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论文题目：Battery ID and the Reuse－Recycling Allocation of Retired EV Batteries

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Abstract

Imperfect quality information affects how retired electric-vehicle batteries are allocated between reuse and direct recycling. This paper develops a rational-expectations participation model with a single quality threshold and a pre-committed pricing rule, then compares investment maximizing aggregate economic returns (Π) with investment maximizing social welfare (SW). Better information reduces reuse volume and raises average reuse quality when economic screening binds, but neither change alone establishes a welfare gain. Illustrative Uniform benchmarks give Π-optimal investment of 0.3179 for NCM and 0.3373 for LFP, compared with social optima of 0.0701 and 0.1643. Choosing the economic optimum lowers net social welfare by 2.26% and 0.83%, respectively, relative to the social optimum. Across the ten chemistry–distribution combinations, economic-optimal investment exceeds social-optimal investment under the maintained parameters; five of eight non-Uniform cases select zero social investment. The objective gap depends on reuse environmental benefits relative to the difference between social and private recycling values. In the illustrative owner-survey/taxi scenario, the objectives differ only by a constant and therefore share their investment optima. A matched Bayesian benchmark and parameter and density sensitivity checks delimit these findings. Battery ID policy should align investment incentives with environmental benefits and battery heterogeneity, evaluating incremental net welfare alongside reuse volume and quality.

Keywords: Retired EV batteries; Battery ID; Quality information; Economic returns; Social welfare; Information investment

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Contents

1 Introduction **4**

2 Literature Review **5**

3 Methods **7**

3.1 The Market for Retired Batteries 9

3.2 Buyers and the Price of Quality 9

3.3 The Effect of Information on Selection 12

3.4 Information Infrastructure Investment 13

3.5 Social Welfare 13

3.6 Economic and Social Investment 14

4 Results and Findings **15**

4.1 Parameters and Numerical Design 15

4.2 Uniform Benchmark: Allocation and Social Welfare 16

4.3 Distributional Robustness 17

4.4 Economic versus Social Optima 18

4.5 Matched Bayesian Benchmark 20

4.6 Owner-Survey and Taxi Scenarios 21

4.7 Key Findings 22

5 Discussion **23**

5.1 Sensitivity Analysis 23

5.2 Policy Implications 24

5.3 Contributions and Limitations 24

5.4 Future Research 25

6 Conclusion **25**

7 Acknowledgement **26**

A Bayesian Benchmarks and Pricing Interpretation **31**

A.1 Unbounded Gaussian Illustration 31

A.2 Selected Uniform Pool with Exact Posterior 31

B Detailed Numerical Results **31**

B.1 Economic and Social Objective Comparison 32

B.2 One-Parameter Sensitivity 32

C Equilibrium Boundaries and Numerical Verification **33**

2026 S.-T. Yau High School Science Award
仅用于2026丘成桐中学科学奖论文公示

1 Introduction

Critical-mineral security provides a practical motivation for studying battery circularity in China. Industry data for 2024 report that lithium-ion batteries accounted for approximately 84.9% of China's lithium-salt consumption and 82% of its primary-cobalt consumption (Ge, 2025). These are annual end-use consumption shares for all lithium-ion batteries: they are neither EV-only shares nor the percentage of China's metal stocks physically stored in vehicles. They nevertheless show why the collection and allocation of used batteries matter for resource circulation. China's annual generation of used power batteries is projected to exceed one million tonnes by 2030 (Xinhua, 2026). The question is not only how to recover their metals, but also when their remaining storage function should be used before recycling.

Two broad pathways are relevant. Batteries with sufficient residual performance can be inspected and reconfigured for a suitable secondary application; other batteries can go directly to material recovery. The relative benefits depend on chemistry, condition, processing requirements, and the application. For example, Ma et al. (2024) compare reuse-before-recycling with direct recycling and obtain different economic benefits for lithium iron phosphate (LFP) and nickel–cobalt–manganese (NCM) batteries under their modeled pathways. In a separate China power-system scenario, repurposed batteries meet 67.09% of storage demand in 2050 and lower system cost by 2.49% (Ma et al., 2026). These are conditional modeling results, rather than realized national outcomes. Together they motivate an allocation question: which batteries should retain their storage function, and which should move directly to recycling?

Quality information is central to that decision. State of health (SOH), operating history, and degradation affect reuse value, while a potential buyer may observe them only imperfectly. The information problem resembles the quality uncertainty emphasized by Akerlof (1970), but the direction of selection depends on the trading mechanism and outside options. This paper does not assume a market-collapse spiral. Instead, it studies a specified pricing and channel-commitment mechanism in which better information reduces the price cross-subsidy received by lower-quality reuse participants. This can reduce reuse volume while improving its average quality. Whether that reallocation is socially desirable depends on the value of the batteries moved to recycling.

China's policy framework makes this information question timely. Decree No. 73, issued on December 31, 2025 and effective from April 1, 2026, establishes a national traceability framework and digital identification requirements for NEV power batteries (Ministry of Industry and Information Technology et al., 2025). Articles 4 and 12 address traceability and digital battery identification. These provisions motivate studying Battery ID as information infrastructure; they do not demonstrate that traceability automatically produces accurate SOH estimates or an optimal level of reuse. Data quality, testing, access, and the market's response to disclosed information remain separate questions.

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Accordingly, this paper asks how information investment changes reuse participation, average reuse quality, and social welfare, how economic and social investment objectives differ, and how these effects depend on battery chemistry and the SOH distribution. A pre-committed signal-contingent pricing rule links information pass-through to sellers' expected returns. Rational expectations require the quality pool anticipated by buyers to match actual reuse participation. The model produces one threshold subject to a technical floor, and economic and social objectives are optimized over this same participation response. Numerical analysis combines NCM/LFP benchmarks, Beta-distribution robustness, an exact-posterior Bayesian comparison under a matched noise calibration, and two illustrative vehicle-SOH scenarios.

The contribution is to separate the screening mechanism, aggregate economic incentives, and the conditions for socially worthwhile investment. The analytical model explains why a smaller reuse market can have better average quality, while the objective comparison identifies how omitted environmental benefits change the investment recommendation. The distribution exercises also distinguish more concentrated SOH from higher average SOH, and the vehicle exercise connects the mechanism to observed sample shapes without treating illustrative economic parameters as empirical estimates. Section 2 reviews related work; Section 3 defines the model; Section 4 presents the numerical results; Section 5 discusses sensitivity, implications, limitations, and future research; Section 6 concludes.

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 (1970) established the foundational mechanism of adverse selection leading to the withdrawal of high-quality goods. Spence (1973) and 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 (2010) in their review of quality disclosure and certification practices. Subsequent research turned toward the granularity of information: Ganuza and Penalva (2010) established a comparative static framework for signal precision based on dispersion orderings, while Roesler and Szentes (2017) proved that buyer-optimal learning precision is not

2026 S.T.Yau High School Science Award
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necessarily maximal. Recently, 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 (2023) characterized optimal attribute disclosure and its pricing implications for multi-attribute products; Lou and 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 (1993) identified adverse selection in wholesale used-car markets, while Gavazza et al. (2014) quantified market inefficiency caused by transaction frictions using structural estimation. Tadelis and 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. (2022) examined digital credentials, testing the price and transaction effects of multi-party blockchain certification in lemon markets. These studies motivate the present analysis, which focuses specifically on allocation across battery reuse and recycling channels when information pass-through is a continuous policy input.

Regarding channel selection and policy tool design for returned products, Savaskan et al. (2004) established the baseline framework for reverse channel structure choices, Debo et al. (2005) examined market segmentation and technology selection for remanufacturable products, Galbreth and Blackburn (2010) analyzed optimal acquisition quantities under condition uncertainty, Vedantam and Iyer (2021) demonstrated how quality uncertainty reshapes revenue-sharing contracts in remanufacturing, and Guide and Van Wassenhove (2009) reviewed the field's evolution from operational issues to business models. In the context of rapid EV expansion, Gu et al. (2021) built a closed-loop supply chain game model for battery secondary use under government subsidies, Zhang and Dou (2021) analyzed subsidy design for EVs and charging networks, Shi and Hu (2024) investigated flexible battery ownership structures, and Wang et al. (2024) re-evaluated remanufacturing and e-waste management policies from environmental perspectives. Incorporating information mechanisms, Wu and Wang (2025) 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 (2011) conducted early economic evaluations of retired batteries in stationary storage, Martinez-Laserna et al. (2018) provided a critical review of second-

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life feasibility, and 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. (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. (2019) showed that early cycle data can accurately predict battery lifetime, while Sulzer et al. (2021) and Aitio and 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. (2022) proposed a conceptual framework for digital battery IDs in circular value chains, and 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. (2023) and 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.

These streams motivate a specific comparison: how does an endogenous reuse threshold transmit information investment into aggregate economic returns and social welfare? This paper holds the participation mechanism common across the two objectives, separates private recycling revenue from social recycling value, and studies how the SOH distribution changes the resulting investment gap. The comparison complements the strategic, engineering, and institutional approaches reviewed above.

3 Methods

This study develops a static participation model motivated by China's battery traceability policy. It compares NCM and LFP parameter bundles and then varies the quality distribution. The model is an analytical and numerical scenario exercise, not a forecast for China's 2027–2030 battery market. The owner-survey data used in an extension are international observations, whereas the taxi observations come from a Chinese commercial fleet. Their comparison illustrates distributional mechanisms and does not estimate nationally representative retired-battery SOH or the causal effect of private versus commercial use.

