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Allocation of Retired EV Batteries

## Abstract

China's retired battery sector is growing rapidly. Regulatory authorities have introduced Decree No.73 to roll out fullcycle Battery ID infrastructure to fix market frictions for battery cascade reuse. Nevertheless, the second—use market is plagued by adverse—selection “lemon market” failures, since core battery quality attributes remain private information and trigger misallocation between reuse and direct recycling channels. This paper builds a rational expectation equilibrium model capturing adverse selection driven quality screening thresholds that shape reuse scale and average battery quality, and further constructs a social welfare function to evaluate optimal information infrastructure investment. Model and numerical simulation results show that higher information investment raises the economic screening threshold, reduces reuse market volume and improves average reuse battery quality; the paper also identifies socially optimal information investment and reveals divergent market responses between NCM and LFP chemistries. This study contributes to existing literature by endogenizing information precision as an adjustable policy tool, offering quantitative references for China's battery ID circular economy governance.

**Keywords:** Retired power battery; Battery ID; Lemon market; Adverse selection; Information investment; Circular economy; NCM; LFP

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# 1 Introduction

China's new energy vehicle (NEV) power battery market is entering a phase of large-scale retirement. By the end of 2024, the national fleet of NEVs reached 31.4 million units, with battery installations consistently ranking first worldwide. Based on service life projections, annual retired power batteries in China will exceed 1 million metric tons by 2030 (Ministry of Industry and Information Technology, National Development and Reform Commission, Ministry of Ecology and Environment, et al., 2025). Retired batteries are not ordinary waste; rather, they represent valuable assets holding substantial critical metals and residual storage capacity. Globally, the technical capacity of electric vehicle (EV) batteries available for grid services could reach 32 to 62 TWh by 2050 (Xu et al., 2023). Diverting approximately 40% of retired EV batteries to secondary use would suffice to cover the European Union's energy storage demands in 2040 and significantly reduce virgin material demand between 2020 and 2050 (Aguilar Lopez et al., 2024). For China, under the carbon neutrality trajectory, clean energy deployment will substantially expand the supply-demand deficit for critical materials. Achieving the 2060 electrification goals requires cumulative demands for cobalt and manganese that are 54 and 116 times higher, respectively, than their 2022 output levels; a recycling rate exceeding 84% could secure stable domestic supply before 2060 (B. Zhang et al., 2025). Thus, the scale of retired power batteries has grown large enough to reshape the landscape of energy storage and material supply, making their disposition a matter of systemic importance.

A retired power battery removed from an EV theoretically faces two primary disposition pathways: first, entering secondary reuse applications outside the automotive domain following testing, sorting, and reconfiguration, including small-scale off-grid energy storage and small-capacity backup power; second, direct dismantling to recover critical metals such as nickel, cobalt, manganese, and lithium. The disposition of retired batteries is essentially a resource allocation problem. Compared to direct hydrometallurgical recycling without secondary utilization, prioritizing secondary use before recycling increases economic returns by 58% and reduces emissions by 18% for lithium iron phosphate (LFP) batteries, while boosting returns by 19% and reducing emissions by 18% for nickel-manganese-cobalt (NCM) batteries (Ma et al., 2024). In other words, allocating high-residual-value batteries to secondary reuse and low-residual-value batteries to direct recycling maximizes total social welfare; conversely, misallocation results in a net loss of functional value.

Achieving allocation efficiency requires a stringent condition: symmetric information between trading counterparties regarding battery quality. However, key attributes such as residual capacity, internal resistance, and degradation rates are primarily dictated by operational history, which remains private information held solely by the current owner. Buyers must incur costly efforts to obtain only noisy estimates. Quality thus becomes private information, endowing the retired battery market with the structure of a classic "lemon market" (Akerlof, 1970): buyers

bid based on average market quality, preventing high-quality batteries from earning deserved premiums. Consequently, holders of high-quality units exit toward recycling channels, deteriorating the average quality of remaining batteries and driving transaction prices further down. Crucially, pushing batteries with high residual capacity and functional value out of reuse channels causes their potential storage value to go unrealized, hindering national carbon reduction targets. Conversely, if low-quality batteries flow unselectively into the secondary market due to information friction, severe safety hazards emerge.

This structural difficulty is reflected in China's regulatory practice. The *Interim Measures for the Administration of Recycling and Comprehensive Utilization of Waste Power Batteries from New Energy Vehicles* (Decree No. 73 of six ministries including the Ministry of Industry and Information Technology), effective April 1, 2026 (Ministry of Industry and Information Technology, National Development and Reform Commission, Ministry of Ecology and Environment, et al., 2025), removed the long-standing term "cascade utilization" (tici liyong). This policy adjustment stems primarily from market heterogeneity: products in the market vary widely in whether they comply with quality standards of target application fields, making it difficult for enterprises and consumers to distinguish conforming products from non-conforming ones. The motivation behind regulatory tightening lies not in a lack of secondary value, but in the market's lack of a credible quality identification mechanism.

Recognizing this, major economies have shifted their regulatory focus from price-based instruments to information infrastructure in recent years. China established the outline of traceability management via the 2018 *Interim Provisions on the Traceability Management of Recycling and Utilization of Power Batteries for New Energy Vehicles* (Ministry of Industry and Information Technology, Ministry of Commerce, Ministry of Science and Technology, et al., 2018). The 2021 *Measures for the Administration of Cascade Utilization of Power Batteries for New Energy Vehicles* (Article 10) (Ministry of Industry and Information Technology, Ministry of Science and Technology, Ministry of Ecology and Environment, et al., 2021) encouraged auto manufacturers and battery makers to negotiate data-sharing agreements with reuse enterprises regarding factory specifications and monitoring data; however, this remained a voluntary arrangement without quality requirements. In contrast, Decree No. 73 (Ministry of Industry and Information Technology, National Development and Reform Commission, Ministry of Ecology and Environment, et al., 2025) explicitly mandates that the Ministry of Industry and Information Technology, in coordination with relevant departments, establish a national traceability information platform for NEV power batteries and implement digital battery ID management. By assigning battery codes, the platform links data across production, sales, swapping, maintenance, retirement, recycling, and comprehensive utilization, while imposing administrative penalties for non-reporting or fraudulent reporting. Similarly, the EU Battery Regulation (EU 2023/1542) mandates battery IDs starting February 18, 2027, for EV batteries, light means of transport (LMT) batteries, and industrial batteries above 2 kWh placed on the EU market,

specifying mandatory data attributes. The essence of these initiatives is public investment in information infrastructure to supply verifiable quality signals to the market. Yet a fundamental question remains unanswered: to what extent should such public investment be made? Does higher information accuracy unequivocally lead to a larger cross-scenario reuse market?

Parallel to information governance, an opposing external shock is unfolding: the rapid decline in lithium-ion battery costs, which directly impacts recycling and reuse incentives. Re-evaluations of historical price data from 1991 onward by Ziegler and Trancik (Ziegler & Trancik, 2021) demonstrate that the cost reduction rate of lithium-ion batteries was systematically underestimated, with the actual annual decline exceeding 13% on a capacity basis. Mauler et al. (Mauler et al., 2021), synthesizing 53 cost forecasting studies, noted that median projections for pack costs around 2030 have fallen below \$100/kWh. In 2024, the global average price of lithium-ion battery packs dropped by 20% year-on-year to \$115/kWh, with BEV battery packs dropping to \$97/kWh globally and \$94/kWh in China; meanwhile, commissioned cell manufacturing capacity worldwide reached 3.1 TWh, roughly 2.5 times the annual demand. Because the valuation of reused batteries is anchored to the price of new cells where buyers' willingness to pay roughly equals new cell price multiplied by expected quality minus processing costs—falling new cell prices compress both the absolute returns and relative advantages of secondary batteries. This indicates that the effectiveness of information policy is not independent of technological context: information investments worthwhile under high cell prices may no longer be justified under low price regimes. Therefore, whether an interaction exists between information policy and price shocks, and in which direction it operates, must be analyzed within a unified analytical framework.

