Ke-Cheng Hsu (Clio)
Ph.D. Candidate, Department of Economics, HKUST
(852) 6840 9753 | khsu@connect.ust.hk
cliohsu1997.github.io | github.com/cliohsu1997

16 November 2026

Hiring Team
Our Hong Kong Foundation Limited
19/F, Nan Fung Tower, 88 Connaught Road Central, Hong Kong
Re: Researcher

Dear Hiring Team,

I am writing to apply for the Researcher position at Our Hong Kong Foundation. I am a Ph.D. candidate in Economics at HKUST (expected June 2027; I can finish as early as February 2027 and am available to start afterward), a Hong Kong permanent resident with the right to work in Hong Kong, a native Mandarin speaker, and professionally fluent in English. The role calls for evidence-based policy research, clear writing for diverse readers, and collaboration with industry, government, and experts. That is the kind of work I am trained for: build a model that ties evidence to theory and market structure, estimate it carefully on real data, quantify welfare or economic loss under counterfactual scenarios, and write up the result so a non-specialist can follow it—the same quantification skill set used in policy evaluation and in commercial disputes, valuation, and damages analysis.

The day-to-day described in the posting is close to what I already do. My sole-authored job market paper is a Ph.D.-level structural industrial-organization study of Taobao apparel return policy: I assemble a large proprietary transaction panel, develop an original welfare framework that separates ex-ante purchase inefficiency from ex-post return inefficiency, estimate demand, fit uncertainty, and return responses by GMM with bootstrap inference, and rank counterfactual policies by seller profit, consumer surplus, and social welfare. A menu that pairs a discounted price with a moderate restocking fee raises social welfare by about 2 million RMB (roughly a 5% gain) and seller profit by about 1.2 million RMB relative to the status-quo insurance policies, attaining about 75–78% of first-best welfare outside dresses. With Professors Kohei Kawaguchi and Kei Kawai, I clean and link large bookstore point-of-sale records and estimate pricing and inventory under demand uncertainty, where we compare a dynamic model against the classical static model and show the static version overstates marginal cost by about 20%. Ph.D.-level industrial-organization coursework covered merger simulations, entry/exit counterfactuals, and firm-conduct identification. I run tested pipelines in Python, R, and C++ on SLURM and AWS, and I use Excel, Word, and PowerPoint for figures, summaries, and presentations. I work independently and in bilingual teams and meet deadlines.

I want to put this training to work on Hong Kong and Greater Bay Area policy questions, including economic development, land and housing, and related market and regulatory issues. My present compensation is a postgraduate studentship at HKUST; my expected monthly basic salary is HKD 28,000–35,000. I attach my resume, transcript, and a writing sample (job market paper). Thank you for your consideration.

Sincerely,

Ke-Cheng Hsu (Clio)

HSU, Ke-Cheng (Clio)

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Professional Summary

PhD candidate in Economics at HKUST with strong statistical training in empirical industrial organization and market structure. Works with large proprietary datasets (e-commerce transactions and retail point-of-sale records), builds structural models that go beyond typical regression and descriptive analysis, and estimates welfare and economic loss under counterfactual scenarios—the same quantification skill set used in policy evaluation and in commercial disputes, valuation, and damages analysis. Clear written and verbal communicator who structures complex ideas for non-specialists, delivers careful work to deadlines, and picks up new industries and methods quickly; collaborates in Mandarin and English. Hong Kong permanent resident.

Education

The Hong Kong University of Science and Technology, Hong Kong

Doctor of Philosophy in Economics Expected Graduation: June 2027 (available as early as February 2027)

Research interests: Empirical industrial organization and digital economics.

Master of Philosophy in Economics 2020–2022

CGA: 4.1/4.3.

Bachelor of Science in Mathematics and Economics, Minor in Actuarial Mathematics 2015–2019

CGA: 3.9/4.3.

Awards: Dean's List (2016–2019); University Scholarship (730K HKD); Academic Achievement Medal (top 1%); Postgraduate studentship (1.5M HKD); Redbird scholarship (40K HKD).

Experience

Research Assistant, National Taiwan University 2020

- Modeled crisis intervention as regulator–creditor negotiation; derived and simulated equilibrium predictions to support policy design.

Teaching Assistant & Lecturer, Department of Economics, HKUST 2020–present

- Lecturer for MSc Math Camp (4.53/5); TA for PhD and undergraduate economics (avg 4.72/5); present technical material clearly to non-specialist audiences.

Projects

Inventory and Pricing under Resale Price Maintenance (RPM) *(w/ K. Kawaguchi, HKUST; K. Kawai, U. Tokyo)*

- Built a dynamic oligopoly model of pricing and inventory under demand uncertainty and RPM, with equilibrium stockouts and unsold returns (35–40% of Japanese books printed are discarded); constructed title-by-market-by-month panels from monthly bookstore POS data (deliveries, sales, returns; tens of billions of records across 1,000+ stores), linked via standardized ISBNs and merged with local demographics and detailed title-level information scraped from Amazon in Python.

- Estimated demand and supply with instrumental variables (2SLS) and Hausman-style price instruments; validated the estimator with Monte Carlo on simulated equilibria; selected controls with LASSO and panel fixed effects; implemented iterative equilibrium simulation in C++.

- Compared the dynamic model against the classical static model and showed the static version overstates marginal cost by ∼20% once demand uncertainty and inventory decisions are ignored; uncovered stockout-driven intertitle and intertemporal substitution (not interregional) through weekly descriptive statistics, regressions, and figures.

Return Policy Design in E-Commerce *(Sole-authored Job Market Paper)*

- Sole-authored Ph.D. structural industrial-organization study: built and estimated a model of purchase, return-shipping-insurance take-up, and return under monopoly pricing, using within-retailer switches between automatic provision and selective adoption of return-shipping insurance on Taobao (2017–2023; ∼62M RMB revenue; six apparel categories; ∼20–30% return rates); scraped and OCR-digitized product attributes in Python.

- Developed an original welfare framework that decomposes losses into ex-ante purchase inefficiency and ex-post return inefficiency; recovered category-specific demand, fit uncertainty, and return responses via GMM with bootstrap inference; built a reproducible estimation pipeline on AWS and HPC/SLURM (Python, R, C++) with Monte Carlo validation of policy rankings for seller profit, consumer surplus, and social welfare.

- Documented a purchase–return efficiency trade-off and showed that a menu pairing a discounted price with a moderate (∼10–15%) restocking fee raises social welfare by about 2 million RMB (∼5%) and seller profit by about 1.2 million RMB relative to status-quo insurance policies, attaining ∼75–78% of first-best welfare outside dresses; automatic provision expands valuable purchases in high-margin categories while selective adoption outperforms it by ∼15–30 pp of first-best welfare in thinner-margin categories.

Skills

Languages: Mandarin (Native), English (Fluent), Cantonese (Basic).

Technical: Python, R, Stata, C++, Microsoft Excel, Word, PowerPoint, LaTeX, AWS, HPC/SLURM; MLE, GMM, minimum distance, EM algorithm, bootstrap.

References: Kei Kawai (UTokyo; Compass Lexecon), Kohei Kawaguchi (HKUST; UTokyo Econ Consulting), Pak Hung Au (HKUST).

Name: **HSU, Ke-cheng** 許可證
Student ID: **20312538**
Year of Study: **4th Year** **Reg Status:** **Active in Program**
Print Date: **24 August 2026 17:23:09**

Unofficial Transcript of Academic Record (as of 24 August 2026)

Advisor(s): AU, Pak Hung

Degree Awarded

Degree: Bachelor of Science in Mathematics and Economics
Classification: First Class Honors
Conferred Date: 18 June 2020

Minor: Actuarial Mathematics

Degree: Master of Philosophy in Economics
Conferred Date: 26 November 2022

Academic Program

Admit Date: 1 September 2015
Program: Bachelor Degree in School of Science (International Research Enrichment Track)

Program Change: 2016-17 Fall
Program: Bachelor of Science
Major: Mathematics and Economics

On Leave: 2 January 2018 to 2 September 2018

Effective: 2018-19 Fall
Add Minor: Actuarial Mathematics

Admit Date: 7 September 2020
Program: Master of Philosophy
Field of Study: Economics

Admit Date: 1 September 2022
Program: Doctor of Philosophy
Field of Study: Economics

Academic Records

2015-16 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
COMP1022P	Introduction to Computing with Java	3.0	3.0	B+
HLTH1010	Healthy Lifestyle	0.0	-	PP
LANG1002A	English for University Studies I	3.0	3.0	A-
MATH1023	Honors Calculus I	3.0	3.0	B+
PHYS1113	Laboratory for General Physics I	1.0	1.0	A-
PHYS1312	Honors General Physics I	3.0	3.0	B+
SCIE1000	Science School Induction	0.0	-	PP