All numerical values are normalized. The scalar quality indicator q represents SOH in the data extension, but does not jointly measure safety, remaining useful life, and application suitability. The assumed $q_{\min} = 0.40$ is a model floor, not an engineering recommendation or a legal standard for safe reuse.

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Table 1: Key model symbols. Monetary quantities are normalized; $C(I)$ is the aggregate information cost.

Symbol	Meaning	Domain / unit
I	Information investment	$[0,\infty)$
q	Battery quality (SOH indicator)	$[0,1]$
$q_{\min}$	Technical eligibility floor	$(0,1)$
q^*	Actual reuse participation threshold	$[q_{\min},1]$
$F(q), f(q)$	Quality distribution and density	$\int_0^1 f = 1$
$\mu(q^*)$	Mean quality among reuse participants	$(q^*,1)$
K	Total battery supply	$K = 1$
$\theta(I)$	Information pass-through into prices	$[0,1)$
s, ε	Quality signal and zero-mean noise	$s = q + \varepsilon$
p_N	Base value scale for battery services	Per battery
c_U	Reuse preparation cost	Per battery
w	Seller's direct recycling revenue	Per battery
ρ	Relative recycling attractiveness	$(c_U + w)/p_N$
$P(s), \bar{P}(q)$	Realized and expected transaction prices	Per battery
Δe_{avoid}	Net environmental benefit from reuse	Per battery
R	Net social value of direct recycling	Per battery
$C(I)$	Information infrastructure cost	Aggregate
Y_U, Q_U	Reuse volume and mean reuse quality	$[0,K], [0,1]$
Π, SW	Aggregate economic returns and social welfare	Aggregate
I_P^*, I_S^*	Economic- and social-optimal investment	$[0, I_{\max}]$

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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 density $f(q) > 0$ for $0 < q < 1$, 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 ID records. An exogenous technical requirement $q_{\min} \in (0,1)$ rules out reuse below that quality, independently of sellers' economic incentives.

Market timing and commitments. In Stage 1, information investment and the signal-contingent pricing rule are established. In Stage 2, sellers use their private quality information to calculate expected transaction revenues and commit to reuse or recycling. In Stage 3, buyers observe realized signals for the batteries offered, and transaction prices follow the pre-established rule. The pricing mechanism and channel choices are committed before signal realization. Rational expectations require the pooled-quality term in the announced rule to match the actual equilibrium participation set. This is a reduced-form participation equilibrium, not a derivation of strategic Bayesian bidding.

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.

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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

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

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 θ 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 θ approaching one represents a market in which prices respond strongly to observed quality.

Let q^* denote the actual participation threshold, incorporating both economic selection and the physical minimum. Buyers know the distribution and the equilibrium selection rule before observing individual signals. The average quality of batteries actually offered for reuse is

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

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:

$$P(s) = p_N \left[(1-\theta)\mu(q^*) + \theta s \right].$$

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 $\mu(q^*)$. As θ increases, the observed quality signal receives greater weight in determining the market price. Thus, θ 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

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

2026 S. T. Yau High School Science Award
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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 $\theta = 0$,

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

so high- and low-quality batteries receive the same expected price. As θ 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 both the technical and economic conditions hold:

$$q \geq q_{\min}, \quad \bar{P}(q) - c_U \geq w.$$

Define $\rho \equiv (c_U + w)/p_N$ and, for $t < 1$,

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

For $0 < \theta \leq 1$ and $\rho < 1$, the positive-volume equilibrium has a single actual participation threshold q^* characterized by

$$\begin{cases} q^* = q_{\min}, & H(q_{\min}, \theta) \geq 0, \\ (1 - \theta)\mu(q^*) + \theta q^* = \rho, \quad q^* > q_{\min}, & H(q_{\min}, \theta) < 0. \end{cases} \tag{1}$$

In the first case, every technically eligible seller weakly prefers reuse. In the second, the marginal seller is indifferent between reuse and recycling, and expected revenue is strictly increasing in quality. Buyers' anticipated average quality is therefore consistent with the actual participation set $[q^*, 1]$.

The zero-information case requires a separate participation selection. If $\theta = 0$ and sellers are indifferent, a unique allocation by quality need not follow from payoffs alone. Numerical results use the quality-sorted limit as $\theta \to 0^+$. If $\rho \geq 1$, there is no positive-volume reuse equilibrium

2026 S. T. Yau High School Science Award
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for a continuous distribution on $[0,1]$; we use $q^* = 1$ and $Y_U = 0$, with average reuse quality undefined. Appendix C details these boundaries.

3.3 The Effect of Information on Selection

For a continuous full-support distribution with a positive interior density, the conditional mean satisfies

$$\mu'(t) = \frac{f(t)}{1-F(t)}[\mu(t) - t] > 0, \qquad t < 1. \tag{2}$$

Hence $H_t = (1-\theta)\mu'(t) + \theta > 0$, while $H_\theta = t - \mu(t) < 0$. Moreover, $\lim_{t\to 1^-} H(t,\theta) = 1 - \rho > 0$ when $\rho < 1$. Thus, for positive information, the technical-binding case or the unique interior root in equation (1) determines one actual threshold.

When economic screening binds, implicit differentiation gives

$$\frac{dq^*}{d\theta} = \frac{\mu(q^*) - q^*}{(1-\theta)\mu'(q^*) + \theta} > 0. \tag{3}$$

When the technical constraint binds throughout an interval, $q^* = q_{\min}$ and $dq^*/d\theta = 0$. A switch between regimes can create a kink, so differentiability is not asserted at the switch.

Reuse quantity, direct-recycling quantity, and average reuse quality are

$$Y_U^* = K[1 - F(q^*)], \qquad Y_R^* = KF(q^*), \qquad Q_U^* = \mu(q^*).$$

On an interior economic-screening interval, equations (2)–(3) imply

$$\frac{dY_U^*}{d\theta} = -Kf(q^*)\frac{dq^*}{d\theta} < 0, \tag{4}$$

and

$$\frac{dQ_U^*}{d\theta} = \mu'(q^*)\frac{dq^*}{d\theta} > 0. \tag{5}$$

Thus, more information produces a smaller reuse market with higher average quality when economic screening binds. These allocations are locally unchanged while the technical constraint binds. Neither a contraction in volume nor an improvement in average quality alone determines the sign of the welfare effect.

The histogram extension allows a nonnegative, piecewise constant density. At a density discontinuity the derivatives are interpreted one-sided; inside an empty bin, $f = 0$ and $\mu' = 0$. For $\theta > 0$, $H_t \geq \theta > 0$ still gives a unique threshold, but quantity and average quality can remain constant while the threshold crosses a density gap. Strict changes in equations (4)–(5) therefore require positive density at the marginal quality.

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3.4 Information Infrastructure Investment

Let $I \geq 0$ denote investment in Battery ID records and related information infrastructure. The same market response is used when optimizing social welfare and the aggregate economic-return objective defined below.

The signal remains $s = q + \varepsilon$ with $\mathbb{E}[\varepsilon \mid q] = 0$. Better testing and traceability motivate an increasing information pass-through function $\theta(I)$. The numerical specification is:

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

so that

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

This is a reduced-form mapping from investment to price responsiveness. It does not require a distribution-specific Bayesian posterior or impose a formula linking signal variance to θ.

When economic screening binds, equation (3) yields

$$\frac{dq^*}{dI} = \frac{\mu(q^*) - q^*}{(1-\theta)\mu'(q^*) + \theta} \alpha e^{-\alpha I} > 0. \tag{6}$$

When the technical threshold binds over an interval, $dq^*/dI = 0$. Investment changes allocation through market participation rather than by directly assigning individual batteries to channels.

3.5 Social Welfare

Let $\Delta e_{\text{avoid}} \geq 0$ denote the net environmental benefit from reuse. Let R denote the net social value of direct recycling, including material recovery benefits and environmental or resource costs. The seller's reservation revenue w determines private channel choice, whereas R enters social welfare; these are distinct objects.

The welfare function is

$$\begin{aligned} SW(I) = K \int_{q^*(I)}^{1} [p_N q - c_U + \Delta e_{\text{avoid}}] f(q)\, dq \\ + KRF(q^*(I)) - C(I), \qquad C(I) = \frac{\gamma}{2} I^2. \end{aligned}$$

Transfers between buyers and sellers cancel in aggregate welfare. The planner chooses

$$I_S^* \in \arg\max_{0 \leq I \leq I_{\max}} SW(I).$$

All social-optimum results use I_S^*; I_P^* below denotes the economic optimum.

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When economic screening binds, differentiation gives

$$\frac{dSW}{dI} = Kf(q^*)\left[R - (p_N q^* - c_U + \Delta e_{\text{avoid}})\right]\frac{dq^*}{dI} - \gamma I.$$

If a smooth interior optimum exists, it satisfies

$$Kf(q^*)\left[R - (p_N q^* - c_U + \Delta e_{\text{avoid}})\right]\frac{dq^*}{dI} = \gamma I_S^*,$$

with the threshold and derivative evaluated at I_S^*. This first-order condition is not sufficient for global optimality; zero investment, regime switches, and the upper boundary must also be compared. While the technical threshold binds, $dSW/dI = -\gamma I$.

