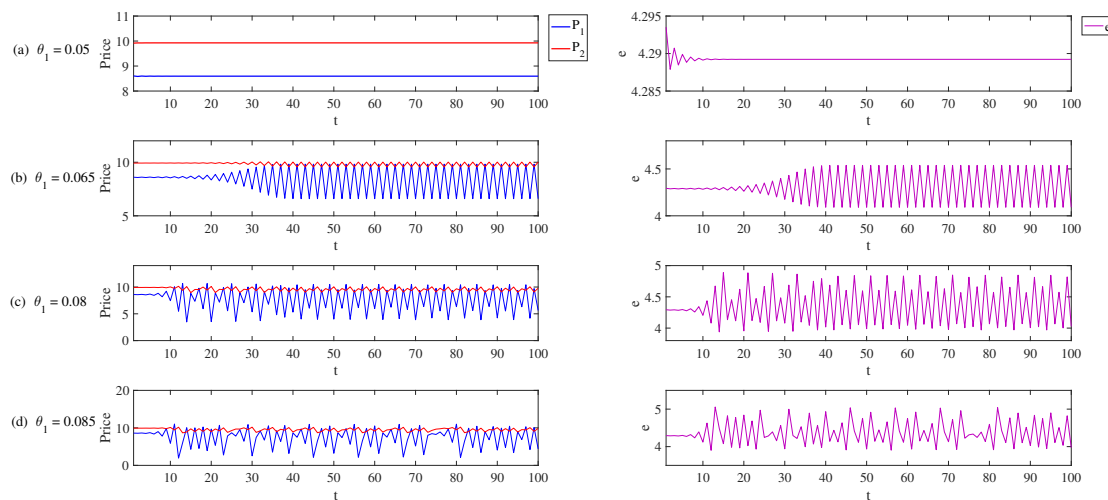


Figure 8. Time series evolution under different values of θ_1 .

Figure 8 illustrates the time-domain evolution of pricing P_i and R&D effort e under different values of adjustment parameter θ_1 . The results reveal a clear transition from stable equilibrium to periodic oscillations and eventually chaotic dynamics as θ_1 increases. When $\theta_1 = 0.05$, all state variables converge to a unique steady state. Both prices stabilize rapidly without oscillations, and R&D effort e converges smoothly to its equilibrium level. This corresponds to the stable region in the bifurcation diagram, where the LLE is negative. When $\theta_1 = 0.065$, the steady state loses stability, and a stable periodic oscillation emerges. P_i and e both exhibit sustained oscillations. This behavior aligns with the first bifurcation observed in the bifurcation diagram, indicating that instability arising from excessive parameter adjustments has begun to manifest. When $\theta_1 = 0.08$, the trajectories of P_i and e display high-frequency fluctuations with more complex multi-periodic oscillations. This indicates that the dynamic behavior becomes increasingly complex as θ_1 increases. At $\theta_1 = 0.085$, the system transitions into a chaotic state. Here, the fluctuations of P_i and e become highly irregular, exhibiting non-periodic oscillations with dramatically fluctuating amplitudes. This phenomenon corresponds to the irregular scatter region in the bifurcation diagram, accompanied by positive LLE values. Collectively, these results indicate that the excessively rapid price adjustment rate of recycler R_1 is sufficient to destabilize the entire recycling market system, even when other adjustment rates remain moderate.

4.2.4. Phase portraits and dynamic characteristics

Since the above numerical simulations mainly focus on the local stability issue of the system, this part further explores the dynamic behavior from the phase-space perspective. We fix $\theta_2 = \theta_3 = 0.02$, vary θ_1 , and examine the resulting evolution of P_i and e through phase portraits. Accordingly, Figure 9

illustrates the phase portraits of the system when $\theta_1 = 0.06$, $\theta_1 = 0.08$, $\theta_1 = 0.085$, and $\theta_1 = 0.09$, with $\theta_2 = \theta_3 = 0.02$.