Accordingly, this paper constructs a rational expectations equilibrium model capturing the channel allocation of retired power batteries. Battery quality is private information to holders, while buyers observe only a noisy quality signal, the noise variance of which is determined by enterprise information infrastructure investment. Buyers form willingness to pay via Bayesian posterior updating, and sellers select disposition channels by comparing reuse market prices against the reservation value of direct dismantling. The quality screening threshold is thus endogenously determined, governing both the market scale and average quality of cross-scenario reuse. On this basis, we characterize the optimal enterprise information investment level and its response to new cell price shocks.

The marginal contributions of this paper are threefold. Theoretically, by embedding enterprise information investment into market equilibrium through signal precision, information governance becomes a comparable and optimizable policy tool alongside subsidies and taxes, rather than an exogenous parameter or discrete adoption choice as treated in prior literature. Methodologically, without pre-assuming the directional effect of information enhancement, we model the channel separation threshold as an endogenous fixed-point result of rational expectations,

illuminating the underlying mechanics between scale effects and quality effects. Policy-wise, this study provides a quantitative evaluation benchmark for public investments in battery IDs and traceability platforms, characterizing their interaction with battery technological progress to offer scientific references for policy design in China.

The remainder of this paper is organized as follows: Section 2 reviews the related literature; Section 3 lays out the model setting, information mechanisms, comparative statics, and optimal social investment; Section 4 presents the results of numerical simulation; Section 5 discusses limitations and implications.

## 2 Literature Review

This study builds upon three streams of literature: how information shapes market allocation under quality unobservability, which provides the analytical tools for modeling signal precision and self-selection; channel selection and policy design for returned products in closed-loop supply chains, which defines our problem domain; and techno-economic assessments along with digital governance regarding retired batteries, which supply empirical and institutional foundations.

In information economics, research on unobservable quality has transitioned from examining "whether to disclose" to analyzing "disclosure precision." Akerlof (Akerlof, 1970) established the foundational mechanism of adverse selection leading to high-quality driving out. Spence (Spence, 1973) and Milgrom (Milgrom, 1981) demonstrated that informed parties actively transmit information under specific conditions via signaling and voluntary disclosure, respectively. However, full disclosure relies on strong assumptions such as costless disclosure and verifiable information. When these conditions are relaxed, external information intermediaries become necessary, as systematized by Dranove and Jin (Dranove & Jin, 2010) in their review of quality disclosure and certification practices. Subsequent research turned toward the granularity of information: Ganuza and Penalva (Ganuza & Penalva, 2010) established a comparative static framework for signal precision based on dispersion orderings, while Roesler and Szentes (Roesler & Szentes, 2017) proved that buyer-optimal learning precision is not necessarily maximal. Recently, Asriyan et al. (Asriyan et al., 2020) examined information aggregation and design in asset markets with adverse selection, finding non-monotonic effects of precision on trade volume; Smolin (Smolin, 2023) characterized optimal attribute disclosure and its pricing implications for multi-attribute products; Lou and Rahi (Lou & Rahi, 2023) showed that the welfare effects of information improvements depend on market structure and are not universally positive. Scholars have extended these insights to empirical studies of durable goods: Genesove (Genesove, 1993) identified adverse selection in wholesale used-car markets, while Gavazza et al. (Gavazza et al., 2014) quantified market inefficiency caused by transaction frictions using structural estimation. Tadelis and Zettelmeyer (Tadelis & Zettelmeyer, 2015) experimentally

showed that disclosing third-party inspection reports in wholesale car auctions increases transaction prices and improves matching quality, though gains are unevenly distributed benefiting high-quality units while harming low-quality ones. Bauer et al. (Bauer et al., 2022) examined digital credentials, testing the price and transaction effects of multi-party blockchain certification in lemon markets. However, disclosure regimes in these studies are taken as given and exogenous mostly provided by private entities where disclosure precision is not modeled as a continuously adjustable choice variable, nor is social optimal precision within the analytical scope.

Regarding channel selection and policy tool design for returned products, Savaskan et al. (Savaskan et al., 2004) established the baseline framework for reverse channel structure choices, Debo et al. (Debo et al., 2005) examined market segmentation and technology selection for remanufacturable products, Galbreth and Blackburn (Galbreth & Blackburn, 2010) analyzed optimal acquisition quantities under condition uncertainty, Vedantam and Iyer (Vedantam & Iyer, 2021) demonstrated how quality uncertainty reshapes revenue-sharing contracts in remanufacturing, and Guide and Van Wassenhove (Guide & Van Wassenhove, 2009) reviewed the field's evolution from operational issues to business models. In the context of rapid EV expansion, Gu et al. (Gu et al., 2021) built a closed-loop supply chain game model for battery secondary use under government subsidies, Zhang and Dou (Zhang & Dou, 2021) analyzed subsidy design for EVs and charging networks, Shi and Hu (Shi & Hu, 2024) investigated flexible battery ownership structures, and Wang et al. (Wang et al., 2024) re-evaluated remanufacturing and e-waste management policies from environmental perspectives. Incorporating information mechanisms, Wu and Wang (Wu & Wang, 2023) studied the boundary conditions for platform-led blockchain adoption for traceability. A common feature of this literature is that policy instruments primarily focus on price and organizational mechanisms such as subsidies, taxes, contractual terms, and channel design while returned product quality is assumed symmetric or exogenously distributed. Even when traceability is addressed, it is treated as a discrete adoption decision by firms rather than a continuous public information supply level regulated by governments. While we inherit this modeling tradition of channel self-selection, the analytical mechanism governing quality information generation warrants further development.

A third stream focuses on techno-economic assessments and digital governance of battery reuse and battery IDs. Neubauer and Pesaran (Neubauer & Pesaran, 2011) conducted early economic evaluations of retired batteries in stationary storage, Martinez-Laserna et al. (Martinez-Laserna et al., 2018) provided a critical review of second-life feasibility, and Steckel et al. (Steckel et al., 2021) evaluated utility-scale secondary battery storage systems using levelized cost of storage (LCOS) methodologies. On pathway selection between reuse and recycling, Ma et al. (Ma et al., 2024) integrated economic and environmental objectives, demonstrating that optimal pathways depend heavily on residual battery status estimates. Simultaneously, advancements in state-estimation technologies support accuracy improvements through targeted investment: Severson

et al. (Severson et al., 2019) showed that early cycle data can accurately predict battery lifetime, while Sulzer et al. (Sulzer et al., 2021) and Aitio and Howey (Aitio & Howey, 2021) discussed opportunities and limitations of field-data-driven life prediction. These studies confirm that quality information is technically accessible, with precision depending on testing investment and data availability a key prerequisite for modeling precision as a decision variable. Berger et al. (Berger et al., 2022) proposed a conceptual framework for digital battery IDs in circular value chains, and Berger et al. (Berger et al., 2023) examined data requirements across value chain actors, identifying actors' reporting willingness and costs as primary constraints rather than technology. Jansen et al. (Jansen et al., 2023) and Jensen et al. (Jensen et al., 2023) defined technical and data requirements for product life-cycle decision-making. However, these studies remain at the institutional and engineering level, without modeling IDs as public investments requiring cost-benefit trade-offs, providing an optimizable continuous scale for information precision, or characterizing market equilibrium re-allocation following precision enhancement.