TGA: 3.423
CGA: 3.423

Cumulative Credits Earned: 13.0

Awards: University Scholarship

Courses taken in this term are weighted 0.5 towards the classification of degree honors

2015-16 Winter (Full-Time)

Awards: University Scholarship

2015-16 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
CHEM1020	General Chemistry IB	2.0	2.0	A
HLTH1010	Healthy Lifestyle	0.0	-	P
LANG1003A	English for University Studies II	3.0	3.0	A-
LIFS1901	General Biology I	3.0	3.0	A+
MATH1024	Honors Calculus II	3.0	3.0	A-
PHYS1115	Laboratory for General Physics II	1.0	1.0	A
PHYS1314	Honors General Physics II	3.0	3.0	B+
SCIE1000	Science School Induction	0.0	-	P
SCIE1500	Guided Study on Research I	1.0	1.0	A+

TGA: 3.831
CGA: 3.648

Cumulative Credits Earned: 29.0

Awards: Dean's List

Name: **HSU, Ke-cheng** 許可證
Student ID: **20312538**
Year of Study: **4th Year** **Reg Status:** **Active in Program**
Print Date: **24 August 2026**
17:23:09

Unofficial Transcript of Academic Record (as of 24 August 2026)

University Scholarship

Courses taken in this term are weighted 0.5 towards the classification of degree honors

2015-16 Summer (Full-Time)

Awards: University Scholarship

2016-17 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON2103	Principles of Microeconomics	3.0	3.0	A
LANG2010	English for Science I	3.0	3.0	A-
MATH2023	Multivariable Calculus	4.0	4.0	A+
MATH2121	Linear Algebra	4.0	4.0	A+
MATH2411	Applied Statistics	4.0	4.0	A-

TGA: 4.017
CGA: 3.789

Cumulative Credits Earned: 47.0

Awards: Dean's List
University Scholarship

2016-17 Winter (Full-Time)

Awards: University Scholarship

2016-17 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON3113	Microeconomic Theory I	4.0	4.0	A-
ECON3123	Macroeconomic Theory I	3.0	3.0	A
MATH2033	Mathematical Analysis	4.0	4.0	A-
MATH2421	Probability	4.0	4.0	A-

TGA: 3.760
CGA: 3.782

Cumulative Credits Earned: 62.0

Awards: Dean's List
University Scholarship

2016-17 Summer (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
HUMA1250	Themes in Literature: Love and Death	3.0	3.0	A-
MATH2511	Fundamentals of Actuarial Mathematics	3.0	3.0	A+
PHYS1006	Astronomy for Beginners	3.0	3.0	A+

TGA: 4.100
CGA: 3.823

Cumulative Credits Earned: 71.0

Awards: University Scholarship

2017-18 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
COMP2011	Introduction to Object-oriented Programming	4.0	-	W
ECON3133	Microeconomic Theory II	4.0	4.0	A+
ECON3143	Macroeconomic Theory II	4.0	-	W
ECON3334	Introduction to Econometrics	4.0	4.0	A
HUMA1000A	Cultures and Values: Language, Communication and Society	3.0	3.0	A-
MATH3033	Real Analysis	4.0	4.0	A
MATH4427	Loss Models and Credibility Theory	3.0	3.0	A+

TGA: 4.067
CGA: 3.872

Cumulative Credits Earned: 89.0

Awards: Dean's List
University Scholarship

2018-19 Fall (Full-Time)

Name: HSU, Ke-cheng 許可證
Student ID: 20312538
Year of Study: 4th Year
Print Date: 24 August 2026 17:23:09
Reg Status: Active in Program

Unofficial Transcript of Academic Record (as of 24 August 2026)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON3143	Macroeconomic Theory II	4.0	4.0	B+
ECON4284	Econometrics for Cross-Section and Panel Data	4.0	4.0	A
ECON4670	Economics Research and Communication	0.0	-	P
LANG3010	English for Mathematics and Economics	3.0	3.0	A-
PHYS1003	Energy and Related Environmental Issues	3.0	3.0	A+
UROP1100V	Undergraduate Research Opportunities Series 1	1.0	1.0	P

TGA: 3.800

Transfer Credit(s) from Putonghua Oral Proficiency Assessment and equivalent course(s) of HKUST:

LANGCCOM	Chinese Language Proficiency Achieved	3.0	3.0	T

CGA: 3.862

Cumulative Credits Earned: 104.0
Cumulative Transfer Credits: 3.0

Awards: Dean's List
University Scholarship

2018-19 Winter (Full-Time)

Awards: University Scholarship

2018-19 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
COMP1942	Exploring and Visualizing Data	3.0	3.0	A-
ECON4304	Time Series Econometrics and Business Forecasting	4.0	4.0	A
MATH3425	Stochastic Modeling	3.0	-	W
MATH4512	Fundamentals of Mathematical Finance	3.0	3.0	A+
MATH4514	Financial Economics in Actuarial Science	3.0	3.0	A+
MATH4999	Independent Capstone Project	3.0	3.0	A+

TGA: 4.113
CGA: 3.896

Cumulative Credits Earned: 120.0
Cumulative Transfer Credits: 3.0

Awards: Dean's List
University Scholarship

2018-19 Summer (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
COMP1029V	Excel VBA Programming Bridging Course	1.0	1.0	P
SOSC1960	Discovering Mind and Behavior	3.0	3.0	A-

TGA: 3.700
CGA: 3.891

Cumulative Credits Earned: 124.0
Cumulative Transfer Credits: 3.0

Awards: University Scholarship

2019-20 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
MATH3423	Statistical Inference	3.0	3.0	P
MATH4983R	Independent Study: Mathematical Models in Economics: Voting and Matching	3.0	3.0	A+

TGA: 4.300
CGA: 3.901
GGA: 3.934 (BSc)

Name: HSU, Ke-cheng 許可證
Student ID: 20312538
Year of Study: 4th Year
Print Date: 24 August 2026 17:23:09
Reg Status: Active in Program

Unofficial Transcript of Academic Record (as of 24 August 2026)

Cumulative Credits Earned: 130.0
Cumulative Transfer Credits: 3.0
Cumulative Credits Counted towards Degree: 130.0

Awards: University Scholarship
Hong Kong University of Science and Technology Academic Achievement Medal

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2020-21 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON5100	Mathematics for Business and Economics	3.0	3.0	P
ECON5210	Microeconomic Theory I	4.0	4.0	A+
ECON5250	Macroeconomic Theory I	4.0	4.0	A
MATH5411	Advanced Probability Theory I	3.0	3.0	A
PDEV6770C	Professional Development for Research Postgraduate Students	1.0	-	PP
PDEV6800H	Introduction to Teaching and Learning in Higher Education	0.0	-	P

TGA: 4.109
CGA: 4.109

Cumulative Credits Earned: 14.0

Awards: Postgraduate Studentship

2020-21 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON5220	Microeconomic Theory II	4.0	4.0	A+
ECON5260	Macroeconomic Theory II	4.0	4.0	A+
ECON5300	Econometrics	4.0	4.0	A
PDEV6770C	Professional Development for Research Postgraduate Students	1.0	-	PP
SBMT6780	Professional Development in Ethics, Innovation and Technology for Research Postgraduate Students	1.0	1.0	P

TGA: 4.200
CGA: 4.157

Cumulative Credits Earned: 27.0

Qualifying Exam completed on 23 June 2021

Awards: Postgraduate Studentship

2021-22 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON5620	Theory of Industrial Organization	4.0	4.0	A+
ECON6120T	Applied micro-econometrics	4.0	4.0	A-
PDEV6770C	Professional Development for Research Postgraduate Students	1.0	1.0	P

TGA: 4.000
CGA: 4.116

Cumulative Credits Earned: 36.0

Awards: Postgraduate Studentship

2021-22 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON6120V	Platform Economics	1.0	1.0	A
ECON6990	MPhil Thesis Research	0.0	-	P
FINA7900A	Doctoral Seminar: Theoretical Corporate Finance	3.0	3.0	A-
FINA7900B	Doctoral Seminar: Theoretical Asset Pricing	0.0	-	AU

TGA: 3.775
CGA: 4.077
GGA: 4.084 (MPhil)

Cumulative Credits Earned: 40.0
Cumulative Credits Counted towards Degree: 34.0

Exclude in MPhil GGA: ECON5100, MATH5411 (GGA after exclusion: 4.084)