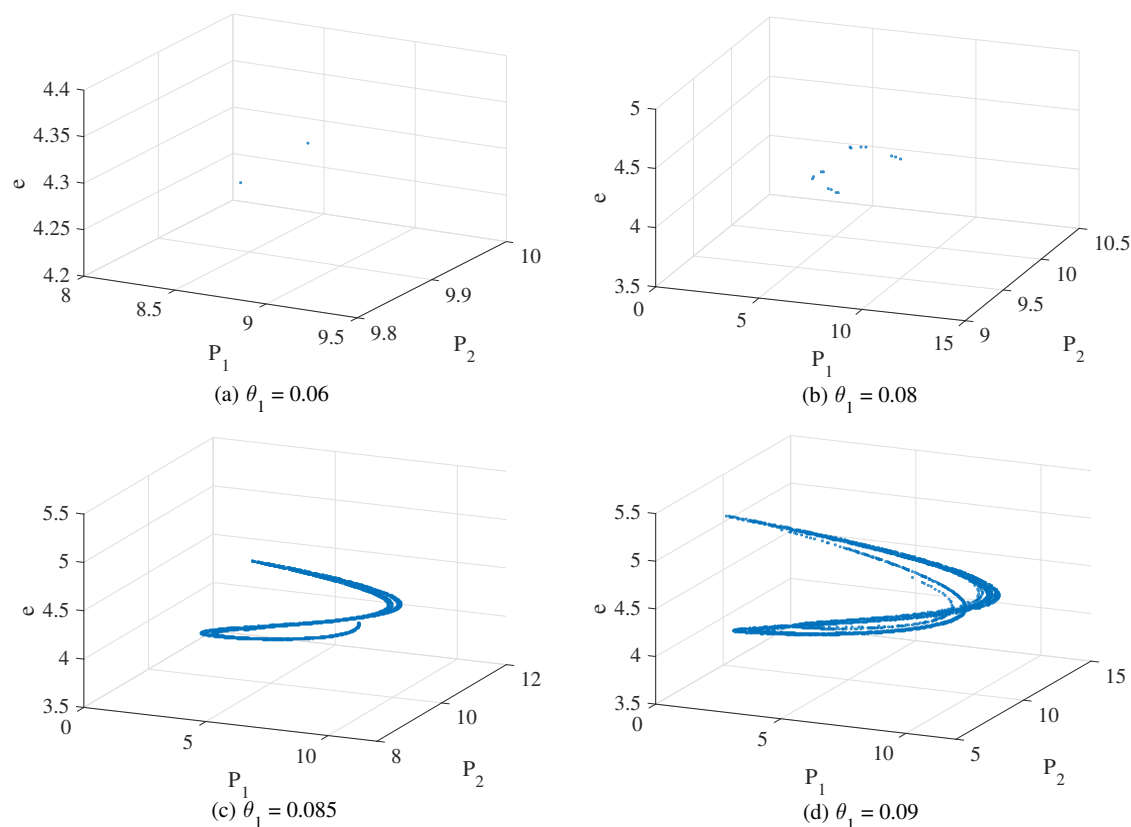


Figure 9. Phase portraits of system (3.10) under different values of θ_1 .

The evolution of the system exhibits a clear transition from stable equilibrium to periodic oscillations and eventually to chaotic dynamics as θ_1 increases. When $\theta_1 = 0.06$, the system is close to the boundary at which the stable equilibrium loses stability. As shown in Figure 9(a), the trajectories remain relatively concentrated, indicating relatively regular dynamic behavior. When $\theta_1 = 0.08$, the equilibrium point becomes unstable, and the system exhibits persistent oscillations, as illustrated in Figure 9(b). The phase trajectory forms closed trajectories, implying that the system fluctuates in a regular oscillatory pattern around the equilibrium rather than converging to it. This suggests that adjustment introduces cyclical behavior in the decision variables. When $\theta_1 = 0.085$, the oscillations become more pronounced. Figure 9(c) shows more complex phase trajectories, indicating increasingly complicated fluctuations. In this regime, the system no longer settles at the equilibrium point but instead maintains sustained fluctuations over time. When $\theta_1 = 0.09$, the phase trajectory becomes irregular, as shown in Figure 9(d). The system no longer follows a regular cycle, reflecting the emergence of complex and unstable dynamics. Overall, the phase portraits provide an intuitive visualization of how the system's behavior evolves as θ_1 increases. Combined with the analysis of bifurcation and LLE, these findings suggest that excessively rapid adjustments may destabilize the system, implying that overly aggressive adjustment behaviors by market participants could undermine market stability in the long run.