In summary, these three literature streams supply the analytical tools, problem context, and empirical grounding for this study. However, information economics models precision choice by private actors without addressing allocation between reuse and recycling; closed-loop supply chain literature models channel choices but treats quality information as symmetric or exogenous; and techno-economic literature addresses information infrastructure directly but views precision as an engineering parameter rather than an economic decision requiring cost-benefit optimization. Combining these perspectives, this paper embeds enterprise information investment into adverse selection framework quality identification intensity, making information governance a tool comparable to subsidies and taxes. On this basis, we address one specific question: how does Battery ID as information infrastructure impact the economic and social viability of the battery reuse market.

### 3 Methods

To quantify the behavior of second-hand battery sellers and buyers acting with improved information from battery traceability infrastructure, this study develops an Adverseselection model for retired battery resource allocation. The geographical scope of this study is limited to mainland China (excluding Hong Kong and Macau), with a temporal horizon extending from 2027 to 2030. The primary battery products concerned are LFP (Lithium Iron [Fe] Phosphate) batteries, which contain key metals Lithium and Iron. NCM batteries are considered as an extension due to their more complex metal compositions (Ni, Mn, Co, as well as Li). Only passenger EVs are considered because of their vast growth in volume and dominant market share. The analysis focuses exclusively on the domestic EV battery market, excluding exported batteries to isolate the effects of factors unrelated to international trade.

Table 1: List of key mathematical parameters and variables of the model.

| Symbol                                        | Description                                                                                                 | Specification        |
|-----------------------------------------------|-------------------------------------------------------------------------------------------------------------|----------------------|
| <b>Policy &amp; Decision Variables</b>        |                                                                                                             |                      |
| $I$                                           | Enterprise information investment                                                                           | RMB / $[0, +\infty)$ |
| $q^*$                                         | Effective minimum quality threshold for reuse                                                               | $[q_{\min}, 1)$      |
| $q_m^*$                                       | Endogenous economic quality threshold                                                                       | $(0, 1)$             |
| $q_{\min}$                                    | Physical/technical minimum quality threshold                                                                | $(0, 1)$             |
| <b>Quality &amp; Distribution Variables</b>   |                                                                                                             |                      |
| $q$                                           | True quality of a retired battery                                                                           | $[0, 1]$             |
| $f(q), F(q)$                                  | Quality density (PDF) and cumulative distribution (CDF)                                                     | $f(q) \geq 0$        |
| $\mu_m$                                       | Conditional average quality ( $E[q \mid q \geq q_m^*]$ )                                                    | $(0, 1)$             |
| $K$                                           | Total volume of retired batteries                                                                           | kWh                  |
| <b>Information &amp; Signal Parameters</b>    |                                                                                                             |                      |
| $\theta(I)$                                   | Quality identification intensity function                                                                   | $[0, 1)$             |
| $s$                                           | Imperfect quality signal ( $s = q + \varepsilon$ )                                                          | $(-\infty, +\infty)$ |
| $\varepsilon$                                 | Signal noise with zero mean ( $E[\varepsilon] = 0$ )                                                        | $(-\infty, +\infty)$ |
| <b>Cost, Price &amp; Valuation Parameters</b> |                                                                                                             |                      |
| $p_N$                                         | Market price of new battery cells                                                                           | RMB/kWh              |
| $c_U$                                         | Front-end preparation cost for reuse                                                                        | RMB/kWh              |
| $w$                                           | Reservation revenue from direct recycling                                                                   | RMB/kWh              |
| $\rho$                                        | Relative recycling attractiveness $((c_U + w)/p_N)$                                                         | Dimensionless        |
| $\bar{P}_U(q)$                                | Seller expected transaction price offer                                                                     | RMB/kWh              |
| $P_U(s)$                                      | Buyer competitive bidding price                                                                             | RMB/kWh              |
| $\Delta e_{\text{avoid}}$                     | Net environmental benefit of secondary reuse                                                                | RMB/kWh              |
| $C(I)$                                        | Fiscal cost function of information infrastructure                                                          | RMB                  |
| $R$                                           | Net social value of direct recycling, including material recovery benefits and environmental/resource costs | RMB/kWh              |

### 3.1 The Market for Retired Batteries

Consider a market in which retired EV batteries can be sold either for reuse or for direct recycling. There is a continuum of batteries, with total supply denoted as  $K$ . Each battery has a quality level, or state of health indicator,  $q \in [0, 1]$ . The quality of a battery is known to its current owner but cannot be perfectly observed by potential buyers. Let the distribution of quality be described by a continuously differentiable cumulative distribution function  $F(q)$  and a

strictly positive distribution density  $f(q) > 0$ , satisfying

$$\int_0^1 f(q) dq = 1$$

There are two possible uses for a retired battery. A battery may be prepared for reuse in a secondary application, such as stationary energy storage. Alternatively, it may be sent directly to recycling, where its material value is recovered.

The seller receives a return  $w \geq 0$  from direct recycling. The return from direct recycling is independent from the battery's quality. If the battery is offered for reuse, it creates a preparation cost  $c_U > 0$ , representing inspection, refurbishment, repackaging, and logistics. The seller therefore compares the return from reuse with the return from recycling.

The essential feature of the market is that quality is privately known. A seller knows the condition of his own battery, whereas a buyer must infer quality from Battery IDs.

### 3.2 Buyers and the Price of Quality

Let the gross economic value of a battery of quality  $q$  to a reuse buyer be

$$v(q) = p_N q,$$

where  $p_N > 0$  is a scale parameter related to the value of a new battery.

The buyer has linear utility,

$$U_B = M + p_N q - P,$$

where  $M$  is the consumption of other goods and  $P$  is the price paid for the battery.

Due to information asymmetry, buyers do not directly observe the seller's true battery quality. Instead, they observe a noisy quality signal

$$s = q + \varepsilon, \quad \mathbb{E}[\varepsilon | q] = 0.$$

The signal therefore provides information about quality but does not perfectly reveal the underlying condition of the battery.

Let  $\theta \in [0, 1]$  measure the extent to which the information contained in the signal is incorporated into the market price. A higher  $\theta$  represents greater price responsiveness to observed quality information. In particular,  $\theta = 0$  corresponds to a fully pooled market in which individual quality signals do not affect prices, whereas  $\theta$  approaching one represents a market in which prices respond strongly to observed quality.

Suppose that only batteries with quality at least  $q_m$  are offered for reuse. The average quality of batteries in the reuse market is then

$$\mu(q_m) = \mathbb{E}[q \mid q \geq q_m] = \frac{\int_{q_m}^1 q f(q) dq}{1 - F(q_m)}.$$

Rather than imposing a fully specified Bayesian pricing model for an arbitrary quality distribution, we represent the incorporation of quality information into prices using the following reduced-form linear pricing rule:

$$P(s) = p_N [(1 - \theta)\mu(q_m) + \theta s].$$

This specification captures the transition from pooled pricing to quality-sensitive pricing. When  $\theta = 0$ , all batteries offered for reuse receive a price based on the average quality  $\mu(q_m)$ . As  $\theta$  increases, the observed quality signal receives greater weight in determining the market price. Thus,  $\theta$  should be interpreted as an information pass-through parameter rather than as a universally valid Bayesian posterior weight.

Taking expectations conditional on the seller's true quality gives

$$\bar{P}(q) = \mathbb{E}[P(s) \mid q] = p_N [(1 - \theta)\mu(q_m) + \theta q],$$

where the second equality follows from  $\mathbb{E}[\varepsilon \mid q] = 0$ .

Thus,

$$\frac{\partial \bar{P}(q)}{\partial q} = p_N \theta.$$

This expression describes how information affects price differentiation across batteries. When  $\theta = 0$ ,

$$\bar{P}(q) = p_N \mu(q_m),$$

so high- and low-quality batteries receive the same expected price. As  $\theta$  increases, expected prices become more sensitive to individual battery quality, reducing the cross-subsidy from high-quality to low-quality batteries.