For intuition, the socially efficient allocation cutoff before information cost is

$$q_{\text{soc}} = \frac{R + c_U - \Delta e_{\text{avoid}}}{p_N},$$

when it lies in $[0,1]$; technical eligibility also applies. Moving the threshold upward improves gross allocation welfare below this cutoff and reduces it above the cutoff. If $q^*(0) \geq q_{\text{soc}}$, the nondecreasing threshold and nonnegative investment cost make $I_S^* = 0$ globally optimal under the stated zero-information selection. Thus, the existence of a strictly positive investment optimum depends on the distribution and calibration.

3.6 Economic and Social Investment

To compare economic incentives with the social objective, define the aggregate economic return as the value generated by reuse plus direct recycling revenue, net of information cost:

$$\begin{aligned}\Pi(I) = K\int_{q^*(I)}^{1}[p_N q - c_U]f(q)\,dq \\ + K\int_{0}^{q^*(I)} w f(q)\,dq - C(I).\end{aligned} \tag{7}$$

The economic-optimal investment is

$$I_P^* \in \underset{0\leq I\leq I_{\max}}{\arg\max}\,\Pi(I).$$

Both objectives retain the same $q^*(I)$, information technology, and investment cost. The subscript P distinguishes the economic benchmark from the social benchmark; Π aggregates economic value across the modeled market rather than specifying an individual firm's profit or a decentralized investment equilibrium.

2026 S.-T. Yau High School Science Award
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Subtracting the objectives gives

$$SW(I) - \Pi(I) = K\{\Delta e_{\text{avoid}}[1 - F(q^*)] + (R - w)F(q^*)\}. \tag{8}$$

The difference consists of the reuse environmental benefit and the social value of recycling beyond seller revenue. On a differentiable economic-screening interval,

$$\frac{d\Pi}{dI} = Kf(q^*)[w - (p_N q^* - c_U)]\frac{dq^*}{dI} - \gamma I,$$

and

$$\frac{d(SW - \Pi)}{dI} = Kf(q^*)[R - w - \Delta e_{\text{avoid}}]\frac{dq^*}{dI}.$$

The allocation cutoff maximizing economic value before information cost is $\rho = (w + c_U)/p_N$, whereas the social cutoff is $q_{\text{soc}} = (R + c_U - \Delta e_{\text{avoid}})/p_N$. If $\Delta e_{\text{avoid}} > R - w$, screening reduces the external benefit omitted from Π; the sign reverses when the inequality reverses. If $\Delta e_{\text{avoid}} = R - w$, equation (8) reduces to $SW(I) = \Pi(I) + K\Delta e_{\text{avoid}}$, so the two objectives have identical sets of optimal investments. Boundary points and regime switches must still be checked when optimizing either objective.

4 Results and Findings

4.1 Parameters and Numerical Design

The baseline uses $q \sim U[0,1]$. Table 2 defines the chemistry bundles and the separate common-parameter vehicle scenario. Pathway studies motivate the qualitative differences (Ma et al., 2024; Quan et al., 2022), but the numerical values are illustrative and normalized rather than empirically estimated or expressed in RMB.

Table 2: Illustrative normalized parameter sets

Parameter	Meaning	NCM	LFP	Vehicle scenario
p_N	Base value scale	1.00	1.00	1.00
c_U	Reuse preparation cost	0.42	0.42	0.42
w	Seller's recycling revenue	0.28	0.24	0.38
$q_{\min}$	Technical model floor	0.40	0.40	0.40
Δe_{avoid}	Net reuse environmental benefit	0.24	0.16	0.24
R	Net social recycling value	0.34	0.29	0.62
Common: $K = 1$, $\alpha = 4$, $\gamma = 0.035$, search range $0 \le I \le 2$.				

All main experiments use $\theta(I) = 1 - e^{-4I}$, $C(I) = 0.035I^2/2$, and $K = 1$. Both objectives are optimized over $[0,2]$ by comparing boundaries, regime switches, and continuously refined candidates, with independent dense-grid checks. Four-decimal social optima refine the previous

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0.0004-step grid values: 0.0700/0.1644 become 0.0701/0.1643 for NCM/LFP. Appendix C records numerical verification and the common zero-information selection.

4.2 Uniform Benchmark: Allocation and Social Welfare

Under Uniform quality,

$$q^*(I) = \max\left\{q_{\min}, \frac{2\rho - 1 + \theta(I)}{1 + \theta(I)}\right\}.$$

At a common information level, economic screening lowers reuse volume and raises its conditional mean quality (Figure 1). LFP's lower w gives a lower threshold than NCM, with an initial technical-binding interval until $\theta = 2/15$; these are changes in participation, not physical improvements to batteries.

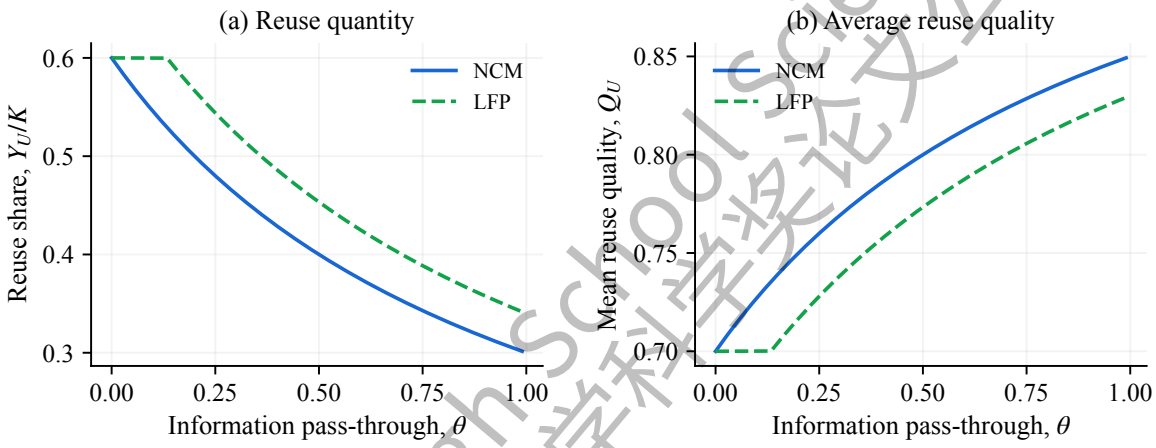


Figure 1: Reuse share and mean reuse quality at a common information pass-through θ.

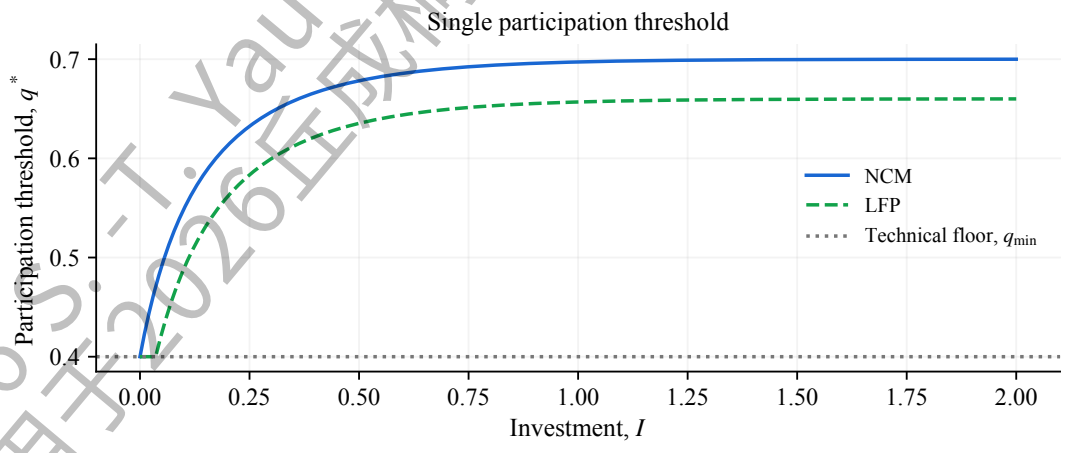


Figure 2: Participation threshold versus investment. The technical floor binds initially for LFP; economic screening determines the threshold thereafter.

Figure 3 separates net welfare levels from gains over zero investment. Social-optimal investment is $I_S^* = 0.0701$ for NCM and 0.1643 for LFP, yielding welfare 0.4551 and 0.3907 and gains of

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1.59% and 2.83%. At these separate optima, reuse shares are 0.4821/0.4590 and mean reuse quality is 0.7590/0.7705 for NCM/LFP, reversing the quality ranking at a common θ because LFP receives more investment. LFP welfare initially falls while the technical floor binds; both optima lie below their social allocation cutoffs, 0.52/0.55, because further screening is costly.