4.2.5. Individual and joint effects of policy interventions on dynamic stability

In addition to the adjustment speeds, government interventions may also affect the dynamic stability of the recycling market. In the dual-track recycling system, the regulatory intensity ξ imposes additional constraints on the black-market workshop R_1 , whereas the subsidy t provides direct economic incentives for the whitelist-compliant recycler R_2 . Therefore, this section further examines the individual and joint effects of these two policy instruments on stability regions and long-term dynamic outcomes. Specifically, we first analyze the dynamic effects of regulatory intensity ξ and then investigate the effects of government subsidy t . Finally, we examine their joint effects in the t - ξ plane under different adjustment-speed configurations to identify how policy combinations shape the system's dynamic states.

First, we examine the dynamic effect of regulatory intensity ξ . For the stability-region analysis in Figure 10(a), θ_3 is fixed at 0.020, while θ_1 and θ_2 vary to determine the stability boundary under different values of ξ . For the dynamic analysis in Figure 10(b)–(h), we set $\theta_1 = 0.080$, $\theta_2 = 0.025$, and $\theta_3 = 0.020$, while keeping the other benchmark parameters unchanged. Figure 10 presents the changes in the stability region and the long-term dynamic outcomes as ξ varies.

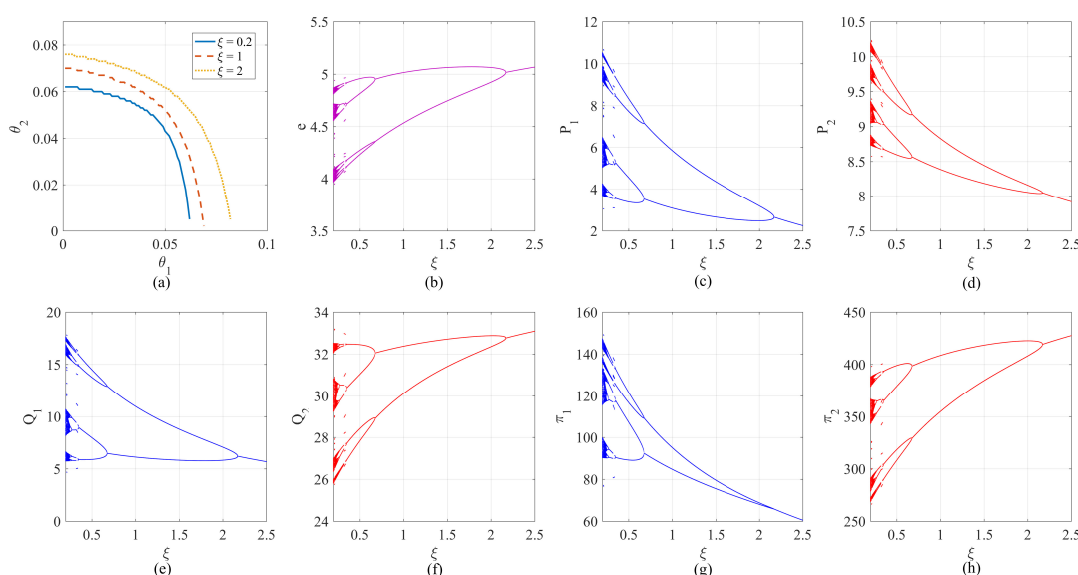


Figure 10. Impacts of regulatory intensity ξ on system stability and dynamic outcomes.