A seller who sends a battery to the reuse market receives

$$U_S^U(q) = M + \bar{P}(q) - c_U,$$

whereas direct recycling yields

$$U_S^R = M + w.$$

The seller chooses reuse if and only if

$$\bar{P}(q) - c_U \geq w.$$

Since  $\bar{P}(q)$  is increasing in  $q$ , there exists a critical quality level  $q_m$  such that batteries above this level are offered for reuse and batteries below it are sent to recycling. The critical type satisfies

$$\bar{P}(q_m) - c_U = w.$$

Define

$$\rho \equiv \frac{c_U + w}{p_N}.$$

The marginal seller is therefore characterized by

$$(1 - \theta)\mu(q_m) + \theta q_m = \rho. \quad (1)$$

Equation (1) is the equilibrium condition for the reuse market.

It is worth observing the source of the selection effect. A low-quality battery is excluded from the reuse market because its value to the buyer is insufficient to compensate the seller for the cost of preparing it for reuse and for the return forgone by not recycling it.

### 3.3 The Effect of Information on Selection

The average quality of batteries remaining in the reuse market satisfies

$$\mu'(q_m) = \frac{f(q_m)}{1 - F(q_m)} [\mu(q_m) - q_m]. \quad (2)$$

For  $q_m < 1$ ,

$$\mu(q_m) > q_m,$$

and hence

$$\mu'(q_m) > 0.$$

Consider the equilibrium condition

$$H(q_m, \theta) = (1 - \theta)\mu(q_m) + \theta q_m - \rho = 0.$$

Its partial derivatives in respect to  $\theta$  are

$$H_{q_m} = (1 - \theta)\mu'(q_m) + \theta > 0$$

and

$$H_\theta = q_m - \mu(q_m) < 0.$$

The implicit function theorem therefore gives

$$\frac{dq_m^*}{d\theta} = -\frac{H_\theta}{H_{q_m}} = \frac{\mu(q_m^*) - q_m^*}{(1-\theta)\mu'(q_m^*) + \theta} > 0. \quad (3)$$

Thus, greater information raises the quality required for participation.

There is a technological lower bound for reuse. Let  $q_{\min} \in (0, 1)$  denote the minimum quality required for a battery to be physically suitable for reuse. The effective market threshold is therefore

$$q^* = \max\{q_{\min}, q_m^*\}.$$

The number of batteries entering the reuse market is

$$Y_U^* = K[1 - F(q^*)],$$

while their average quality is

$$Q_U^* = \mu(q^*).$$

When the economic selection constraint is binding,  $q_m^* > q_{\min}$ , equations (2) and (3) imply

$$\frac{dY_U^*}{d\theta} = -Kf(q_m^*)\frac{dq_m^*}{d\theta} < 0, \quad (4)$$

whereas

$$\frac{dQ_U^*}{d\theta} = \mu'(q_m^*)\frac{dq_m^*}{d\theta} > 0. \quad (5)$$

Hence an improvement in information produces two opposing effects: the quantity of batteries entering reuse falls, while the average quality of those batteries rises. The market therefore becomes smaller but better. In a market characterized by adverse selection, information can instead reveal that some transactions should not take place. The disappearance of these transactions is not necessarily a failure of the market. It may represent an improvement in the composition of trade.

### 3.4 Enterprise Investment

The preceding analysis takes the information environment, summarized by  $\theta$ , as given. In practice, the quality of information available to market participants depends on investment in information infrastructure. Let  $I \geq 0$  denote investment in Battery IDs and related information

infrastructure.

We model investment as improving the precision of the quality signal. Specifically, suppose that

$$s = q + \varepsilon,$$

where

$$\mathbb{E}[\varepsilon | q] = 0, \quad \text{Var}(\varepsilon) = \sigma_\varepsilon^2(I),$$

with

$$\frac{d\sigma_\varepsilon^2(I)}{dI} < 0.$$

Thus, greater investment reduces the noise contained in the signal and makes the information available to buyers more precise.

The effect of signal precision on market pricing is represented through the information pass-through parameter introduced in the previous section. We therefore write

$$\theta = \theta(I),$$

with

$$\theta'(I) > 0.$$

The relationship can be understood as a two-stage mechanism: Investment first improves signal precision by reducing measurement noise, which in turn allows quality information to be incorporated more strongly into market prices.

For the numerical analysis, we use the parsimonious specification

$$\theta(I) = 1 - e^{-\alpha I}, \quad \alpha > 0.$$

This specification captures increasing but diminishing effects of investment on information pass-through:

$$\theta'(I) = \alpha e^{-\alpha I} > 0, \quad \theta''(I) = -\alpha^2 e^{-\alpha I} < 0.$$

Combining this relationship with equation (3), the effect of investment on the economic screening threshold is

$$\frac{dq_m^*}{dI} = \frac{dq_m^*}{d\theta} \theta'(I) > 0. \quad (6)$$

Companies do not need to determine which individual batteries should be reused. Instead, investment improves the information available to market participants and allows sellers and buyers to make the selection themselves. The private equilibrium does not by itself determine

the socially desirable information level. A battery that leaves the reuse market may be valuable to society even when it is not profitable for a buyer, and conversely, a privately profitable reuse transaction may generate environmental costs that are not reflected in its market price.

### 3.5 Social Welfare

Let  $\Delta e_{\text{avoid}} \geq 0$  denote the environmental benefit generated by reusing a retired battery, primarily through the avoided production of an alternative new battery or storage unit. Let  $R$  denote the net social value of direct recycling, incorporating the value of recovered materials as well as the environmental and resource costs associated with recycling.

The social welfare generated by the allocation of retired batteries is therefore

$$SW(I) = K \int_{q^*(I)}^1 [p_N q - c_U + \Delta e_{\text{avoid}}] f(q) dq + K \int_0^{q^*(I)} R f(q) dq - C(I),$$

where  $C(I)$  denotes the social cost of investing in information infrastructure.

When the economic screening threshold is binding, such that  $q^*(I) = q_m^*(I)$ , differentiation with respect to information investment gives

$$\frac{dSW}{dI} = K f(q_m^*) [R - (p_N q_m^* - c_U + \Delta e_{\text{avoid}})] \frac{dq_m^*}{dI} - C'(I).$$

Since

$$\frac{dq_m^*}{dI} = \frac{dq_m^*}{d\theta} \theta'(I) > 0,$$

the welfare effect of information investment depends on the relative social value of recycling and reuse.

In particular, the gross allocation effect of greater information transparency is positive when

$$R > p_N q_m^* - c_U + \Delta e_{\text{avoid}},$$

and negative when

$$R < p_N q_m^* - c_U + \Delta e_{\text{avoid}}.$$

An interior optimal level of information investment  $I^* > 0$  therefore satisfies

$$K f(q_m^*) [R - (p_N q_m^* - c_U + \Delta e_{\text{avoid}})] \frac{dq_m^*}{dI} = C'(I^*).$$

Thus, information investment need not monotonically increase social welfare: its effect depends on whether the marginal battery shifted from reuse to recycling has a higher social value

in recycling than in reuse, net of the cost of providing additional information.

## 4 Results and Findings

### 4.1 Parameter Calibration

The numerical simulation considers two representative lithium-ion battery chemistries, nickel-manganese-cobalt (NCM) and lithium iron phosphate (LFP). The new-battery value is normalized to  $p_N = 1$ , while the reuse cost is set to  $c_U = 0.42$  for both chemistries. The direct recycling value is set to  $w = 0.28$  for NCM and  $w = 0.24$  for LFP, reflecting the higher material recovery value of NCM batteries. The minimum feasible state of health is set to  $q_{\min} = 0.40$  for both chemistries, while the incremental service value from reuse is calibrated as  $\Delta e_{\text{avoid}} = 0.24$  for NCM and  $\Delta e_{\text{avoid}} = 0.16$  for LFP. The residual recycling value is set to  $R = 0.34$  for NCM and  $R = 0.29$  for LFP. These values are calibrated using evidence on the economic and environmental differences between NCM and LFP second-life and recycling pathways (Cobb et al., 2026; Quan et al., 2022).