Name: HSU, Ke-cheng 許可證
Student ID: 20312538
Year of Study: 4th Year
Print Date: 24 August 2026 17:23:09
Reg Status: Active in Program

Unofficial Transcript of Academic Record (as of 24 August 2026)

Thesis Title [MPhil(ECON)]: Brand Search and Item Search

Awards: Postgraduate Studentship

2022-23 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
PDEV6800C	Introduction to Teaching and Learning in Higher Education	0.0	-	P

TGA: **
CGA: **

Cumulative Credits Earned: 32.0 (Internal Credit Transfer: 32.0)

Awards: Postgraduate Studentship
HKUST RedBird PhD Recruitment Award

2022-23 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON5610	Cheap-Talk: Theory and Experiment	0.0	-	AU
LANG5002	Postgraduate English for Business and Social Science Studies	1.0	1.0	P

TGA: **
CGA: **

Cumulative Credits Earned: 33.0

Awards: Postgraduate Studentship

2023-24 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON7800F	Economics Seminar	1.0	1.0	P
ECON7990	Doctoral Thesis Research	0.0	-	PP

TGA: **
CGA: **

Cumulative Credits Earned: 34.0

Awards: Postgraduate Studentship

2023-24 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON7990	Doctoral Thesis Research	0.0	-	PP

TGA: **
CGA: **

Cumulative Credits Earned: 34.0

Awards: Postgraduate Studentship

2024-25 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON7990	Doctoral Thesis Research	0.0	-	PP

TGA: **
CGA: **

Cumulative Credits Earned: 34.0

Awards: Postgraduate Studentship

2024-25 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON7990	Doctoral Thesis Research	0.0	-	PP

TGA: **
CGA: **

Cumulative Credits Earned: 34.0

Awards: Postgraduate Studentship

Name: HSU, Ke-cheng 許可證
Student ID: 20312538
Year of Study: 4th Year **Reg Status:** Active in Program
Print Date: 24 August 2026 17:23:09

Unofficial Transcript of Academic Record (as of 24 August 2026)

2025-26 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON7990	Doctoral Thesis Research	0.0	-	PP

TGA: **
CGA: **

Cumulative Credits Earned: 34.0

Awards: Postgraduate Studentship

2025-26 Spring (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON7990	Doctoral Thesis Research	0.0	-	PP

TGA: **
CGA: **
Current GGA: ** (PhD ECON)

Cumulative Credits Earned: 34.0

Awards: Postgraduate Studentship

2026-27 Fall (Full-Time)

Course Code	Course Title	Credit Attempted	Credit Earned	Grade
ECON7990	Doctoral Thesis Research	0.0	-	**

TGA: **
CGA: **

Cumulative Credits Earned: 34.0

- End of Transcript -

Designing Return Policy in E-Commerce: A Trade-off between Purchase and Return Efficiency

Ke Cheng HSU*

November 5, 2026

Abstract

We study the effect of return policies by asking whether they encourage efficient returns and purchases. A stricter return policy curbs inefficient ex-post returns, but the resulting lower return rates make higher product prices more attractive for sellers, leading to possible exclusion of ex-ante efficient purchases. We compare automatic coverage that reimburses return-shipping costs (RI) with optional coverage (CI) by estimating a structural model of purchase, insurance, and return decisions under monopoly pricing across six apparel categories. A lenient return policy like RI performs better in a category with a high margin, high net scrap value, and high uncertainty by expanding efficient purchases, whereas a stricter return policy like CI performs better in a category with the opposite attributes by curbing excessive returns. Partial RPD, a menu pairing a discounted price with a medium restocking fee as a penalty, performs better than RI and CI for most categories by better balancing purchase and return efficiency.

Keywords: structural modeling, product returns, return policy, welfare analysis, online retailing.

1 Introduction

Product returns are a central challenge in online retail. Return rates have reached 19.3% in the United States and exceed 35% in China.[1] In monetary terms, total retail returns in the United States are projected to reach $849.9 billion in 2025. The problem is especially acute for apparel, whose fit and quality are difficult to assess online. Industry benchmarks place online apparel return rates in the United States between 20%

*Department of Economics, School of Business and Management, Hong Kong University of Science and Technology. Email: khsu@connect.ust.hk

[1]National Retail Federation (2025), 2025 Retail Returns Landscape; Wu Dan Li (2024), Zhejiang University School of Management.

and 40%.[2] These high rates arise in part because consumers must purchase before inspecting the product. They learn fit only after delivery and then decide whether to keep or return it. Under a typical return policy, consumers are refunded the product price but bear the cost of return shipping, while the seller incurs handling costs and recovers only part of the product's value. Because the consumer does not bear the seller's handling cost, returns can exceed the efficient level. When the expected value from keeping is not enough to offset that loss, the purchase itself can generate negative expected social surplus and be ex-ante inefficient.

By considering the efficiency of both purchases and returns, the platform can design a return policy to improve the joint welfare of consumers and sellers. A return should occur when the seller's recovery value from the returned product exceeds the consumer's value from keeping it plus return shipping and handling costs. A purchase should occur when the expected value the transaction creates exceeds the expected costs of production and returns. From a welfare perspective, the existing return literature mostly asks whether consumers return efficiently conditional on purchase (Su, 2009), but not whether the purchase itself should occur in the first place.[3] A return policy changes how costly a return is, which shifts return probabilities and consumers' willingness to pay, so the two margins are linked. Only by evaluating purchases and returns jointly can we determine when purchase and return efficiency trade off, when both can improve together, and when each margin matters more for welfare.

Return Shipping Insurance (RSI), which is commonly used on Chinese e-commerce platforms, changes both purchases and returns by reimbursing the buyer's return-shipping expense. We examine two RSI policies, *retailer insurance* (RI), under which the seller purchases the insurance and provides automatic coverage for all buyers, and *consumer insurance* (CI), under which the consumer self-selects whether to buy optional coverage at checkout. Automatic coverage induces inefficient returns that benefit the buyer privately while reducing social surplus, yet it also enables socially valuable purchases by buyers who would otherwise be deterred by return-shipping risk. On the other hand, optional coverage disciplines returns by limiting reimbursement to those who buy insurance, but consumers with a high chance of returning may be especially likely to select into it. Since a seller's profit from a sale depends on whether the product is ultimately kept or returned, each insurance policy changes expected profit at any given price and therefore the price the seller chooses. Once the seller adjusts the price, it is not obvious which arrangement creates more value, or

[2] Eightx (2026), Average eCommerce Return Rate by Category; McKinsey & Company (2020), Returning to order.

[3] In Che (1996), ex-ante homogeneous consumers all purchase, and allowing returns lets the seller charge a price above retail cost, which induces inefficient returns when realized valuation falls between cost and price. In a cheap-talk setting, Inderst and Ottaviani (2013) show that a refund above salvage value makes seller advice credible, generating overpurchase and over-return relative to the signal, without screening heterogeneous buyers by expected social surplus.

whether that ranking changes with the margin, net scrap value, and ex-post match-value uncertainty.

These observations lead to three research questions. First, how do automatic and optional return-shipping insurance affect purchases, returns, insurance selection, and seller pricing? Second, is automatic coverage superior to optional insurance, and how does the result vary across product categories? How much of the difference comes from purchases, and how much from returns? Third, can alternative policies that better balance purchases and returns create greater social value than the existing insurance policies?

In our model, a monopolistic seller sets the product price, anticipating consumers' purchase and return decisions. Consumers know only their expected valuation at checkout and learn their realized match value after delivery before deciding whether to keep or return the item. Under either policy, consumers receive a full refund of the product price upon return, and insurance reimburses return-shipping fees. The seller pays production cost on every sale, earns a margin between the price and production cost when the product is kept, and recovers net scrap value (salvage value net of return-handling costs) on return.

Our model generates direct behavioral effects and an indirect effect through the equilibrium price response. At a given product price, RI raises willingness to purchase more broadly because every buyer receives coverage without paying a separate premium, but it also lowers the return cost of every purchaser. Under CI, the premium limits coverage and participation, but uninsured purchasers bear the return shipping costs. Equilibrium price effects are ambiguous because three forces interact. First, the seller-paid RI premium creates *cost pass-through*. Second, raising the price screens out low-valuation, frequent returners while raising return rates among remaining buyers, so a *return-mitigation* force can go both ways. Third, *surplus extraction* depends on the share of consumers who ultimately keep the product. The higher that share, the more attractive a higher price becomes.