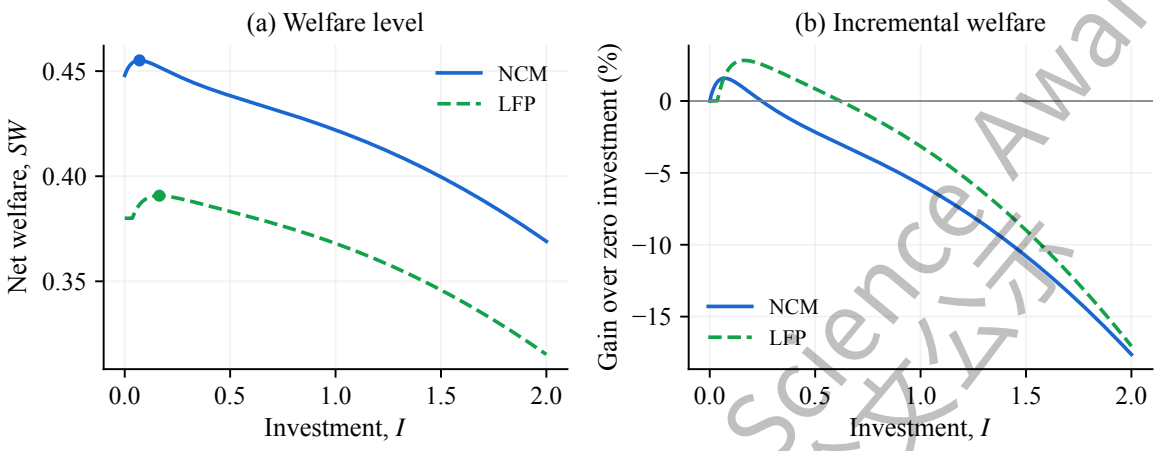


Figure 3: Net welfare and percentage gain over each chemistry's zero-investment benchmark; dots mark I_S^*.

4.3 Distributional Robustness

Uniform, Beta$(2,2)$, and Beta$(5,5)$ share mean 0.5 but differ in concentration; Beta$(5,2)$ and Beta$(2,5)$ have means $5/7$ and $2/7$ (Figure 4). Only the distribution changes within each chemistry, so these stylized cases isolate composition effects rather than estimate national SOH profiles.

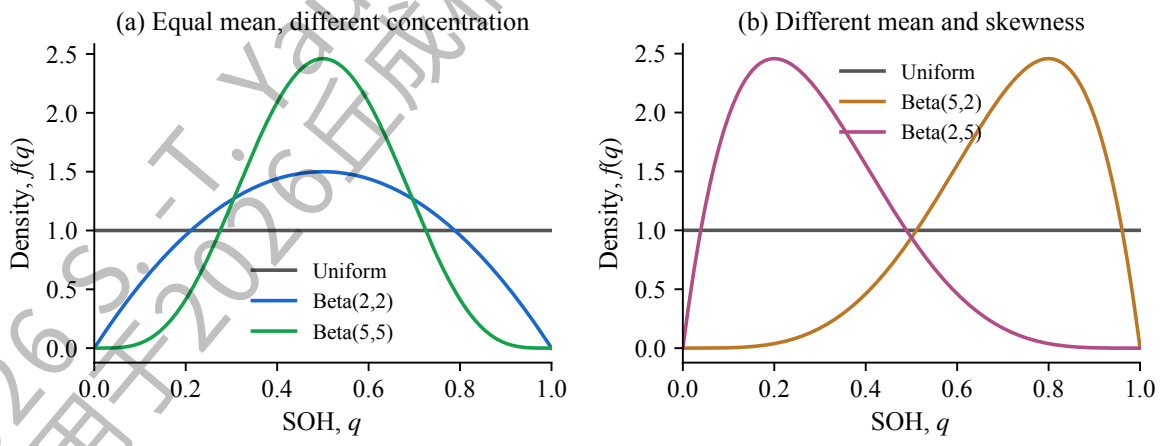


Figure 4: Quality distributions with equal means and different concentration, or different means and skewness.

Figure 5 compares each distribution at its own I_S^*. Similar thresholds can leave very different

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reuse volumes: NCM–Beta$(5,2)$ retains 87.22% of supply versus 48.21% under Uniform, principally because more quality mass lies above the threshold.

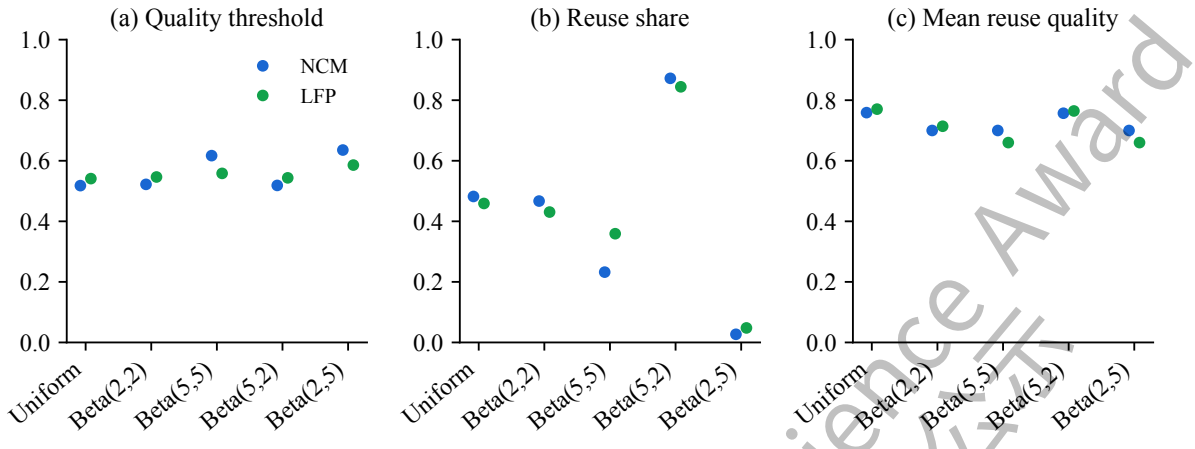


Figure 5: Threshold, reuse share, and mean reuse quality at distribution-specific social optima; values appear in Appendix B.

Five of eight non-Uniform cases choose $I_S^* = 0$: NCM with Beta$(2,2)$, Beta$(5,5)$, and Beta$(2,5)$, and LFP with Beta$(5,5)$ and Beta$(2,5)$. Their zero-information thresholds already exceed q_{soc}, so additional screening and cost cannot improve the modeled allocation channel. The remaining non-Uniform optima are 0.0683 for NCM–Beta$(5,2)$, and 0.0972/0.1601 for LFP–Beta$(2,2)$/Beta$(5,2)$ (Figure 6); absolute welfare differences across distributions should not be read as information returns.

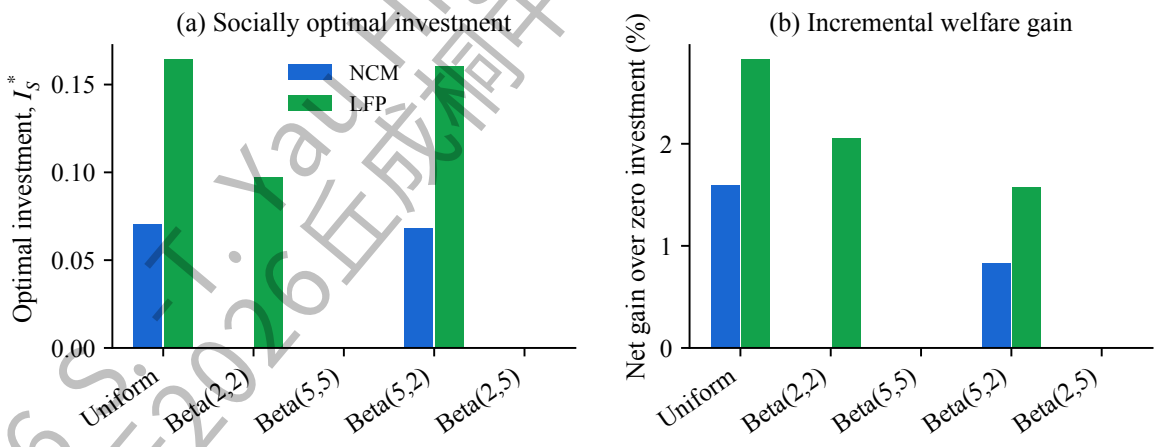


Figure 6: Social-optimal investment and percentage welfare gains over the zero-investment allocation of the same chemistry and distribution.

4.4 Economic versus Social Optima

Figure 7 compares the two objectives after subtracting their respective zero-investment levels. The economic optima, $I_P^* = 0.3179$ for NCM and 0.3373 for LFP, exceed the corresponding

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social optima, 0.0701/0.1643. This accords with equation (8): the omitted reuse benefit exceeds $R - w$ by 0.18/0.11, so the economic objective favors screening beyond the socially preferred level.

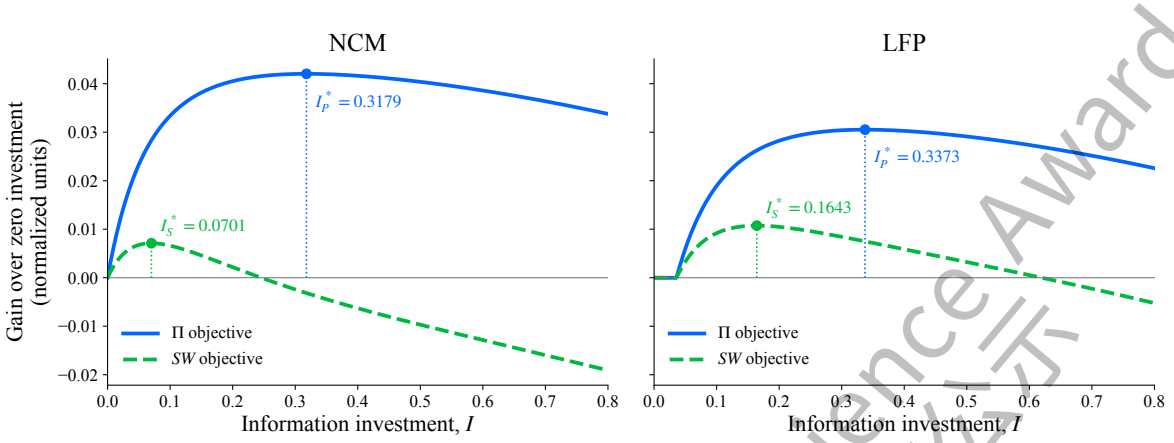


Figure 7: Gains in Π and *SW* relative to their own zero-investment values, in common normalized units; dots mark separate optima.