The information environment is characterized by  $\sigma_0^2 = 0.10$  and  $\sigma_{\varepsilon,0}^2 = 0.80$ . Following the investment specification in Section 3, information investment affects market information through  $\theta(I) = 1 - e^{-\alpha I}$ , with  $\alpha = 4.0$ . The information parameters are calibrated structural assumptions rather than direct market estimates.

Finally, the cost of information investment is specified as

$$C(I) = \frac{\gamma}{2} I^2,$$

with  $\gamma = 0.035$ . The battery supply is normalized to  $K = 1$ , and the numerical search is conducted over  $0 \leq I \leq I_{\max} = 2.0$ . The resulting baseline values are summarized in Table 2.

Table 2: Baseline parameterization for NCM and LFP batteries

| Parameter                            | Description                             | NCM   | LFP  |
|--------------------------------------|-----------------------------------------|-------|------|
| $p_N$                                | Normalized value of a new battery       | 1.00  | 1.00 |
| $c_U$                                | Cost of reuse preparation and diagnosis | 0.42  | 0.42 |
| $w$                                  | Direct recycling value                  | 0.28  | 0.24 |
| $q_{\min}$                           | Minimum feasible SOH for reuse          | 0.40  | 0.40 |
| $\Delta e_{\text{avoid}}$            | Incremental service value from reuse    | 0.24  | 0.16 |
| $R$                                  | Residual recycling value after reuse    | 0.34  | 0.29 |
| <i>Common information parameters</i> |                                         |       |      |
| $\sigma_0^2$                         | Prior variance of battery quality       | 0.10  |      |
| $\sigma_{\varepsilon,0}^2$           | Baseline measurement-noise variance     | 0.80  |      |
| $\alpha$                             | Effectiveness of information investment | 4.00  |      |
| $\gamma$                             | Information-cost coefficient            | 0.035 |      |
| $I_{\max}$                           | Maximum investment in numerical search  | 2.00  |      |
| $K$                                  | Battery supply normalization            | 1.00  |      |

## 4.2 Numerical Simulation

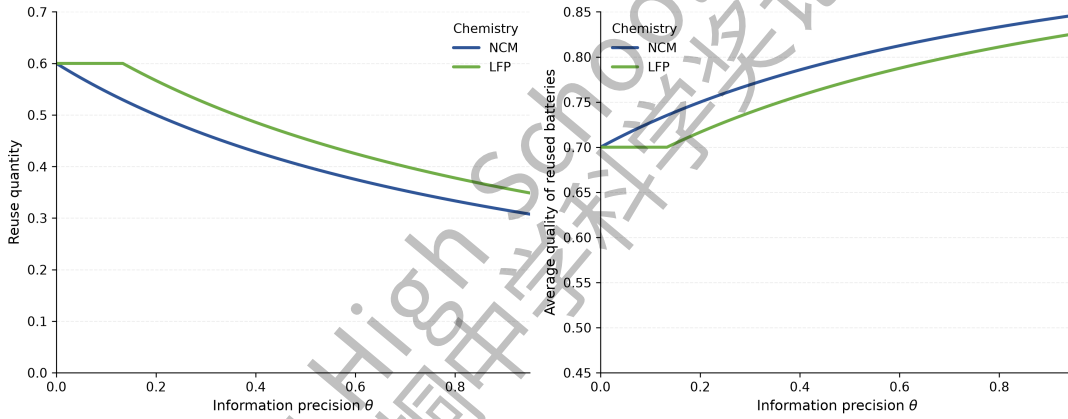
Figure 1: Effect of Information Precision ( $\theta$ ) on Market Equilibrium Outcomes.

Figure 1 shows how information precision affects the equilibrium allocation of retired batteries. When  $\theta$  is low, the economic screening threshold remains below the physical threshold  $q_{\min}$ , so the physical threshold determines the actual reuse market size. As information precision increases, prices become more sensitive to battery quality, causing the economic threshold to rise. Consequently, lower-quality batteries are gradually excluded from reuse, reducing reuse quantity while increasing the average quality of reused batteries. LFP batteries maintain a larger reuse market because their lower recycling value makes reuse attractive for a wider range of battery qualities. NCM batteries, in contrast, exhibit a higher average quality among reused batteries because their higher recycling value results in a stricter economic screening threshold.

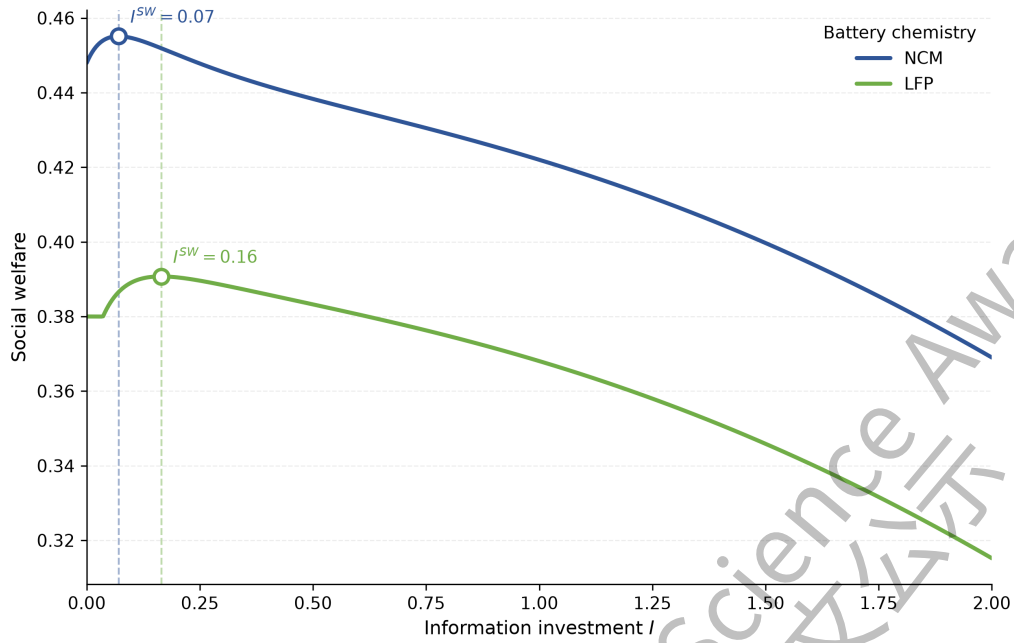


Figure 2: Optimal Information Investment ( $I^*$ ) and Social Welfare Maximization.

Figure 2 illustrates the relationship between information investment and social welfare. Social welfare initially increases as information investment improves the market's ability to distinguish battery quality, but eventually declines as the increasing investment cost outweighs the resulting allocation benefits. This generates an interior optimum  $I^*$ . The difference between NCM and LFP reflects their different reuse, recycling, and environmental values.