We formalize the welfare consequences of these two effects along the ex-ante and ex-post margins. *Ex-ante efficiency* concerns whether purchases create positive expected social surplus. Broader participation under RI can mitigate monopoly underprovision when marginal buyers are socially valuable, but it can also create overprovision by attracting frequent returners whose purchases impose more cost than value. *Ex-post efficiency* concerns whether a purchased product is returned only when doing so creates social value after accounting for shipping, hassle, handling, and recovery value. Return policies should therefore preserve valuable purchases while discouraging inefficient purchases and excessive returns. RI tends to perform better when the margin, net scrap value, and uncertainty are high. High margin, high net scrap value, and the option value arising from high uncertainty (Anderson et al., 2009) raise the expected social surplus from

a purchase, and automatic reimbursement of return shipping enables RI to capture more of those valuable purchases. High uncertainty also lowers the ex-post cost of a lenient return policy, because reimbursement shifts return rates little when returns depend mainly on realized match value.

We study these tradeoffs with transaction data from a mid-sized women's clothing retailer on Taobao that repeatedly switched between RI and CI during 2017–2023. Within-retailer switches provide policy variation that is not confounded by retailer identity. In the raw data, for products sold under both policies, a larger share of products have lower average prices and higher return rates under RI. Under CI, insured transactions return much more often than uninsured ones, consistent with frequent returners selecting into coverage and a behavioral response to reimbursement. Price comparisons vary with product composition and aggregation, which motivates a framework in which prices, purchases, insurance, and returns adjust jointly.

We estimate a structural model of these decisions under monopoly pricing for six apparel categories. The estimates recover ex-ante valuation heterogeneity and ex-post match-value uncertainty, along with estimated seller production cost and calibrated net scrap value, to evaluate equilibrium welfare. The model reproduces the main qualitative differences between the policies. It underpredicts purchases by a similar amount under both policies and modestly overstates the return gap that matters for welfare, so we rank policies within each category and discuss how this bias overstates CI's advantage. To measure how much of the welfare loss reflects distortion from market structure that return-policy design cannot correct, we study a benchmark in which returns are socially efficient while the monopoly seller still sets the price. About 24%–29% of first-best welfare remains unrealized because prices exclude efficient purchases.

For dresses, where the margin, net scrap value, and uncertainty are high, both RSI policies underprovide by excluding marginal purchases that would generate positive social surplus. RI performs better by expanding efficient purchases, reaching 76% of first-best welfare compared with 74% under CI. For outerwear, pants, sweaters, and two-piece sets, where the margin is low to medium and net scrap value and uncertainty are medium, CI underprovides, whereas RI overprovides for pants and sweaters and slightly underprovides for outerwear and two-piece sets. CI performs better in these categories, achieving much higher ex-post efficiency with only slightly lower ex-ante efficiency. For tops, where the margin is intermediate and both net scrap value and uncertainty are low, RI performs worse than CI on both efficiency margins through poor ex-ante screening and ex-post over-return, dissipating about 51% of first-best welfare.

To address the third research question, we evaluate a counterfactual price-refund menu, which we call *return-penalty discount (RPD)*, where buyers choose between a full price with a full refund and a discounted

price with a partial or zero refund on return. While prior theory shows that such menus raise seller profit (Najafi et al., 2024; Altug et al., 2021), we study their welfare impact. To stay consistent with practice, in our model the platform sets the return penalty while the seller chooses the list price and the discount.[4] Although a return penalty curbs excessive returns, RPD is not necessarily more efficient. Stricter refund terms can strengthen surplus extraction and exclude socially valuable buyers. If the penalty is too severe, it can also deter returns that would be socially efficient. We evaluate both full forfeiture of the refund and partial forfeiture implemented as restocking fees.

Full-forfeiture RPD shows why stronger return discipline is not enough by itself. In most categories, purchases concentrate on the discounted branch, full-price demand is negligible, and return probability on the discount branch is near zero. The policy therefore replaces over-return under RSI with under-return, deterring returns that would be socially efficient. Even so, it substantially reduces ex-post inefficiency. It also strengthens surplus extraction and raises the purchase cutoff, excluding marginal consumers, even though the average price paid is lower. Outside dresses, this reduction in return inefficiency outweighs the participation loss relative to RI, so full-forfeiture RPD outperforms RI by about 8–34 percentage points of first-best welfare, beats CI by about 4 percentage points for sweaters, and roughly ties CI in the remaining categories. For dresses, however, it falls short of both RSI policies by roughly 18–21 percentage points because it excludes many buyers whose purchases would generate positive social surplus.

Partial-forfeiture RPD softens both failures of full forfeiture. Restocking fees of 10%–15% of the discounted price preserve much of the return discipline while reducing under-return and restoring participation, outperforming both RSI policies outside the dress category and attaining about 75%–78% of first-best welfare. For dresses, they recover much of the full-forfeiture loss (raising welfare from about 56% to about 69%–70% of first best) but remain below RI (about 76%). At low net scrap value, the partial-forfeiture advantage outside dresses survives. At high net scrap value, partial RPD remains ahead for sweaters and tops and below CI by at most 1.5 percentage points for the other categories. This evidence favors a category-specific return policy. A lenient policy such as RI is best suited to dresses, where the margin, net scrap value, and uncertainty are all high, whereas a stricter policy is better suited to categories with the opposite attributes. When tailoring is infeasible, moderate partial-forfeiture RPD may serve as a practical alternative.

[4] In practice, refund amounts are often constrained by platform rules or law. Best Buy charges $45 on opened phones and 15% on opened cameras, drones, and projectors. Amazon permits merchant-fulfilled sellers to charge a restocking fee of up to 20% for change-of-mind returns received after the return window (Amazon Seller Central Help).

1.1 Literature Review

Many existing empirical studies of return policy examine, from the seller's perspective, a trade-off between stimulating purchase and managing return cost. For purchases, return leniency raises current purchases (Wood, 2001), and a completed return raises later demand and lifetime value (Petersen and Kumar, 2009, 2015; Bower and Maxham, 2012; Griffis et al., 2012). For costs, extra reverse-logistics cost can exceed extra orders (Patel et al., 2021), profit falls when the seller pays return shipping (Hjort and Lantz, 2016), and free shipping promotions raise returns enough to cut profit (Shehu et al., 2020). A meta-analysis finds that different return-policy dimensions, such as time or scope, affect purchases and returns differently (Janakiraman et al., 2016). Although this literature generally treats additional purchases as beneficial to the seller, they can reduce the joint surplus of consumers, the seller, and the insurer when return probabilities are high and the margin and net scrap value are low. To our knowledge, no empirical study asks whether return policy causes under- or overprovision or compares this distortion across policies. We quantify participation distortions using both ex-ante inefficiency (the surplus lost from distorted entry relative to first best when returns are efficient) and the purchase-efficient gap (the purchase cutoff minus the efficient cutoff under actual return behavior, where positive values indicate underprovision and negative values indicate overprovision). By the latter measure, CI and full-forfeiture RPD underprovide in every category, whereas RI underprovides for dresses, outerwear, and two-piece sets and overprovides for pants, sweaters, and tops.

Price determines who participates, and greater return leniency can push the equilibrium price in either direction. In existing work, more generous returns can raise prices by allowing the seller to extract option value (Su, 2009), screen keepers (Che, 1996), make demand less elastic (Newberry and Zhou, 2024), or pass return-related costs and seller-paid RI premiums through to consumers (Ren et al., 2021; Li et al., 2023b).[5] Conversely, a full refund can induce a lower price to deter trial-and-return behavior (Davis et al., 1995). We highlight two forces, *surplus extraction* and *return mitigation*, and show that both can push the price under a more lenient return policy in either direction depending on ex-ante heterogeneity and ex-post uncertainty. For example, when ex-ante heterogeneity is small and ex-post uncertainty is large, return probabilities are less sensitive to reimbursement and price while purchase volume responds strongly, so RI expands net demand and the seller reduces return volume mainly by raising the price to screen out frequent returners. Both forces push the RI price higher than under CI.

On the ex-post margin, returns need not be socially wasteful. Su (2009) shows that when the refund

[5] These RI–CI models hold each buyer's return probability fixed.

equals net scrap value (salvage value), a return reallocates the good to the party with the higher value. Subsequent theory explains why a profit-maximizing seller departs from this benchmark. The private refund exceeds salvage value when the seller compresses information rents (Courty and Hao, 2000; Matthews and Persico, 2007) or makes sales talk credible (Inderst and Ottaviani, 2013). Conversely, it falls below salvage value to deter clearance deferrals (Altug and Aydinliyim, 2016), discourage returns and extract surplus from returners (Shulman et al., 2009; Shang et al., 2017a), or deter switching to a rival (Shulman et al., 2011), while manufacturer buy-backs can correct an excessively strict retail refund (Shulman et al., 2010) and opportunistic renting can push the optimal refund to either side of salvage value (Altug et al., 2021). Whereas these studies characterize theoretical departures from the efficient refund, we empirically quantify the resulting ex-post inefficiency (the welfare lost when purchasers do not return efficiently, holding fixed who buys) and find that it is smallest under RPD, larger under CI, and largest under RI in every category.