The ordering $I_P^* > I_S^*$ holds in all ten chemistry–distribution combinations (Figure 8). In the five cases with zero social-optimal investment, the economic optimum remains positive, showing that an incentive to increase aggregate economic returns does not by itself establish a social benefit.

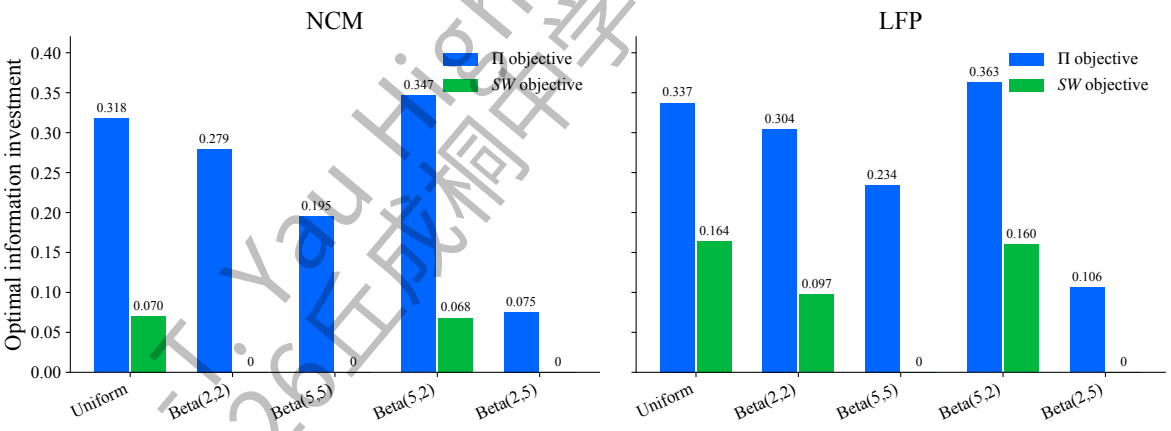


Figure 8: Economic- and social-optimal investment under each quality distribution, holding the chemistry-specific parameters fixed.

At the economic optimum, reuse shares fall to 34.89%/39.07% and mean reuse SOH rises to 82.55%/80.47% for NCM/LFP (Figure 9). Nevertheless, net social welfare is 2.26%/0.83% below its maximum, measured as $100[SW(I_S^*) - SW(I_P^*)]/SW(I_S^*)$. Better average reuse quality therefore does not imply a more efficient allocation; the stronger screening also diverts socially valuable batteries and incurs additional information cost. The comparison concerns the supplied aggregate economic objective, rather than an estimated individual-firm investment response.

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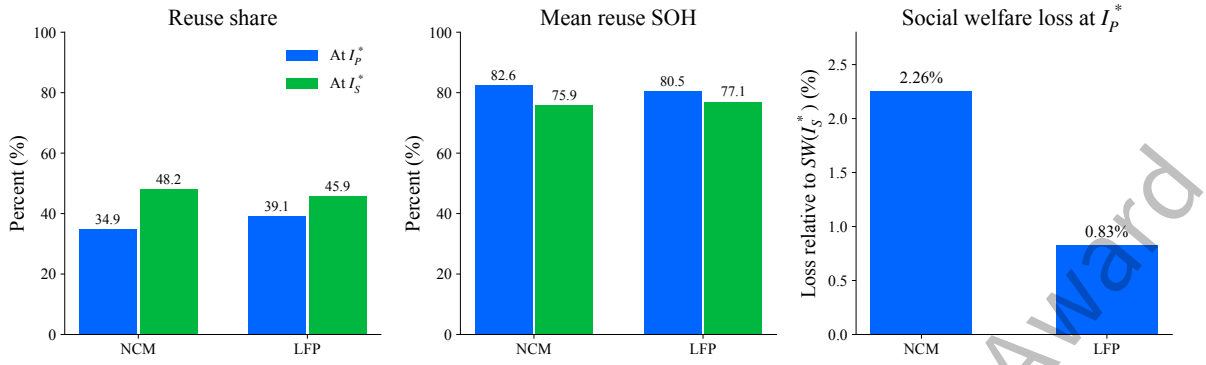


Figure 9: Uniform allocation outcomes at I_P^* and I_S^*, and the percentage loss in net social welfare at I_P^* relative to $SW(I_S^*)$.

4.5 Matched Bayesian Benchmark

An exact-posterior check replaces the linear price rule with Bayesian pricing for the selected Uniform pool and Gaussian noise, calibrated as $\sigma_\varepsilon^2 = (1-t)^2/[12(e^{4I}-1)]$ for $I > 0$. This matches the pool signal-to-noise ratio to the information index while allowing a nonlinear posterior; its pool-dependent noise scale is a scenario assumption (Appendix A).

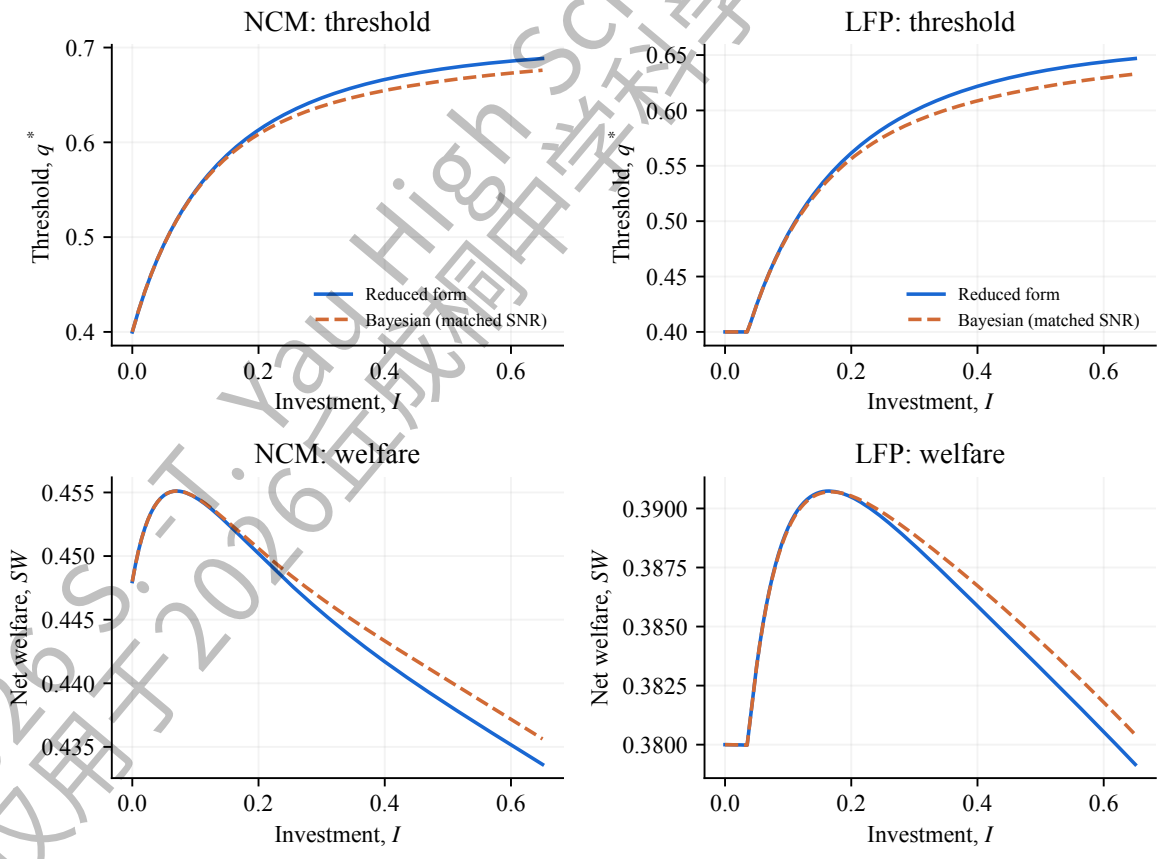


Figure 10: Reduced-form and matched exact-posterior thresholds and social welfare. Display: $I \leq 0.65$; optimization: $[0, 2]$.

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Bayesian social optima are 0.0703/0.1679 for NCM/LFP, versus reduced-form 0.0701/0.1643, with small welfare differences. Figure 10 supports the Uniform social benchmark under this noise calibration; it does not establish equivalence for the economic objective or other distributions.

4.6 Owner-Survey and Taxi Scenarios

The owner scenario uses 156 voluntary international Nissan LEAF reports, with mean SOH 83.48% and standard deviation 11.40 percentage points (Saxton, n.d.). The taxi scenario uses 20 vehicles from Deng et al. (2023), with the taxi classification supported by Tian et al. (2025); mean estimated SOH is 79.29% with standard deviation 1.69 percentage points. These unmatched samples are neither representative retired-battery populations nor evidence of a causal vehicle-use effect.