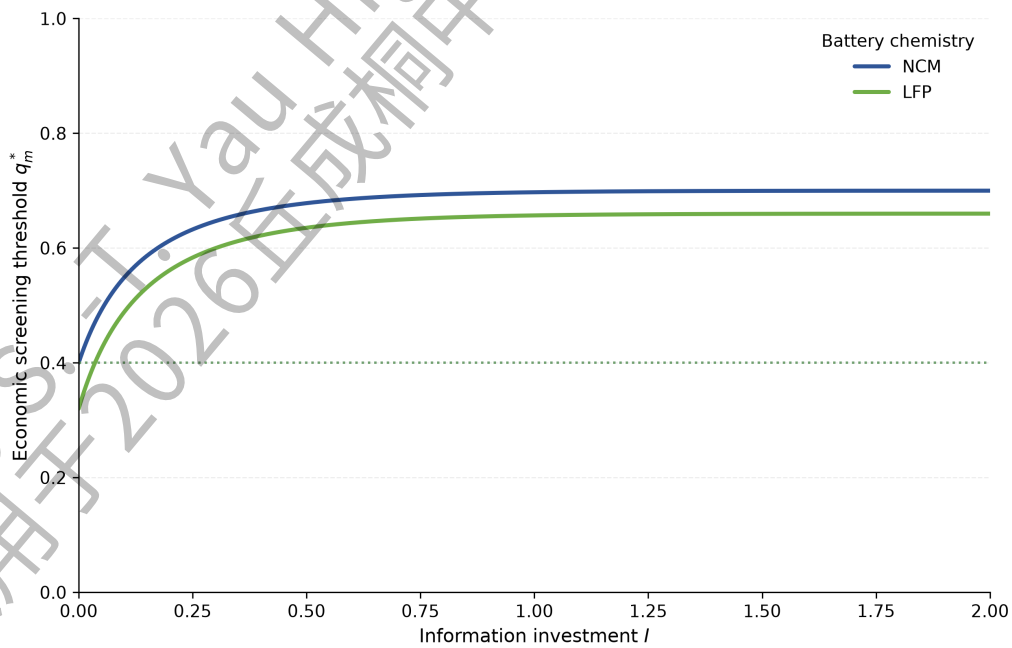


Figure 3: Effect of Information Investment on the Economic Screening Threshold.

Figure 3 isolates the mechanism connecting information investment to market screening. As  $I$  increases, information precision  $\theta(I)$  increases, which raises the economic screening threshold  $q_m^*$ . This means that greater information investment allows the market to distinguish battery quality more effectively and shifts the reuse market toward higher-quality batteries. The horizontal physical threshold  $q_{\min}$  provides a benchmark for determining whether economic or physical screening is binding.

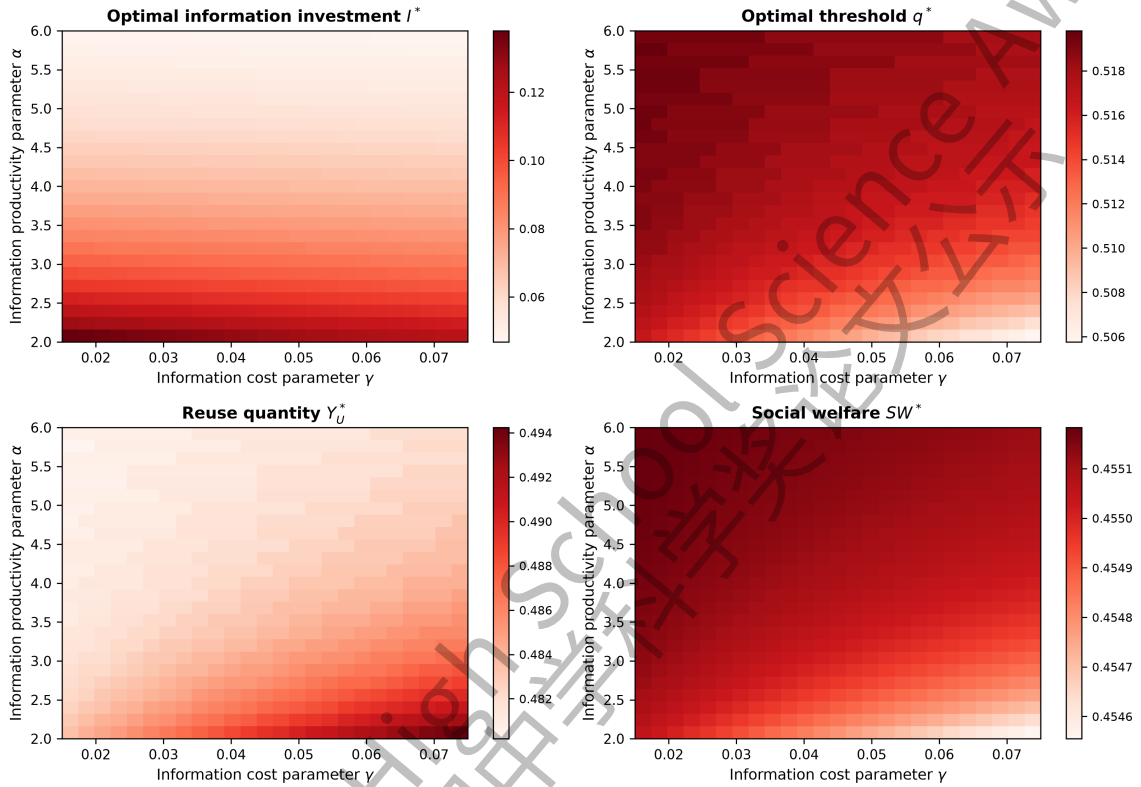


Figure 4: Sensitivity of Equilibrium Outcomes to Information Productivity ( $\alpha$ ) and Investment Cost ( $\gamma$ ).

Figure 4 examines the robustness of the model to changes in the information technology and investment cost parameters. A higher  $\alpha$  makes information investment more effective, while a higher  $\gamma$  increases the cost of investment. The resulting variation in  $I^*$ ,  $q^*$ , reuse quantity, and social welfare shows how the model responds to changes in these structural assumptions.

### 4.3 Key Findings

A counter-intuitive implication of this model is that investment in information infrastructure decreased market size yet increased average quality. This demonstrates that quality is more important than scale in the reuse market, with higher quality batteries reducing the risk of accidents while also contributing to revenue for battery sellers. As information precision rises, quality screening becomes more effective as the threshold is raised, thus removing lower quality

batteries. Therefore, equipping battery IDs and information infrastructure can solve the problem of low quality secondhand batteries entering the reuse market, reducing the risk of safety issues. When firms possess high information precision, they voluntarily abandon hazardous low-end reuse. Regulatory frameworks should support this self-selection by establishing strict liability rules for second-life failures.

Our analysis demonstrates that techno-chemical heterogeneity specifically the divergence in direct recycling values ( $R$ ) between high-value nickel-cobalt-manganese (NCM) chemistries and lower-value lithium-iron-phosphate (LFP) chemistries fundamentally alters economic incentives. While high-value NCM cells often generate robust private incentives for recycling and secondary reuse, lower-value LFP cells are particularly vulnerable to premature dismantling or improper disposal due to lower raw material recovery margins. Policy interventions must be chemistry-sensitive rather than uniform. For LFP and lower-tier chemistries, targeted subsidies or mandated minimum second-life utilization quotas are necessary to prevent premature hydrometallurgical processing. Conversely, for high-value NCM chemistries where private overinvestment or excessive rent extraction can occur, regulatory oversight should focus on preventing monopolistic control over proprietary diagnostic data and promoting competitive secondary markets.

## 5 Discussion

### 5.1 Sensitivity Analysis

To examine the robustness of the model, each key parameter is varied by  $\pm 10\%$  while holding all other parameters at their baseline values. The main results are summarized in Table 3. Overall, the optimal information investment is most sensitive to the economic parameters that directly affect the relative attractiveness of reuse and recycling, particularly  $p_N$ ,  $c_U$ , and  $R$ . The effects are qualitatively similar for NCM and LFP batteries.

A higher new-battery value  $p_N$  increases the value of reuse and therefore raises both optimal information investment and the reuse share. In contrast, higher reuse cost  $c_U$  or recycling value  $R$  reduces the incentive to invest in information. The environmental benefit  $\Delta e_{\text{avoid}}$  also affects optimal investment, but its effect is weaker. The physical threshold  $q_{\text{min}}$  has almost no effect within the tested range because the economic screening threshold remains above the physical threshold. These results suggest that the model's main mechanism is robust to moderate parameter changes.