Figure 10 further examines the impact of regulatory intensity ξ on the dynamic stability and long-term outcomes of the recycling system. As shown in Figure 10(a), an increase in ξ expands the local stability region in the plane, indicating that stronger regulation improves the system's tolerance to behavioral adjustment. Figure 10(b)–(h) further show that, under the given adjustment speeds, the dynamic trajectories gradually change from complex fluctuations to more regular patterns as ξ increases. Meanwhile, the overall changes in recycling prices, quantities, R&D effort, and profits are consistent with the main directions identified in the static analysis, although these variables exhibit periodic or complex fluctuations under relatively weak regulation. As regulatory intensity increases, these fluctuations gradually weaken, and the trajectories become more regular, indicating that stronger regulation can suppress the amplification of strategic adjustments between the two recyclers. This

suggests that stronger regulation not only affects the equilibrium decisions identified in the static analysis but also plays a stabilizing role in the dynamic recycling market. Therefore, increasing regulatory intensity within an appropriate range can improve market stability by reducing the dynamic fluctuations arising from the competition between formal and informal recycling channels.

In contrast to regulatory penalties imposed on the black-market workshop, government subsidies directly incentivize the whitelist-compliant recycler. Similarly, for the stability-region analysis in Figure 11(a), θ_3 is fixed at 0.022. For the dynamic analysis in Figure 11(b)–(h), we set $\theta_1 = 0.075$, $\theta_2 = 0.016$, and $\theta_3 = 0.022$. The results are shown in Figure 11.

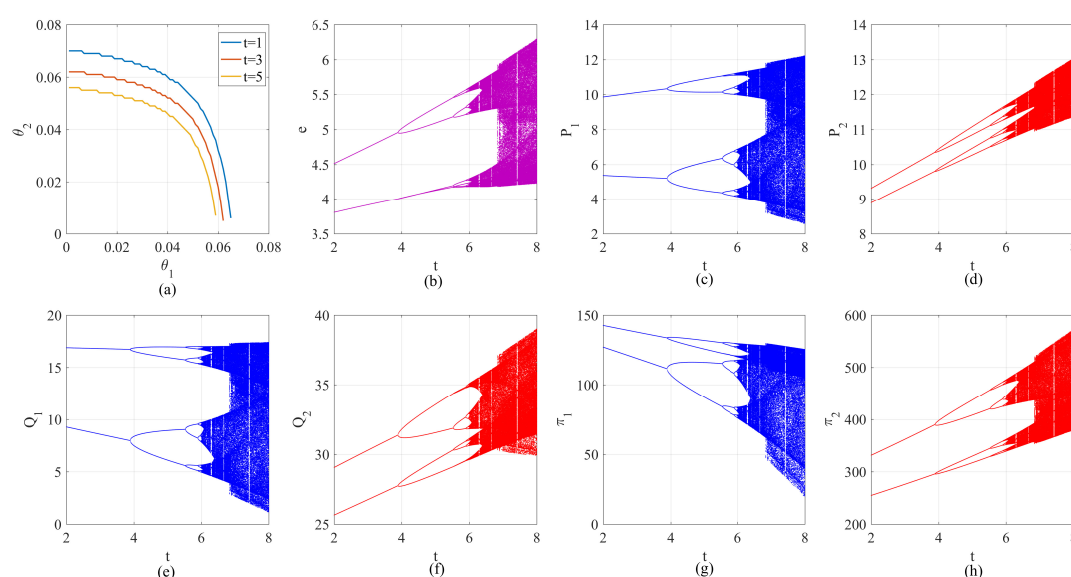


Figure 11. Impact of government subsidy t on dynamic stability and system outcomes.

Figure 11 examines the impact of government subsidy t on the dynamic behavior of the system. As shown in Figure 11(a), the local stability region gradually shrinks as t increases, indicating that higher subsidy levels reduce the range of adjustment speeds under which the equilibrium remains locally stable. Figure 11(b)–(h) further show that increasing t can induce successive bifurcations and increasingly complex fluctuations in recycling prices, quantities, R&D effort, and profits. In particular, although a higher subsidy directly improves the economic incentives of recycler R_2 , it also strengthens its strategic responses in recycling pricing, R&D investment, and market competition. When the subsidy becomes sufficiently high, these stronger feedback effects can amplify fluctuations across the recycling system and eventually destabilize the market. Therefore, government subsidies do not necessarily improve dynamic stability continuously.