Taxi capacity is estimated as $\widehat{C} = [-\int i(t)dt/3600]/(\Delta SOC/100)$ and $\widehat{q} = \widehat{C}/(145\,\text{Ah})$. Each vehicle contributes its median estimate from valid charging segments with at least 100 records and a SOC rise of at least 20 percentage points: 2,883 segments in the common August 16–November 14, 2021 window. The analysis does not substitute SOC for SOH or impute missing SOH.

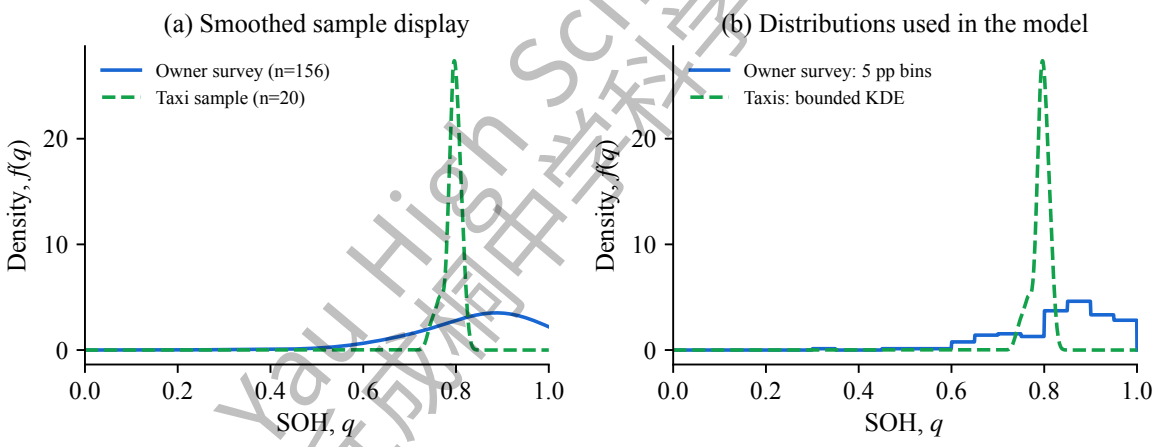


Figure 11: Smoothed sample displays (a) and actual model densities (b): owner five-percentage-point histogram and taxi bounded KDE.

The smoothed displays use bounded Gaussian KDE with likelihood-selected bandwidths of 8.11/0.88 percentage points for owners/taxis. Main market calculations retain the owner five-percentage-point histogram and taxi KDE shown in Figure 11(b); changing the owner representation is tested in Section 5.1.

Both groups use the vehicle column of Table 2, giving $\rho = q_{\text{soc}} = 0.80$. At common investment, selection raises mean reuse quality more in the wider owner distribution (Figure 12); at zero investment, reuse shares are 0.9936/0.8109 and mean reuse qualities 0.8395/0.8000 for owners/taxis.

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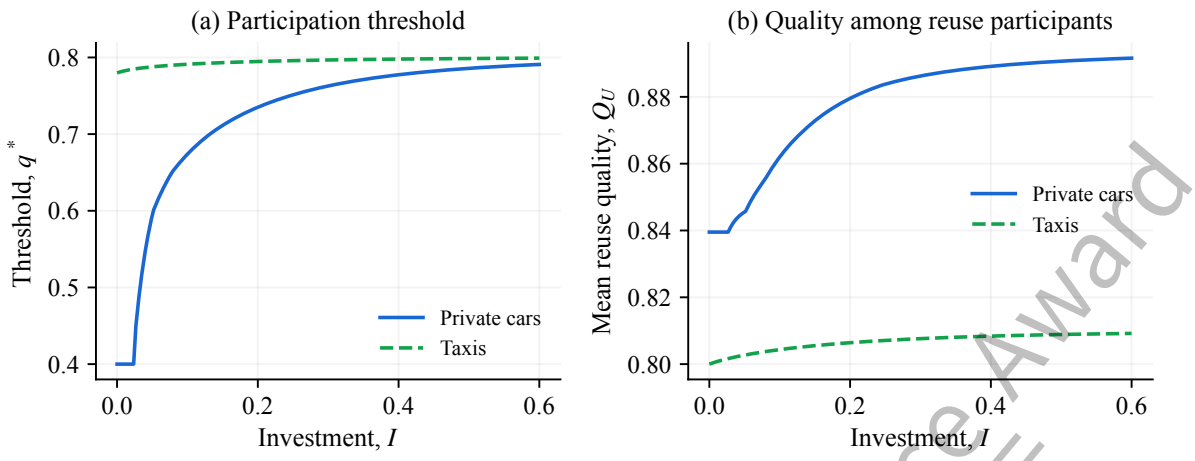


Figure 12: Participation thresholds and mean reuse quality at common investment; blue denotes the owner-survey scenario and green the taxi scenario.

Social optima are 0.2921/0.1597 for owners/taxis, with mean reuse quality 0.8859/0.8057 and net welfare gains of 3.91%/0.44% (Figure 13). Here $R - w = \Delta e_{\text{avoid}} = 0.24$, so $SW(I) = \Pi(I) + 0.24$: both objectives have the same optima and identical gains over zero investment. This equality follows from the common economic assumptions, whereas the difference between the two vehicle scenarios reflects their modeled distributions.

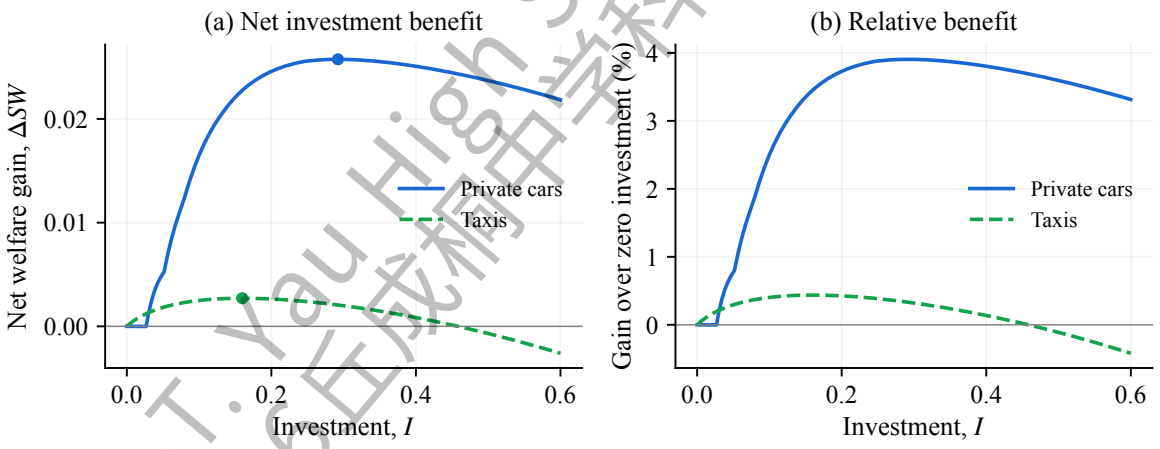


Figure 13: Net and percentage gains over each group's zero-investment social welfare; dots mark group-specific optima.

4.7 Key Findings

More information can improve conditional reuse quality while reducing reuse volume. Under the chemistry baselines, economic incentives select more investment than social welfare, while the vehicle parameter equality makes the objectives coincide. Distributional differences affect the size of both investment benefits and objective gaps; none of these numerical comparisons alone identifies actual firm behavior or national spending needs.

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5 Discussion

5.1 Sensitivity Analysis

Each economic or information parameter is varied by $\pm 10\%$ and social investment is reoptimized, with gains measured against the perturbed case's own zero-investment allocation (Appendix B). Higher w strengthens private screening and lowers I_S^* in the tested range, whereas higher R raises the social value of recycling and increases I_S^*. Changing $q_{\min}$ leaves the optimized allocation unchanged because the economic threshold remains binding. Joint changes in α and γ show why investment input and the welfare benefit should be reported separately (Figure 14): more productive information can require less expenditure.