Theory on RSI compares RI and CI mainly in terms of seller profit, with some analysis of consumer surplus and social welfare. Li et al. (2023b) distinguish informed buyers, who never return, from uninformed buyers, who return at a fixed rate, and show that RI is more profitable when handling costs are low, whereas CI can benefit the seller, insurer, and consumers when uninsured buyers anticipate regret. Li et al. (2021) find that RI yields higher seller profit when the premium is low and the refund equals salvage value, whereas CI can leave more surplus to buyers. Low premiums and high compensation also favor RI in Fan and Chen (2020), although adding RSI to a money-back guarantee need not raise seller profit (Ren et al., 2021). With quality signaling, RSI can harm both high- and low-quality sellers while benefiting consumers, and higher-rated sellers are more likely to adopt RI (Zhang et al., 2022).[6] We complement this literature by evaluating RI and CI empirically in terms of seller profit, expected consumer surplus, and expected social surplus, showing how their ranking varies across categories with margins, net scrap value, and uncertainty.

Return-policy design uses both nonmonetary and monetary penalties (Abdulla et al., 2019). Early models deter opportunistic returns through hassle under a full money-back guarantee (Davis et al., 1998) or nonrefundable shipping charges (Hess et al., 1996). Later models jointly choose prices and partial refunds (Shulman et al., 2009; Hsiao and Chen, 2012) or offer self-selective screening menus (Shang et al., 2017a; Altug et al., 2021; Najafi et al., 2024; Huang and Zhang, 2020). More recently, Costello and Bechler (2026) and Fang et al. (2026) examine returnless policies that refund the buyer in full or in part while letting them keep the product. Empirical work on return policy finds a large return option value in catalog apparel

[6] Empirical work on RSI remains scarce, with Chen et al. (2018) examining how RSI affects stated purchase and return intentions.

(Anderson et al., 2009) but a small willingness-to-pay premium for a full refund in electronics (Shang et al., 2017b). The closest empirical study to ours is Newberry and Zhou (2024), who find that the insurance value of returns accounts for roughly 80% of consumer surplus gains, compared with 20% for quality signaling, which supports abstracting from the signaling channel. They estimate the welfare effects of uniform return policies and show that repricing benefits the seller but harms consumers, because sellers pass return costs through and demand is less elastic. By contrast, we study self-selection under CI and RPD rather than a uniform return policy.

To keep the model parsimonious, we abstract from pre-purchase search (Petrikaitė, 2018; Jerath and Ren, 2024; Janssen and Williams, 2024; Li et al., 2024; Ibragimov et al., 2026), purchase-return interdependence over customer lifetimes (Chen, 2021; Montaguti et al., 2026), quality signaling (Moorthy and Srinivasan, 1995; Zhang et al., 2022; Li et al., 2023a), inter-firm competition over return policy, such as money-back guarantees, restocking fees, or RI (Chesnokova, 2007; McWilliams, 2012; Shulman et al., 2011; Chen and Grewal, 2013; Inderst and Tirosh, 2015), and supply chain buyback contracts (Padmanabhan and Png, 1997; Tran et al., 2018).

Our main contribution is to empirically evaluate return policies from a social welfare perspective rather than seller profit alone, by decomposing welfare losses into purchase and return inefficiency. Comparing these two margins across policies and categories shows when they improve together and when they trade off, and how the optimal balance between participation and return discipline depends on margins, net scrap value, and uncertainty. Applied to RSI and RPD, our framework provides, to our knowledge, the first empirical evaluation in online retail of both RSI and a self-selective price-refund menu across seller profit, expected consumer surplus, expected social surplus, and the inefficiency decomposition.[7] These findings offer practical guidance on when platforms should tighten or relax return terms, and show that a menu with a moderate restocking fee serves as a robust default when category-level tailoring is infeasible.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting of return shipping insurance, introduces the transaction data, and documents key stylized facts on prices and returns. Section 3 sets up the structural model, and Section 4 characterizes equilibrium purchase, insurance, and return decisions, seller pricing incentives, and the welfare framework. Sections 5 and 6 discuss identification, estimation, and calibration. Section 7 reports counterfactual welfare simulations comparing RI, CI, and

[7] Vollmer (2025) structurally compares ticket resale with a uniform partial refund in college football, where the seller posts a single refund per game rather than a self-selective price-refund menu.

return-penalty discount (RPD) by category. Section 8 concludes.

2 Institutional Setting and Data

Apparel accounts for the largest share of online retail in China at 22%.[8] Because consumers cannot inspect garments before delivery, return rates are high, historically generating frequent and costly return-shipping disputes.

2.1 Return Shipping Insurance: RI versus CI

To resolve frequent and costly return-shipping disputes, Taobao and Huatai Insurance introduced Return Shipping Insurance (RSI) in 2010 to standardize reimbursement. The RSI market reached approximately 8 billion RMB in 2022.[9] The insurance market on Taobao is centralized. The platform partners with a small set of insurers and assigns providers algorithmically, so coverage terms are uniform across merchants. On approved returns, buyers receive a full refund of the product purchase price from the seller and reimbursement of the 1 kg delivery fee from the insurer (typically 5 to 25 RMB).

RSI operates under two mutually exclusive regimes. Under RI, the seller enrolls at the store level, without a separate consumer fee. The insurer charges the seller a per-transaction premium (typically 1 to 5 RMB) based on the store's three-month historical return rate and category benchmarks. RI dominates the platform, accounting for over 90% of all RSI policies. Under CI, which is offered *if and only if* the seller has not enrolled the store in RI, individual buyers choose whether to purchase coverage as an add-on at checkout. In contrast to RI, the CI premium is consumer-specific, determined mainly by the buyer's province of residence and return history, *independent of the product*. CI premiums typically exceed RI premiums because optional coverage attracts consumers who anticipate returning, and insurers charge higher rates to buyers with higher return propensities.

2.2 Data and Sample Construction

Our dataset comprises transaction records from a single mid-sized women's clothing retailer on Taobao, spanning from 2017 to 2023. Each transaction falls under one RSI policy. Over this period, total revenue is approximately 62 million RMB.

The data include sales, returns, and insurance at the transaction level, with consumer information limited to addresses. Insurance premium and coverage are observed for nearly all RI transactions, excluding

[8] Ministry of Commerce (2024), *2023 China Online Retail Market Development Report*.
[9] Shanghai Securities News (2022), Sina Finance.

international orders and buyers ineligible because of high historical return rates. Under CI, coverage is recorded only when the consumer buys insurance, while for non-purchasers we impute it from same-province addresses. Premiums are not recorded, so we impute the premium from coverage using the 2025 premium-coverage schedule (Online Appendix A).

We code a return as a binary indicator equal to one when the buyer receives a strictly positive refund and zero otherwise, excluding partial refunds for minor product defects. We keep single-item, single-quantity orders with confirmed shipment and no premium shipping, and drop non-product listings and promotion days on which the store temporarily switched RSI policy. Restricting to one item per order rules out complementarities between purchase and return decisions across products, while restricting to quantity one rules out bracketing, in which buyers order multiple sizes or colors of the same listing and return all but one. We keep six apparel categories with at least 50 transactions per month on average: dress, tops, pants, sweater, two-piece, and outerwear. The cleaned sample contains 361,201 transactions (238,612 under RI and 122,589 under CI).