To further examine the joint effects of the two policy instruments, Figure 12 presents dynamical state diagrams in the t - ξ plane. The same policy parameter ranges, $2 \leq t \leq 8$ and $0.2 \leq \xi \leq 3.5$, are used in all four panels to facilitate comparison. The adjustment-speed configurations $(\theta_1, \theta_2, \theta_3)$ are set to $(0.060, 0.010, 0.015)$, $(0.070, 0.015, 0.020)$, $(0.080, 0.020, 0.025)$, and $(0.090, 0.025, 0.030)$ in Figure 12(a)–(d), respectively, while all other parameters remain at their benchmark values. Different levels of θ_1 and θ_2 are selected to avoid widespread divergence at simultaneously high price adjustment speeds and to capture transitions between dynamic states. The results are shown in Figure 12.

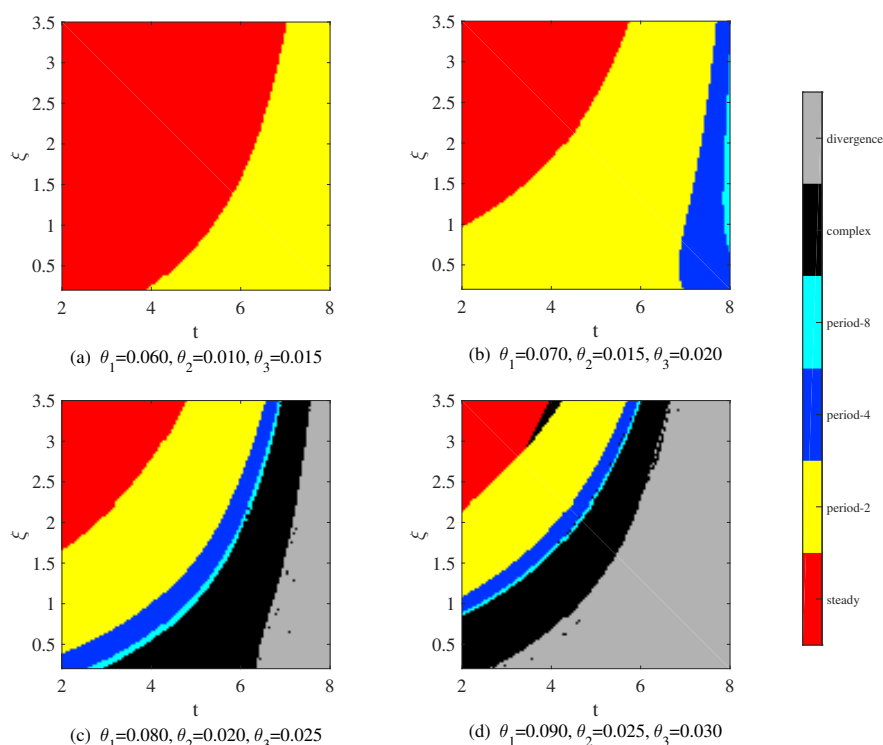


Figure 12. Impact of government subsidy t on dynamic stability and system outcomes.

Figure 12 compares the dynamic states in the t - ξ plane under four configurations, with all three adjustment speeds increasing progressively from Figure 12(a)–(d). In Figure 12(a), most of the parameter space is occupied by the red steady-state region, with period-2 oscillations appearing mainly at higher subsidy levels. In Figure 12(b), the steady-state region becomes smaller, the period-2 region expands, and higher-period states appear near the right boundary. In Figure 12(c), the steady-state region contracts further, while period-4, period-8, and complex states become more prominent, with divergence appearing at high subsidy levels. In Figure 12(d), complex states and divergence occupy larger portions of the parameter space, and steady convergence is mainly confined to combinations of relatively low subsidies and high regulatory intensity. Across the four panels, increasing t at a fixed ξ generally moves the system from steady convergence toward periodic or more complex states, whereas increasing ξ at a fixed t can move it toward more regular states. These patterns suggest that subsidy incentives can intensify competitive responses, while regulation can moderate fluctuations arising from informal recycling. Faster adjustments strengthen firms' responses to marginal profit signals and may cause them to overshoot equilibrium decisions, amplifying fluctuations in prices and R&D effort. Consequently, as adjustment speeds increase from Figure 12(a)–(d), the steady-state region progressively shrinks, and fewer policy combinations sustain convergence to equilibrium.