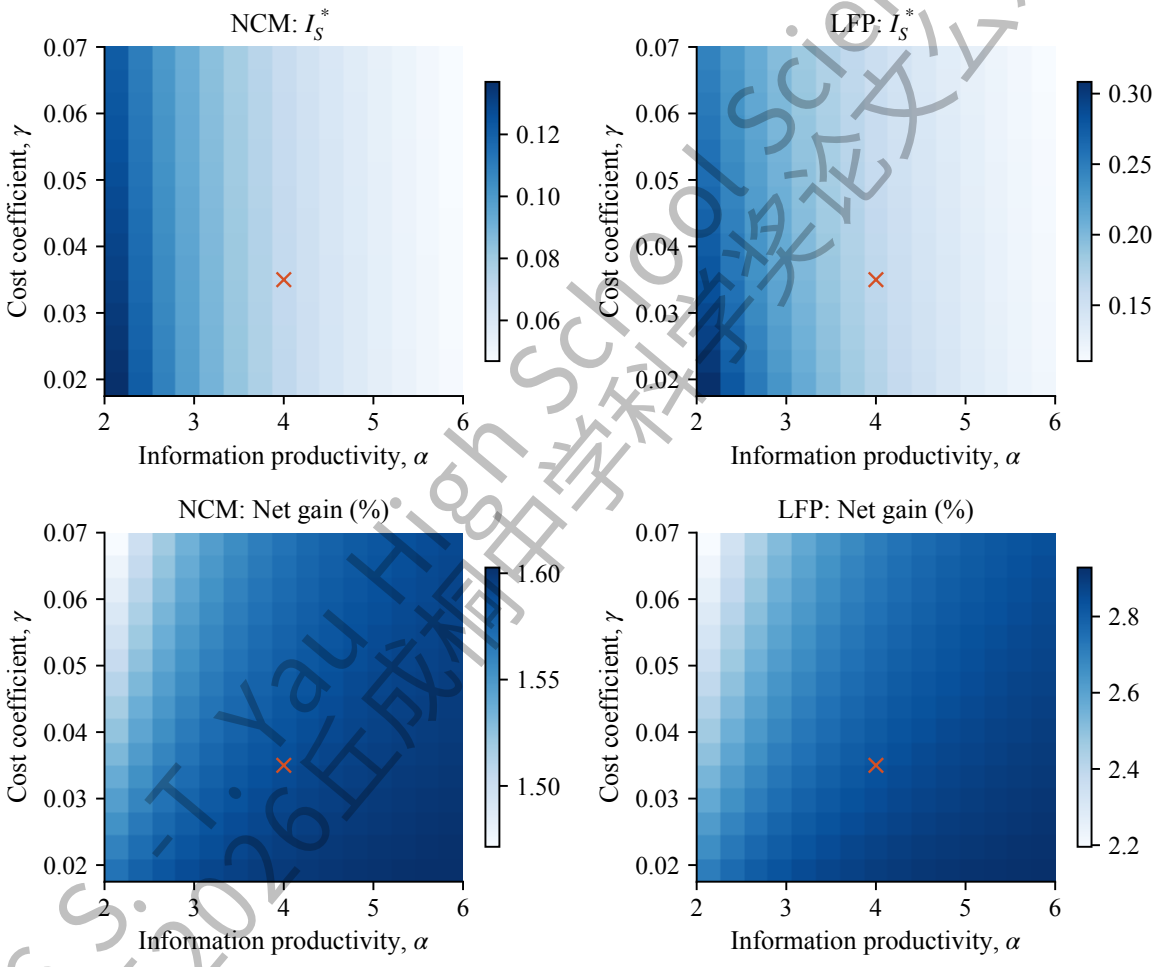


Figure 14: Social-optimal investment (top) and percentage welfare gains (bottom) under joint information-productivity and cost sensitivity; crosses mark the baseline.

The economic/social gap follows equation (8), rather than a universal underinvestment claim. Raising Δe_{avoid} changes SW but not Π, and equality with $R - w$ aligns the objectives' optima. Boundary classifications can also change with negligible welfare impact: reducing the environmental benefit to 0.237 in NCM–Beta$(2,2)$, or 0.151 in LFP–Beta$(5,5)$, creates small positive

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social optima but gains below 6.5×10^{-7}.

For the vehicle distributions, lowering R from 0.62 to 0.34 while holding other parameters fixed gives owner investment 0.0353 with a 0.0444% social gain, and zero taxi investment. Replacing the owner histogram with its display KDE raises the main owner optimum from 0.2921 to 0.3240 (Table 3); hence neither the investment magnitudes nor the vehicle comparison should be attributed to dispersion alone. The reported one-parameter and density tables concern social optima; the economic comparison is reported separately in Section 4.4.

Table 3: Sensitivity to the vehicle-density representation

Representation	I_S^*	Net gain	Gain (%)
Owner 5 pp bins	0.2921	0.025749	3.91
Owner bounded KDE	0.3240	0.033879	5.26
Taxi bounded KDE	0.1597	0.002711	0.44

5.2 Policy Implications

Align investment incentives with environmental benefits and battery heterogeneity. In these chemistry scenarios, maximizing aggregate economic returns encourages more screening than maximizes social welfare, so additional support for information investment cannot be justified solely by its economic return. Evaluation should account for the value of batteries diverted from reuse, recycling externalities, and information costs; the results do not establish a general case for either subsidizing or restraining firm investment.

Reuse volume and mean SOH should be assessed alongside incremental net welfare. A smaller reuse pool can remove low-value participants, but higher average quality can also accompany welfare losses when screening excludes socially valuable batteries. Chemistry-specific values and measured SOH distributions are therefore preferable to a uniform investment target or a budget assigned by vehicle-use labels.

Traceability records, independent testing, and linked transactions can support appraisal of the starting allocation and the marginal value of better information. A zero modeled allocation benefit concerns additional investment within the maintained framework, not suspension of traceability or safety obligations. Converting these normalized comparisons into policy budgets requires estimated costs, benefit incidence, and firm-level incentives.

5.3 Contributions and Limitations

The model links a single participation threshold to quantity, conditional quality, and two investment objectives. Its main distinction is between information's screening effect and the social value of that effect: the economic/social difference is explicitly accounted for by reuse

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and recycling externalities. The Bayesian and distribution exercises test selected assumptions without turning illustrative parameters into empirical estimates.

Quality is one-dimensional, while actual suitability also depends on safety, remaining life, chemistry, and application. The pricing rule, risk neutrality, pre-signal commitments, known distributions, and quality-sorted zero-information selection are maintained assumptions. The matched Bayesian calculation checks the Uniform social benchmark under one noise calibration, not every distribution or the complete economic/social comparison.

Both objectives are aggregate benchmarks, and Π does not specify ownership of information, benefit capture, or cost sharing by individual firms. Economic values and information costs are normalized assumptions; safety benefits, inspection savings, fraud reduction, and matching within reuse are omitted. The comparison therefore quantifies a modeled allocation channel, not an observed private-investment equilibrium or a national program's monetary return.

The voluntary owner survey and single-fleet taxi data differ in age, chemistry, geography, and measurement; neither represents retired batteries nationally. Density choices add uncertainty, and the vehicle equality of objectives depends on $R - w = \Delta e_{\text{avoid}}$, rather than empirical evidence that economic and social interests generally align. The analysis is also static, with fixed supply and outside options.

5.4 Future Research

Linked operating histories, independent SOH tests, transaction prices, and observed channel choices can identify the information technology and economic values in monetary units. Matched retired-vehicle samples, uncertainty intervals, and alternative density estimates would help distinguish use intensity from chemistry, age, and measurement effects.

Beyond the aggregate Π benchmark, a firm-level model should specify benefit capture, investment-cost sharing, pricing, and strategic disclosure to explain decentralized investment. A dynamic extension could follow degradation, secondary-use duration, delayed material recovery, and changing demand, evaluating the timing as well as the scale of information provision.

6 Conclusion

Battery ID information changes allocation through a single reuse participation threshold. When economic screening binds, better information raises the threshold, reduces reuse volume, and increases average reuse quality. Efficient investment nevertheless depends on the social value of marginal batteries and the cost of inducing this selection.

The illustrative Uniform economic optima are 0.3179 for NCM and 0.3373 for LFP, com-

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pared with social optima of 0.0701/0.1643. Choosing the economic optimum reduces net social welfare by 2.26%/0.83% relative to its maximum, even though average reuse quality is higher. Economic-optimal investment exceeds social-optimal investment in all ten chemistry–distribution combinations under the stated parameters; five non-Uniform cases favor zero social investment.

This ordering is conditional on the externality gap. If $R - w = \Delta e_{\text{avoid}}$, the objectives differ only by a constant, as in the vehicle scenario where both yield owner/taxi optima of 0.2921/0.1597. Policy appraisal should therefore align investment incentives with environmental benefits and battery heterogeneity, using incremental net welfare alongside quantity and quality. Empirical costs, benefit incidence, multidimensional quality, and firm-level behavior remain necessary for a monetary investment recommendation.

7 Acknowledgement

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A Bayesian Benchmarks and Pricing Interpretation

A.1 Unbounded Gaussian Illustration

If $q \sim N(\mu, \sigma_0^2)$ and $s = q + \varepsilon$ with independent $\varepsilon \sim N(0, \sigma_\varepsilon^2)$, the posterior mean is

$$E[q \mid s] = (1-\theta)\mu + \theta s, \qquad \theta = \frac{\sigma_0^2}{\sigma_0^2 + \sigma_\varepsilon^2}.$$

This illustrates a linear posterior weight for an unbounded Gaussian prior. It does not derive the exact posterior of the selected Uniform, Beta, histogram, or KDE pools. The main model therefore treats θ as reduced-form price responsiveness.

A.2 Selected Uniform Pool with Exact Posterior

For the robustness calculation in Section 4.5, let the anticipated selected prior be Uniform on $[t, 1]$. With normal observation noise of standard deviation σ, the exact posterior mean is

$$m(s; t, I) = \frac{\int_t^1 u \exp[-(s-u)^2/(2\sigma^2)]\, du}{\int_t^1 \exp[-(s-u)^2/(2\sigma^2)]\, du}.$$

The noise calibration is $\sigma^2 = (1-t)^2/[12(e^{4I}-1)]$. Sellers commit to a channel before observing the realized signal, and expected transaction value for true quality q is

$$p_N E_\varepsilon[m(q+\varepsilon; t, I)].$$

If the expected net return at $q_{\min}$ is at least w, all technically eligible qualities participate. Otherwise the equilibrium cutoff satisfies

$$p_N E_\varepsilon[m(t+\varepsilon; t, I)] - c_U = w.$$

The selected pool used in the posterior must match that cutoff. At $I = 0$, the calculation uses the same quality-sorted limiting selection as the reduced-form benchmark. Numerical integration uses Gauss–Legendre nodes for the bounded prior and Gauss–Hermite nodes for noise; node-count and investment-grid refinements check stability. The calculation retains the same welfare accounting and investment cost. Its matching is in a variance ratio, not an identity of posterior functions, and the noise technology is pool dependent.