2.3 Stylized Facts

Figure 1 plots 30-day moving averages of the daily return rate from 2017 through 2023 across RI and CI periods. Over these six years, the store repeatedly switched between the two policies. These switches do not seem to be based on the return rate. They occur when returns are low or high and when the rate is rising or falling. Separately, the return series drifts upward over the sample and exceeds 40% toward the end of 2023 during a long period of RI. This late-sample climb plausibly coincides with the rapid expansion of *live-stream* commerce on Taobao, where purchases are typically more impulsive and return-prone.[10]

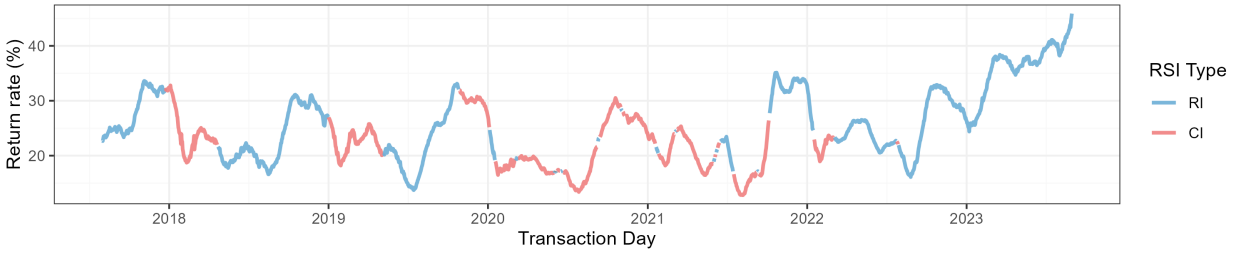


Figure 1: 30-day moving average of the daily return rate (%), 2017–2023, with RI and CI periods shaded.

Table 1 reports prices, premiums, coverage, and return rates under RI and under CI, pooling across categories.

Average list prices in the pooled sample are higher under CI than under RI (about 92 versus about

[10]Removing a pooled annual cycle (day-of-year harmonics 1–4) prior to the same 30-day moving average yields a broadly similar pattern, including the pronounced late-sample increase, and still shows no clear ranking of return rates between RI and CI periods.

Table 1: Summary Statistics

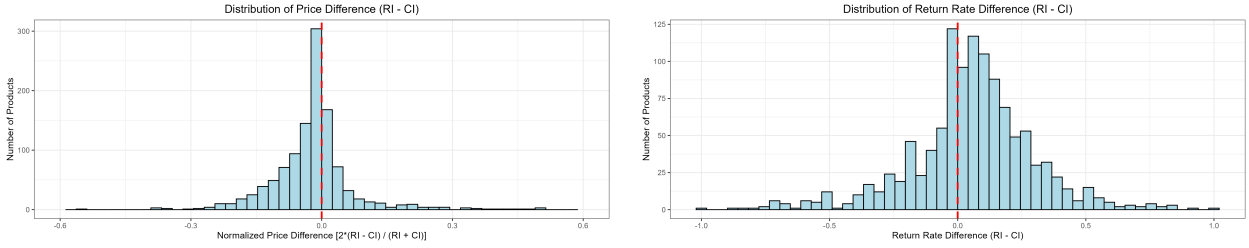
RSI	Variable	Unit	N	Mean	Sd	Min	Median	Max
CI	Price	RMB	122,589	91.50	56.67	18.0	83.65	1038.0
	Premium	RMB	122,589	5.01	0.22	4.6	5.10	7.1
	Coverage	RMB	122,589	10.63	1.46	8.0	11.00	25.0
	Return Rate	%	122,589	21.10	40.80	0.0	0.00	100.0
RI	Price	RMB	238,612	87.36	67.58	15.3	79.00	738.0
	Premium	RMB	238,612	2.67	0.39	1.4	2.50	3.3
	Coverage	RMB	238,612	10.59	1.45	8.0	11.00	25.0
	Return Rate	%	238,612	27.30	44.55	0.0	0.00	100.0

Notes: Return-rate medians are zero because the outcome is binary.

87 RMB), even though cost pass-through of the RI premium alone would predict the opposite. Beyond category composition, other pricing forces can offset pass-through. For example, uninsured buyers under CI bear return shipping costs and return less often, which increases the share of kept purchases and can strengthen the seller's incentive to set a higher price.

Average return rates are higher under RI than under CI, with pooled means of about 27% versus about 21%. Under CI, insurance is purchased on 2.91% of transactions. Return rates are much higher among insured than uninsured transactions (46.3% versus 20.4%). The gap is consistent with lower private return costs among insured buyers and adverse selection into coverage.

Pooled comparisons may be confounded by product selection. Figure 2 restricts the sample to 1,140 products that sold under both RI and CI and have more than five transactions per product. Panel (a) plots the normalized price difference $2(\bar{p}^{\mathrm{RI}} - \bar{p}^{\mathrm{CI}})/(\bar{p}^{\mathrm{RI}} + \bar{p}^{\mathrm{CI}})$, where $\bar{p}$ is the product-level mean transaction price under each policy. As in the pooled sample, a larger share of products still show higher prices under CI than under RI. Panel (b) reports $\bar{r}^{\mathrm{RI}} - \bar{r}^{\mathrm{CI}}$, where $\bar{r}$ is the product-level mean return rate under each policy. Most mass lies to the right of zero, indicating higher return rates under RI.



(a) Normalized price difference. (b) Return-rate difference.

Figure 2: Within-product price and return-rate differences (RI − CI).

Taken together, the time series documents repeated within-store policy switches. Both pooled and within-product comparisons show higher return rates and lower average prices under RI. However, these price comparisons can also reflect category composition and time-varying shocks, which motivates our

structural model.

3 Model

We consider a retail shopping model with RSI in which a monopolistic seller offers apparel category j in period t. The seller faces downward-sloping residual demand, with the outside option absorbing purchases from rivals. Market size N_{jt} varies across categories and seasons (Online Appendix A). Categories are separable, with no cross-category demand spillovers. For notational simplicity, we suppress the category subscript j and period subscript t throughout Sections 3 and 4, reintroducing them in Section 5 for identification across categories and markets.

The game proceeds in three stages. First, the seller sets the retail price p, taking the RSI policy and insurance premiums as given. Second, each consumer decides whether to purchase the product and, under CI, whether to purchase optional insurance. Third, after delivery, consumers observe their idiosyncratic match value shocks and choose whether to keep or return the product.[11]

The insurer provides consumer-specific coverage k_i according to the location-specific 1 kg delivery fee. Under RI, the seller pays premium I^r per transaction, and coverage is automatic for all buyers. Under CI, buyers choose whether to purchase coverage at checkout for premium $I^c(k_i)$.

The seller produces each unit at marginal cost $\theta^c = X\alpha^c + \zeta^c$. The store-level shock ζ^c is common across products and reflects shared inputs such as marketing, customer acquisition and service, labor, utilities, and rent. If a unit is returned, the seller incurs a handling fee and recovers resale value, yielding net return handling cost h. This cost is negative when recovery exceeds the handling cost.

Consumers differ in ex-ante valuation ν_i and location-specific return-shipping coverage k_i. Ex-ante valuation is

$$\nu_i = \mu + \xi + \omega\epsilon_i, \tag{1}$$

where $\mu = X\beta^\mu$ is mean valuation from observed category attributes X, ξ is an unobserved demand shock orthogonal to X, ω is the standard deviation of idiosyncratic ex-ante tastes within the category and is time-invariant, and $\epsilon_i \sim \mathcal{N}(0,1)$, so $\nu_i \sim \mathcal{N}(\mu + \xi, \omega^2)$ with distribution F_ν. Return-shipping coverage k_i is drawn from a location-specific distribution $\Psi(\cdot)$, independent of ν_i.

After delivery, the idiosyncratic match value shocks of consumer i, $\varepsilon_i^{\text{keep}}$ and $\varepsilon_i^{\text{return}}$, are realized. They

[11] Hong and Pavlou (2014) find that, for experience goods, returns are driven more by product-fit uncertainty than by quality uncertainty.

follow a Type I extreme value distribution with mean zero and scale $1/\sigma$, with ex-post precision $\sigma = X^{\sigma}\beta^{\sigma}$.[12] Conditional on purchase, consumer i chooses between keeping and returning. On a return, the buyer receives a refund of p, incurs hassle κ and shipping k_i, and is reimbursed only for k_i when coverage applies. Realized utility on each branch is the sum of mean indirect utility and the idiosyncratic shock, $u_i = \overline{u}_i + \varepsilon_i$. Mean utilities under the respective policies are

$$\overline{u}_i^{\text{keep}} = v_i - p - I^c(k_i)BC_i, \tag{2}$$

$$\overline{u}_i^{\text{return}} = -\kappa - k_i(1 - RSI_i) - I^c(k_i)BC_i, \tag{3}$$

where BC_i is an indicator that consumer i purchases CI coverage, and RSI_i is an indicator of insurance, either under RI or under a CI purchase. Under RI, coverage is automatic, so return shipping is reimbursed up to k_i, yielding $\overline{u}_i^{\text{return}} = -\kappa$. Under CI, an insured buyer receives reimbursement and obtains $\overline{u}_i^{\text{return}} = -\kappa - I^c(k_i)$, whereas an uninsured buyer bears the shipping cost, obtaining $\overline{u}_i^{\text{return}} = -(\kappa + k_i)$.