Overall, Figures 10–12 show that stronger regulation can improve dynamic stability, whereas higher subsidies may intensify fluctuations. As adjustment speeds increase, fewer subsidy-regulation combinations sustain steady convergence. Policy design should therefore coordinate regulation and subsidies while accounting for firms' adjustment speeds.

5. Conclusions and insights

5.1. Conclusions

This paper examines the competitive behavior between whitelist-compliant enterprises and black-market workshops in the battery recycling market. By constructing static and dynamic game models, it provides an in-depth analysis of the decision-making behavior of two battery recyclers from both perspectives. Based on the abovementioned discussion, the main conclusions of our research are as follows:

(1) Recycling R&D, consumer low-carbon preference, and regulatory pressure shape competition between the two recycling channels. Lower R&D costs and higher cost-reduction efficiency encourage the compliant recycler to increase R&D effort and recycling quantity, while regulation strengthens its competitive position. However, the effects on prices and profits depend on technological and consumer characteristics, particularly the relative strength of demand-expansion and cost-reduction effects.

(2) System stability depends jointly on the adjustment speeds of recycling prices and R&D effort. Moderate adjustments support convergence to equilibrium, whereas excessively rapid adjustments can induce periodic oscillations and chaotic dynamics. Two-parameter analyses further show that the stability threshold of each adjustment speed depends on the other speeds, indicating that price and R&D adjustments cannot be assessed independently.

(3) Under the examined parameter settings, stronger regulation expands the local stability region and suppresses complex fluctuations, whereas higher subsidies may shrink it and intensify fluctuations. As the three adjustment speeds increase jointly, the steady-state region in the subsidy-regulation plane contracts, while complex and divergent regions expand. These results indicate that policy combinations compatible with stable convergence depend on firms' adjustment behavior.

5.2. Economic insights

Based on the above conclusions, this paper offers the following insights for corporate managers and relevant personnel:

(1) Policymakers should consider both technological and consumer-side factors when promoting formal battery recycling. Reducing the R&D burden of compliant recyclers and improving the effectiveness of recycling technologies can strengthen their competitiveness, while consumer low-carbon preference can further encourage batteries to flow toward formal recycling channels.

(2) Recycling enterprises should avoid excessively rapid adjustments in prices and R&D decisions. Appropriate adjustment strategies can reduce market fluctuations and maintain stable competition, thereby supporting the long-term development of the formal battery recycling market.

(3) Regulatory authorities should strengthen supervision of informal recycling activities while providing appropriate support for compliant recyclers. Increasing regulatory pressure on black-market workshops can restrict informal recycling and improve market stability, whereas excessive subsidies to compliant recyclers may increase dynamic fluctuations. Therefore, the intensity of different policy instruments should be carefully coordinated.

Author contributions

Haohao Song: Conceptualization, Project administration, Writing-review & editing, Writing-original draft, Software, Visualization, Formal analysis. Wenping Liu: Funding acquisition, Supervision. Xiaobo Wang: Data curation, Validation Jing Zhang: Formal analysis, Methodology, Validation Ying Wang: Writing-original draft, Writing-review & editing, Formal analysis.

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Conflict of interest

We declare that we have no financial or personal relationships with other people or organizations that can inappropriately influence our work. There is no professional or other personal interest of any nature or kind in any product, service, or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

Data Availability Statement

The original contributions and raw data presented in this study are included in this article. Further inquiries can be directed to the corresponding author.

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