B Detailed Numerical Results

The main text emphasizes the mechanism and graphical comparisons. The following tables collect detailed values so that a large results table does not interrupt the simulation figures.

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Monetary and investment units remain normalized. Continuous optimizers account for the minor rounding differences from earlier grid-based presentations.

Table 4: Continuously refined Uniform baseline optima

Chemistry	I_S^*	q^*	Y_U/K	Q_U	SW^*	Gain (%)
NCM	0.0701	0.5179	0.4821	0.7590	0.4551	1.59
LFP	0.1643	0.5410	0.4590	0.7705	0.3907	2.83

Table 5: Optimal investment and allocation across quality distributions

Chemistry	Distribution	I_S^*	q^*	Y_U/K	Q_U	Gain (%)
NCM	Uniform	0.0701	0.5179	0.4821	0.7590	1.59
NCM	Beta(2,2)	0.0000	0.5221	0.4669	0.7000	0.00
NCM	Beta(5,5)	0.0000	0.6169	0.2322	0.7000	0.00
NCM	Beta(5,2)	0.0683	0.5186	0.8722	0.7570	0.83
NCM	Beta(2,5)	0.0000	0.6355	0.0269	0.7000	0.00
LFP	Uniform	0.1643	0.5410	0.4590	0.7705	2.83
LFP	Beta(2,2)	0.0972	0.5464	0.4306	0.7140	2.06
LFP	Beta(5,5)	0.0000	0.5583	0.3591	0.6600	0.00
LFP	Beta(5,2)	0.1601	0.5436	0.8442	0.7645	1.57
LFP	Beta(2,5)	0.0000	0.5858	0.0479	0.6600	0.00

B.1 Economic and Social Objective Comparison

Table 6: Economic and social optima under each quality distribution

Chemistry	Distribution	I_P^*	I_S^*	$SW(I_P^*)$	$SW(I_S^*)$	Loss (%)
NCM	Uniform	0.3179	0.0701	0.4448	0.4551	2.26
NCM	Beta(2,2)	0.2792	0.0000	0.4088	0.4240	3.60
NCM	Beta(5,5)	0.1950	0.0000	0.3701	0.3818	3.05
NCM	Beta(5,2)	0.3467	0.0683	0.5276	0.5466	3.49
NCM	Beta(2,5)	0.0751	0.0000	0.3440	0.3448	0.25
LFP	Uniform	0.3373	0.1643	0.3875	0.3907	0.83
LFP	Beta(2,2)	0.3044	0.0972	0.3555	0.3604	1.36
LFP	Beta(5,5)	0.2343	0.0000	0.3222	0.3295	2.21
LFP	Beta(5,2)	0.3627	0.1601	0.4651	0.4706	1.18
LFP	Beta(2,5)	0.1062	0.0000	0.2944	0.2953	0.30

B.2 One-Parameter Sensitivity

Each row changes only the named parameter relative to its chemistry baseline. The gain column compares the optimum with zero investment under the *same changed parameters*. The quality floor has no effect in this tested range because optimized economic thresholds exceed the altered floors.

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Table 7: Continuously reoptimized one-parameter sensitivity

Chemistry	Parameter	Change	I_S^*	q^*	Q_U	SW^*	Gain (%)
NCM	p_N	-10%	0.0133	0.5774	0.7887	0.4202	0.05
NCM	p_N	+10%	0.1153	0.4690	0.7345	0.4927	0.54
NCM	c_U	-10%	0.0904	0.4752	0.7376	0.4761	0.61
NCM	c_U	+10%	0.0479	0.5606	0.7803	0.4359	0.69
NCM	w	-10%	0.1096	0.5158	0.7579	0.4550	1.56
NCM	w	+10%	0.0352	0.5192	0.7596	0.4552	0.45
NCM	$q_{\min}$	-10%	0.0701	0.5179	0.7590	0.4551	1.59
NCM	$q_{\min}$	+10%	0.0701	0.5179	0.7590	0.4551	0.69
NCM	Δe_{avoid}	-10%	0.0915	0.5407	0.7704	0.4438	2.36
NCM	Δe_{avoid}	+10%	0.0519	0.4947	0.7473	0.4670	0.99
NCM	R	-10%	0.0450	0.4849	0.7425	0.4381	0.84
NCM	R	+10%	0.1014	0.5501	0.7750	0.4733	2.53
NCM	α	-10%	0.0775	0.5174	0.7587	0.4551	1.58
NCM	α	+10%	0.0640	0.5183	0.7591	0.4551	1.59
NCM	γ	-10%	0.0703	0.5181	0.7591	0.4551	1.59
NCM	γ	+10%	0.0699	0.5177	0.7589	0.4551	1.59
LFP	p_N	-10%	0.1085	0.6055	0.8028	0.3578	2.63
LFP	p_N	+10%	0.2074	0.4884	0.7442	0.4267	1.11
LFP	c_U	-10%	0.1842	0.4978	0.7489	0.4104	1.28
LFP	c_U	+10%	0.1423	0.5844	0.7922	0.3728	4.86
LFP	w	-10%	0.2097	0.5357	0.7678	0.3904	2.73
LFP	w	+10%	0.1227	0.5447	0.7723	0.3910	2.89
LFP	$q_{\min}$	-10%	0.1643	0.5410	0.7705	0.3907	4.70
LFP	$q_{\min}$	+10%	0.1643	0.5410	0.7705	0.3907	1.44
LFP	Δe_{avoid}	-10%	0.1864	0.5542	0.7771	0.3835	3.54
LFP	Δe_{avoid}	+10%	0.1441	0.5272	0.7636	0.3982	2.21
LFP	R	-10%	0.1292	0.5155	0.7578	0.3754	1.90
LFP	R	+10%	0.2057	0.5643	0.7822	0.4068	3.87
LFP	α	-10%	0.1796	0.5393	0.7697	0.3906	2.80
LFP	α	+10%	0.1513	0.5424	0.7712	0.3908	2.85
LFP	γ	-10%	0.1655	0.5418	0.7709	0.3908	2.84
LFP	γ	+10%	0.1631	0.5403	0.7701	0.3907	2.81

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C Equilibrium Boundaries and Numerical Verification

For a positive-density, full-support distribution and $0 < \theta \leq 1$, $H_t > 0$ and $\lim_{t\to 1^-} H(t,\theta) = 1-\rho > 0$ if $\rho < 1$. The technical-binding case or the unique interior root therefore determines

the positive-volume threshold. For the histogram, $H_t \geq \theta > 0$ within bins; continuity of the tail mean joins the pieces. This preserves the threshold argument even though density gaps can make outcome changes weak rather than strict.

At $\theta = 0$, sellers facing a pooled price may be indifferent. The numerical benchmark selects the quality-sorted limit as $\theta \to 0^+$. If $\mu(q_{\min}) \geq \rho$, all technically eligible batteries participate; otherwise the limiting threshold solves $\mu(t) = \rho$. Payoffs alone do not establish uniqueness over all possible zero-information participation sets. For $\rho \geq 1$ under a continuous distribution supported on $[0,1]$, the model has no positive-volume reuse equilibrium; $q^* = 1$ is an empty-market convention, with mean reuse quality undefined.

For Beta(a,b), write $S(t) = 1 - F(t)$ and

$$T(t) = \frac{a}{a+b}[1 - \mathscr{I}_t(a+1,b)], \qquad \mu(t) = T(t)/S(t).$$

Survival functions are evaluated directly to avoid subtraction error. All reduced-form welfare calculations use

$$SW = p_N K T(q^*) + K(-c_U + \Delta e_{\text{avoid}})S(q^*) + KRF(q^*) - \gamma I^2/2.$$

For the original ten chemistry–distribution scenarios, independent quadrature checks give maximum welfare-integral discrepancy below 2.3×10^{-16}, and the equilibrium equality/inequality discrepancy is below 1.4×10^{-15}. These checks refer specifically to the Uniform/Beta implementation, not to all subsequent posterior or vehicle computations. Candidate comparisons include zero investment, the upper endpoint, regime changes, derivative roots, and refined grid maxima. A 10,001-point grid provides an independent numerical check. In those ten cases, $q^*(2) > q_{\text{soc}}$, so higher investment cannot improve welfare beyond the search interval.

The updated Uniform sensitivity runs independently compare 5,001- and 10,001-point searches with local continuous refinement. The vehicle representation calculations additionally bound allocation welfare over investment subintervals and compare it with the minimum information cost on each interval, reducing the numerical upper–lower gap below 10^{-10}. A bound using the unconstrained allocation maximum rules out an improvement for $I \geq 2$. These are floating-point numerical bounds, not a proof against data or model misspecification. Bayesian checks separately refine quadrature and investment grids; their diagnostics are supplied with the source package. The selected vehicle records, parameter sets, figure inputs, calculations, and validation records accompany the paper.

The additional Π–*SW* comparison independently reoptimizes both objectives in all ten chemistry–distribution cases. Numerical integration verifies Π within 1.2×10^{-16}, and equation (8) within 1.7×10^{-16}. For each objective, the unconstrained gross allocation maximum minus $C(2)$

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bounds every value at $I \geq 2$ below the computed optimum. The selected vehicle parameters also reproduce $SW - \Pi = 0.24$ and identical optima. These results use the unchanged participation mapping; they do not constitute an estimated decentralized firm equilibrium.

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