4 Equilibrium Analysis

We focus on equilibrium within a single category and period. Superscript l denotes the RSI scheme (r for RI, c for CI). We analyze consumer behavior under each RSI scheme and then compare the mechanisms that matter for pricing and welfare.

4.1 Consumer Behavior under RSI

Under RI, automatic coverage yields mean utilities $\overline{u}_i^{\text{keep}} = v_i - p$ and $\overline{u}_i^{\text{return}} = -\kappa$. Integrating over Type I extreme value shocks yields expected consumer surplus

$$CS_i^r = \frac{1}{\sigma} \ln\left(e^{\sigma(v_i - p)} + e^{-\sigma\kappa}\right). \tag{4}$$

Consumers purchase if $CS_i^r \geq 0$, or $v_i \geq \hat{v}^r \equiv p + \frac{1}{\sigma}\ln(1 - e^{-\sigma\kappa})$. Conditional on purchase, the return probability is

$$q_i^r \equiv \frac{e^{-\sigma\kappa}}{e^{\sigma(v_i - p)} + e^{-\sigma\kappa}}. \tag{5}$$

High uncertainty (low σ) raises the option value, increasing both consumer surplus and return probability.

Under CI, consumers choose between purchasing with optional insurance at premium $I^c(k_i)$, purchasing without insurance, and not purchasing. Expected consumer surplus under the two purchase options is

$$CS_i^{bc} = \frac{1}{\sigma} \ln\left(e^{\sigma(v_i - p)} + e^{-\sigma\kappa}\right) - I^c(k_i), \qquad CS_i^n = \frac{1}{\sigma} \ln\left(e^{\sigma(v_i - p)} + e^{-\sigma(\kappa + k_i)}\right). \tag{6}$$

[12] The variance is $\pi^2/(6\sigma^2)$.

A purchaser prefers insurance if $CS_i^{bc} \geq CS_i^n$, which holds when valuation is below the insurance-indifference cutoff

$$\nu_i \leq \tilde{\nu}^{bc} \equiv p - \kappa + \frac{1}{\sigma} \ln \left(\frac{e^{-\sigma I^c(k_i)} - e^{-\sigma k_i}}{1 - e^{-\sigma I^c(k_i)}} \right). \tag{7}$$

Because return probability falls with valuation, insurance is valued most by lower-valuation buyers.

Setting $CS_i^{bc} \geq 0$ and $CS_i^n \geq 0$ yields purchase thresholds $\hat{\nu}^{bc} \equiv p + \frac{1}{\sigma} \ln \left(e^{\sigma I^c(k_i)} - e^{-\sigma \kappa} \right)$ and $\hat{\nu}^n \equiv p + \frac{1}{\sigma} \ln \left(1 - e^{-\sigma(\kappa + k_i)} \right)$. These cutoffs characterize optimal choice: consumers purchase with insurance if $\hat{\nu}^{bc} \leq \nu_i < \tilde{\nu}^{bc}$, purchase without insurance if $\nu_i \geq \max\{\tilde{\nu}^{bc}, \hat{\nu}^n\}$, and do not purchase otherwise. An insured segment exists when $\tilde{\nu}^{bc} \geq \hat{\nu}^{bc}$,[13] which holds when coverage k_i is large relative to the premium $I^c(k_i)$ and hassle cost is not too large. If hassle cost is too large, return probability is too low for the option value of insurance to outweigh the premium, so all purchasers remain uninsured.

Insured consumers return with probability q_i^r, as under RI, because the premium is sunk at purchase. Uninsured consumers bear the full return cost k_i and return with lower probability

$$q_i^n \equiv \frac{e^{-\sigma(\kappa + k_i)}}{e^{\sigma(\nu_i - p)} + e^{-\sigma(\kappa + k_i)}}. \tag{8}$$

4.2 Retailer's Decisions

The seller prices against gross demand and returns. Let D_i^l denote the purchase indicator implied by the cutoffs above, and let q_i^l denote the corresponding return probability under scheme $l \in \{r, c\}$ conditional on purchase: q_i^r is given by (5), and q_i^c equals q_i^r for insured purchasers and q_i^n in (8) for uninsured purchasers. Aggregating individual purchase choices and return probabilities over F_ν and Ψ yields gross demand $D^l \equiv N \mathbb{E}[D_i^l]$ and return volume $R^l \equiv N \mathbb{E}[D_i^l q_i^l]$. Net demand, $D^l - R^l$, is the number of units ultimately kept. Let *RI* denote an indicator equal to one under RI and zero under CI. The seller's aggregate profit is

$$\pi^l(p) = (p - \theta^c - I^r RI)(D^l - R^l) - (h + \theta^c + I^r RI) R^l. \tag{9}$$

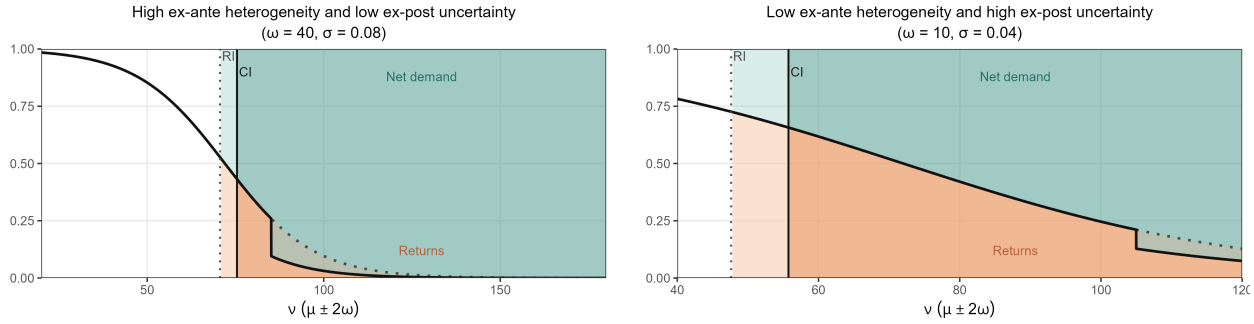
The first term is the margin earned on kept units, while the second is the loss on returned units. At the same price, RI generates higher gross demand than CI because consumers face no explicit premium, but it also attracts more lower-valuation buyers and reimburses return shipping for all buyers. Both raise return volume. The equilibrium price therefore maximizes (9) against net demand $D^l - R^l$ and return volume. Three channels shape pricing: cost pass-through, surplus extraction, and return mitigation. These forces

[13] This is equivalent to $e^{-\sigma\kappa}(1 - e^{-\sigma k_i}) \geq e^{\sigma I^c(k_i)} - 1$.

need not move prices in the same direction.

Cost Pass-through. Under RI, the seller pays the insurance premium I^r, which enters as a marginal cost, so a higher premium raises prices through pass-through. Under CI, the premium does not enter profit directly and affects profit only through demand and returns. Incidence among purchasers also differs. Under CI, consumers pay premiums directly, so insurance costs fall on lower-valuation buyers who return more often. Under RI, premiums are passed through to the product price and borne by all purchasers, so high-valuation keepers effectively subsidize insurance for lower-valuation frequent returners.

Surplus Extraction. Stronger net demand (more keepers) makes a price increase more profitable. We call this force *surplus extraction*. At a common price, RI expands gross demand (no premium) but also raises the return rate (automatic coverage), so net demand need not rise. Figure 3 shows the comparison. The CI purchase cutoff lies to the right of the RI cutoff because gross demand is lower at the same price. Under CI, $q(v)$ also drops sharply at the insurance cutoff, where private return costs jump.



(a) Large ω, large σ ($\omega = 40$, $\sigma = 0.08$).

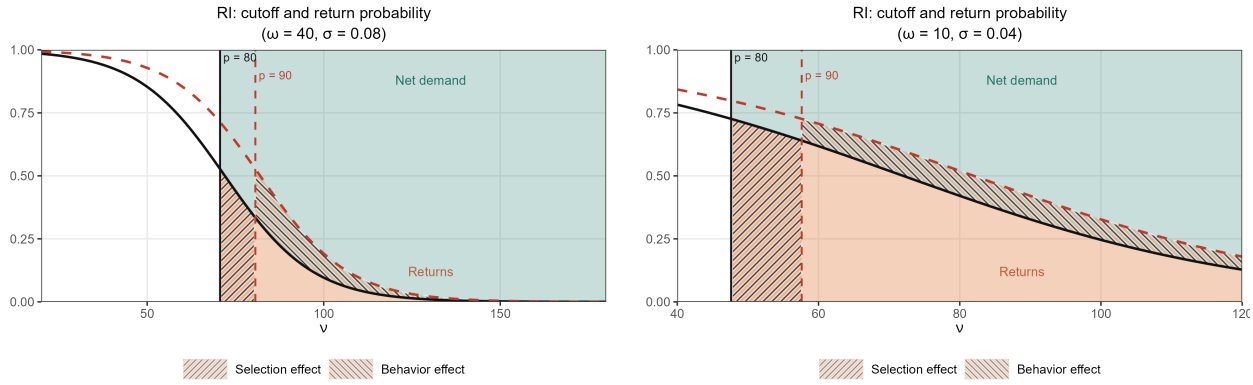
(b) Small ω, small σ ($\omega = 10$, $\sigma = 0.04$).