Table 3: Sensitivity of the model to key parameters

| Parameter                 | $I^*$       | $q^*$       | $Y_U^*$     | $Q_U^*$     | $SW^*$      |
|---------------------------|-------------|-------------|-------------|-------------|-------------|
| $p_N$                     | +           | −           | +           | −           | +           |
| $c_U$                     | −           | +           | −           | +           | −           |
| $w$                       | −           | $\approx 0$ | $\approx 0$ | $\approx 0$ | $\approx 0$ |
| $q_{\min}$                | $\approx 0$ | $\approx 0$ | $\approx 0$ | $\approx 0$ | $\approx 0$ |
| $\Delta e_{\text{avoid}}$ | −           | −           | +           | −           | +           |
| $R$                       | +           | +           | −           | +           | +           |
| $\alpha$                  | −           | +           | −           | +           | $\approx 0$ |
| $\gamma$                  | −           | $\approx 0$ | $\approx 0$ | $\approx 0$ | $\approx 0$ |

Notes: Each parameter is changed by  $\pm 10\%$  around its baseline value. “+” and “−” indicate the dominant direction of change, while “ $\approx 0$ ” indicates a negligible response over the tested range.

## 5.2 Contributions and Limitations

This paper extends the existing literature on information economics, adverse selection, and information design by applying these mechanisms to the circular-economy market for heterogeneous retired EV batteries. Roesler and Szentes (2017) show that information structures can affect monopoly pricing and buyer welfare through their effects on demand, while Asriyan, Fuchs, and Green (2019) demonstrate how adverse selection and trading behavior jointly determine information aggregation in decentralized markets with heterogeneous assets. Lou and Rahi (2021), in turn, examine how information precision affects liquidity, bidding, and welfare in a financial double-auction setting. Building on these insights, this study shifts the focus from pricing, trading, and information aggregation to the allocation of physical assets across competing circular-economy pathways. Specifically, we treat information precision as a technology and policy variable embodied by the Battery ID. By incorporating the Battery ID as a concrete information technology, the framework also provides a microeconomic channel through which digital information infrastructure can affect market and welfare directly.

In literature focusing on the secondhand battery market, this paper shows how information quality can shape the allocation of heterogeneous physical assets. Tadelis and Zettelmeyer (2015) demonstrate that information disclosure can improve matching between heterogeneous products and buyers, while Gu et al. (2021) show that government subsidies can influence the reuse of retired EV batteries within a closed-loop supply chain. Ma et al. (2024) further show that economic and environmental characteristics of retired batteries determine the optimal balance between reuse and recycling pathways. Building on these studies, this model focuses on the information mechanism underlying this allocation rather than treating battery quality as directly observable or policy incentives as the primary driver. By modeling information precision as a technology and policy variable embodied by the Battery ID, this provides a microeconomic link between digital information infrastructure and the physical allocation of resources that is largely absent from existing pathway and supply-chain models. More broadly, our results suggest that

information design should be considered alongside subsidies, technological characteristics, and environmental costs when designing policies for circular EV-battery markets.

This study has several limitations that provide directions for future research. First, the model considers a representative secondary-battery market and abstracts from heterogeneity across battery chemistries, manufacturers, applications, and geographical markets. Second, battery quality is summarized by a one-dimensional quality variable, whereas actual battery condition involves multiple characteristics such as state of health, degradation history, safety, and remaining useful life. Third, the model focuses on information asymmetry between market participants and does not incorporate strategic misreporting or manipulation of battery-quality information by sellers. Fourth, the model's assumption that information creates social value only by moving batteries across the reuse threshold, while excluding within-threshold benefits such as reduced accident risks, lower inspection costs, and improved application matching. Fifth, the current framework is largely static and therefore does not fully capture repeated transactions, technological change, battery degradation, or learning over multiple reuse cycles.

### **5.3 Implications**

Future research can remedy the aforementioned study limitations through targeted optimization and empirical supplementation. First, subsequent studies can adopt multi-dimensional battery quality indicators and adopt real industry transaction data in future years to replace the simplified one-dimensional quality setting, so as to accurately reflect the actual comprehensive condition of recycled batteries. Second, follow-up research can introduce dynamic game analysis and real long-term reuse cycle data to capture battery degradation, technological progress and repeated market transactions, making the model adapt to real changing market environments.

## **6 Conclusion**

This paper constructs an information-economic pricing, threshold, and adverse selection framework, and derives the optimal investment through a social welfare equation. Applying this model to China's retired battery market, we find that investments in information infrastructure raise the remanufacturing quality threshold, contract remanufacturing scale, and enhance average remanufacturing quality. By comparing LFP and NCM batteries, the results demonstrate the need for heterogeneous policy frameworks.

## **7 Acknowledgement**

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research supervisor, Ms. Wang offered discussions on research orientation, methodological suggestions, milestone feedback and formatting checks without conducting research design, core analysis or manuscript writing on my behalf. All supervision provided for this study was unpaid. I proposed the initial research direction, identified the research question, retrieved and screened policies, academic papers and industry datasets, and validated model parameters with documented literature sources. I independently defined key variables and finished the whole model construction and mathematical derivation. I completed numerical simulation, parameter calibration for NCM and LFP batteries, sensitivity tests and figure generation with self verified computational outputs, while the supervisor only gave feedback on the plausibility of model assumptions. I drafted and revised the full paper and incorporated structural and normative suggestions from my supervisor. Major research challenges stemmed from policy updates, unstable baseline calibration results and overlapping private and social welfare formulations, which I resolved through repeated mechanism checks and sensitivity analysis. Generative AI tools including ChatGPT GPT 5.6 and Gemini 3.5 Flash—lite and Doubao AI were used for generating search terms, debugging Python scripts and suggesting plotting code, yet all outputs were manually cross checked and modified by myself. I take full responsibility for the study's research design, mathematical modelling, parameter choices, data interpretation and final manuscript, and confirm that all statements regarding task division, supervision and AI usage in this acknowledgement are true and complete.

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## A Bayesian Benchmark for the Linear Pricing Rule

The linear pricing rule in the main text can be micro-founded under a Gaussian benchmark. This benchmark is not required for the main results and is introduced only to provide a Bayesian interpretation of the reduced-form specification.

Suppose that, before observing the quality signal, battery quality is normally distributed:

$$q \sim N(\mu, \sigma_0^2),$$

and that the observed signal satisfies

$$s = q + \varepsilon, \quad \varepsilon \sim N(0, \sigma_\varepsilon^2),$$

where  $q$  and  $\varepsilon$  are independent.

Under these assumptions, the posterior distribution of  $q$  conditional on  $s$  is normal, and the posterior mean is

$$\mathbb{E}[q | s] = (1 - \theta)\mu + \theta s,$$

where

$$\theta = \frac{\sigma_0^2}{\sigma_0^2 + \sigma_\varepsilon^2}.$$

Thus, under this Gaussian benchmark, competitive pricing at the buyer's posterior expected value gives

$$P(s) = p_N \mathbb{E}[q | s] = p_N [(1 - \theta)\mu + \theta s].$$

The Bayesian interpretation of  $\theta$  therefore holds exactly under the Gaussian signal structure. In particular,

$$\frac{\partial \theta}{\partial \sigma_\varepsilon^2} < 0,$$

so a more precise signal receives greater weight in the posterior expectation.

The main text does not impose this Gaussian structure. For a general quality distribution  $F(q)$  and a general signal-noise distribution, the Bayesian posterior mean  $\mathbb{E}[q | s]$  need not be linear in  $s$ . Accordingly,  $\theta$  in the main model is interpreted as a reduced-form measure of information pass-through into prices. The Gaussian benchmark simply provides one microfoundation under which this reduced-form parameter coincides with a Bayesian signal weight.

## B Sensitivity Analysis: Parameters and Numerical Results

The baseline parameter values are reported in Table 4. All monetary values are normalized by the value of a new battery, such that  $p_N = 1$ . The information investment function is specified as

$$\theta(I) = 1 - \exp(-\alpha I),$$

while the investment cost is

$$C(I) = \frac{\gamma}{2} I^2.$$

Table 4: Baseline parameter values

| Parameter                                         | NCM  | LFP  |
|---------------------------------------------------|------|------|
| $p_N$                                             | 1.00 | 1.00 |
| $c_U$                                             | 0.42 | 0.42 |
| $w$                                               | 0.28 | 0.24 |
| $q_{\min}$                                        | 0.40 | 0.40 |
| $\Delta e_{\text{avoid}}$                         | 0.24 | 0.16 |
| $R$                                               | 0.34 | 0.29 |
| $K = 1, \alpha = 4, \gamma = 0.035, I_{\max} = 2$ |      |      |

The baseline numerical results are shown in Table 5.

Table 5: Baseline numerical results

| Battery | $I^*$  | $\theta^*$ | $q_m^*$ | $Y_U^*$ | $Q_U^*$ | $SW^*$ |
|---------|--------|------------|---------|---------|---------|--------|
| NCM     | 0.0701 | 0.2446     | 0.5179  | 0.4821  | 0.7590  | 0.4551 |
| LFP     | 0.1643 | 0.4816     | 0.5410  | 0.4590  | 0.7705  | 0.3907 |

The sensitivity analysis examines the effect of a  $\pm 10\%$  change in each parameter while holding all other parameters at their baseline values. The results are reported in Table 6.

The results show that  $p_N$ ,  $c_U$ ,  $w$ , and  $\Delta e_{\text{avoid}}$  have substantially larger effects on optimal information investment and social welfare than  $\alpha$  and  $\gamma$ , while changes in  $q_{\min}$  have no effect because the economic threshold remains binding under the baseline calibration. In particular, a higher new-battery value  $p_N$  substantially increases the optimal information investment and shifts more batteries toward second-life use, whereas a higher recycling value  $R$  has the opposite effect on reuse incentives. The qualitatively similar responses for NCM and LFP indicate that the main comparative-static mechanisms are robust across battery chemistries, although LFP generally exhibits a higher optimal information investment under the baseline calibration.

Table 6: Sensitivity analysis of model outcomes to parameter changes

| Battery | Parameter                 | Change | $I^*$  | $\theta^*$ | $q_m^*$ | $Y_U^*$ | $Q_U^*$ | $SW^*$ |
|---------|---------------------------|--------|--------|------------|---------|---------|---------|--------|
| NCM     | $p_N$                     | -10%   | 0.0133 | 0.0518     | 0.5774  | 0.4226  | 0.7887  | 0.4202 |
| NCM     | $p_N$                     | +10%   | 0.1153 | 0.3696     | 0.4690  | 0.5310  | 0.7345  | 0.4927 |
| NCM     | $c_U$                     | -10%   | 0.0904 | 0.3033     | 0.4752  | 0.5248  | 0.7376  | 0.4761 |
| NCM     | $c_U$                     | +10%   | 0.0479 | 0.1744     | 0.5606  | 0.4394  | 0.7803  | 0.4359 |
| NCM     | $w$                       | -10%   | 0.1096 | 0.3549     | 0.5158  | 0.4842  | 0.7579  | 0.4550 |
| NCM     | $w$                       | +10%   | 0.0352 | 0.1314     | 0.5192  | 0.4808  | 0.7596  | 0.4552 |
| NCM     | $q_{\min}$                | -10%   | 0.0701 | 0.2446     | 0.5179  | 0.4821  | 0.7590  | 0.4551 |
| NCM     | $q_{\min}$                | +10%   | 0.0701 | 0.2446     | 0.5179  | 0.4821  | 0.7590  | 0.4551 |
| NCM     | $\Delta e_{\text{avoid}}$ | -10%   | 0.0915 | 0.3064     | 0.5407  | 0.4593  | 0.7704  | 0.4438 |
| NCM     | $\Delta e_{\text{avoid}}$ | +10%   | 0.0519 | 0.1874     | 0.4947  | 0.5053  | 0.7473  | 0.4670 |
| NCM     | $R$                       | -10%   | 0.0451 | 0.1649     | 0.4849  | 0.5151  | 0.7425  | 0.4381 |
| NCM     | $R$                       | +10%   | 0.1014 | 0.3335     | 0.5501  | 0.4499  | 0.7750  | 0.4733 |
| NCM     | $\alpha$                  | -10%   | 0.0775 | 0.2434     | 0.5174  | 0.4826  | 0.7587  | 0.4551 |
| NCM     | $\alpha$                  | +10%   | 0.0640 | 0.2455     | 0.5183  | 0.4817  | 0.7591  | 0.4551 |
| NCM     | $\gamma$                  | -10%   | 0.0703 | 0.2451     | 0.5181  | 0.4819  | 0.7591  | 0.4551 |
| NCM     | $\gamma$                  | +10%   | 0.0699 | 0.2440     | 0.5177  | 0.4823  | 0.7589  | 0.4551 |
| LFP     | $p_N$                     | -10%   | 0.1085 | 0.3520     | 0.6055  | 0.3945  | 0.8028  | 0.3578 |
| LFP     | $p_N$                     | +10%   | 0.2074 | 0.5638     | 0.4884  | 0.5116  | 0.7442  | 0.4267 |
| LFP     | $c_U$                     | -10%   | 0.1842 | 0.5213     | 0.4978  | 0.5022  | 0.7489  | 0.4104 |
| LFP     | $c_U$                     | +10%   | 0.1423 | 0.4341     | 0.5844  | 0.4156  | 0.7922  | 0.3728 |
| LFP     | $w$                       | -10%   | 0.2097 | 0.5678     | 0.5357  | 0.4643  | 0.7678  | 0.3904 |
| LFP     | $w$                       | +10%   | 0.1227 | 0.3879     | 0.5447  | 0.4553  | 0.7723  | 0.3910 |
| LFP     | $q_{\min}$                | -10%   | 0.1643 | 0.4816     | 0.5410  | 0.4590  | 0.7705  | 0.3907 |
| LFP     | $q_{\min}$                | +10%   | 0.1643 | 0.4816     | 0.5410  | 0.4590  | 0.7705  | 0.3907 |
| LFP     | $\Delta e_{\text{avoid}}$ | -10%   | 0.1864 | 0.5255     | 0.5542  | 0.4458  | 0.7771  | 0.3835 |
| LFP     | $\Delta e_{\text{avoid}}$ | +10%   | 0.1441 | 0.4382     | 0.5272  | 0.4728  | 0.7636  | 0.3982 |
| LFP     | $R$                       | -10%   | 0.1292 | 0.4035     | 0.5155  | 0.4845  | 0.7578  | 0.3754 |
| LFP     | $R$                       | +10%   | 0.2057 | 0.5608     | 0.5643  | 0.4357  | 0.7822  | 0.4068 |
| LFP     | $\alpha$                  | -10%   | 0.1796 | 0.4761     | 0.5393  | 0.4607  | 0.7697  | 0.3906 |
| LFP     | $\alpha$                  | +10%   | 0.1513 | 0.4860     | 0.5424  | 0.4576  | 0.7712  | 0.3908 |
| LFP     | $\gamma$                  | -10%   | 0.1655 | 0.4841     | 0.5418  | 0.4582  | 0.7709  | 0.3908 |
| LFP     | $\gamma$                  | +10%   | 0.1631 | 0.4792     | 0.5403  | 0.4597  | 0.7702  | 0.3907 |