Figure 3: Returns and net demand under RI and CI at a common price. Dotted lines are RI and solid lines are CI. Purchasers lie to the right of each cutoff. Downward-sloping curves are return probabilities $q(v)$. Orange is the return region and teal is net demand. The horizontal axis covers $\mu \pm 2\omega$ with $\mu = 100$.

Whether net demand is higher under RI or CI depends on ex-ante heterogeneity ω and uncertainty. When ex-ante heterogeneity is large and uncertainty is small, as in Figure 3 (left), gross demand is relatively inelastic and return probability is sensitive to reimbursement. Return probability is strongly shifted by reimbursement because mean keep-or-return payoffs dominate idiosyncratic shocks. CI then generates higher net demand because uninsured consumers have substantially lower return rates and the reduction in gross demand from requiring consumers to pay the premium is small. When instead ex-ante heterogeneity is small and uncertainty is large, as in Figure 3 (right), return probabilities respond less to coverage and the premium shifts the purchase cutoff more compared to the concentrated value distribution, so RI's broader participation can dominate and lead to a higher net demand than CI.

An important pricing implication is that when return probabilities are highly sensitive to coverage, a smaller but better-composed purchaser pool under CI can raise net demand and give the seller an incentive to charge a higher price. The surplus extraction force should not be equated mechanically with a higher equilibrium price, because the observed price also reflects pass-through and return mitigation.

Return Mitigation. A higher price affects return volume through two opposing forces. It screens out lower-valuation buyers, who return more often, which tends to lower return volume (a selection effect). Among remaining purchasers, however, a higher price raises individual return probabilities, because consumers receive a larger refund upon return (a behavior effect). Because these forces pull in opposite directions, the net effect is again ambiguous. Figure 4 illustrates both channels under RI for the same (ω, σ) cases as Figure 3 (CI is similar).



(a) Large ω, large σ ($\omega = 40$, $\sigma = 0.08$).

(b) Small ω, small σ ($\omega = 10$, $\sigma = 0.04$).

Figure 4: Selection and behavior effects of a price increase under RI. Solid curves are the baseline price. Dashed red curves are a higher price. Striped regions mark selection (between cutoffs) and the behavior effect (the upward shift in $q(v)$ among remaining purchasers). Parameters match Figure 3.

When ex-ante heterogeneity is large and uncertainty is small (Figure 4, left), $q(v)$ responds strongly to price. The seller cuts the price to reduce return volume, because a lower price reduces each buyer's return probability without much increase in sales. When instead ex-ante heterogeneity is small and uncertainty is large (right), purchase volume responds strongly to price and $q(v)$ responds less, so the seller prefers a higher price to curb returns. Raising price mainly discourages purchases. Return probabilities are usually higher under RI, so return mitigation weighs more in pricing. Whether the seller raises or cuts the price to curb returns depends on whether selection or the behavior effect dominates.

The three channels imply that RI need not have higher equilibrium prices than CI even though the seller pays the premium. When the premium is low and pass-through is weak, surplus extraction and return mitigation can reverse the ranking. RI prices tend to be higher when ex-ante heterogeneity is small and

uncertainty is large, because RI can expand net demand and return mitigation then works mainly through screening out frequent returners. The opposite ranking arises when ex-ante heterogeneity is large and uncertainty is small. The price comparison is therefore an equilibrium outcome rather than a direct measure of insurance incidence.

4.3 Welfare Framework

We evaluate return policies using a welfare framework that separates ex-post return inefficiency from ex-ante purchase inefficiency.

Ex-Post Efficiency. Conditional on purchase, production cost θ^c is sunk. A return is ex-post efficient if and only if the social value of keeping falls short of the social value of returning:

$$v_i + \varepsilon_i^{\text{keep}} \leq -(\kappa + k_i + h) + \varepsilon_i^{\text{return}}, \tag{10}$$

yielding the socially optimal return probability

$$q_i^*(v_i, k_i; \sigma, \kappa, h) \equiv \frac{e^{-\sigma(\kappa + k_i + h)}}{e^{\sigma v_i} + e^{-\sigma(\kappa + k_i + h)}}. \tag{11}$$

Because product prices and insurance payments are transfers, q_i^* evaluates returns against valuation v_i and internalizes net handling cost h. Under RSI, buyers instead compare $v_i - p$ against private return costs, ignoring the seller's return losses and generating excessive returns ($q_i^l > q_i^*$).

Ex-Ante Efficiency. Ex-ante efficiency concerns the purchase decision. Expected seller profit from consumer i is $\pi_i^l \equiv (1 - q_i^l)(p - \theta^c - I^r RI) - q_i^l(h + \theta^c + I^r RI)$, and insurer profit $\tilde{\pi}_i^l$ equals premiums collected minus expected reimbursements paid. Summing these with consumer surplus gives the social surplus generated by consumer i, $S_i^l \equiv CS_i^l + \pi_i^l + \tilde{\pi}_i^l$. A transaction is ex-ante efficient if and only if $S_i^l \geq 0$. We evaluate welfare per potential consumer and hence abstract from market size N. Non-purchasers receive zero. Expected consumer surplus and social welfare under scheme l are $CS^l \equiv \mathbb{E}[CS_i^l D_i^l]$ and $W^l \equiv \mathbb{E}[S_i^l D_i^l]$, where the expectation is over v_i and k_i. Under CI, insured and uninsured purchases enter the expectation as separate branches.

Welfare Decomposition and Extensive Margin. To separate purchase and return inefficiency, we compare welfare W^l to first best using an intermediate benchmark that holds observed purchase decisions D_i^l fixed but enforces optimal return behavior q_i^*. Because S_i^l evaluates surplus at private return behavior q_i^l, whether a purchase is efficient depends on return behavior, which can differ across policies. The intermediate benchmark measures ex-ante inefficiency against a common return rule. Substituting q_i^* into individual

social surplus yields the closed form

$$S_i^*(\nu_i, k_i) \equiv -\theta^c + \frac{1}{\sigma} \ln\left(e^{\sigma\nu_i} + e^{-\sigma(\kappa+k_i+h)}\right). \tag{12}$$

Let $\hat{\nu}^*(k_i)$ denote the first-best purchase cutoff solving $S_i^*(\nu_i, k_i) = 0$, and let $D_i^* \equiv \mathbf{1}\big(\nu_i \geq \hat{\nu}^*(k_i)\big)$. Defining $W^{OR} \equiv \mathbb{E}[S_i^*(\nu_i, k_i)D_i^l]$ as welfare with optimal returns at observed purchases and $W^{FB} \equiv \mathbb{E}[S_i^*(\nu_i, k_i)D_i^*]$ as first-best welfare, the welfare gap decomposes into

$$W^{FB} - W^l = \underbrace{\left(W^{OR} - W^l\right)}_{\Delta^{ex\text{-}post}} + \underbrace{\left(W^{FB} - W^{OR}\right)}_{\Delta^{ex\text{-}ante}}. \tag{13}$$

The first term, $\Delta^{ex\text{-}post}$, measures surplus lost to inefficient returns among purchasers under scheme l, holding D_i^l fixed. The second term, $\Delta^{ex\text{-}ante} = \mathbb{E}[S_i^*(\nu_i, k_i)(D_i^* - D_i^l)] = W^{FB} - W^{OR} \geq 0$, measures the remaining loss from distorted market participation relative to first best. While this participation gap can theoretically reflect either under- or overprovision, the option value of return places the first-best cutoff below production cost by that option value ($\hat{\nu}^* < \theta^c$), while the seller's market power pushes the purchase cutoff well above it ($\hat{\nu}^l > \hat{\nu}^*$). In our counterfactuals, $\Delta^{ex\text{-}ante}$ therefore always reflects underprovision relative to first best.

One limitation of $\Delta^{ex\text{-}ante}$ is that it evaluates entry holding returns at the hypothetical first-best rule q_i^*. It therefore does not show whether admitting marginal buyers under actual return behavior creates or destroys surplus. To evaluate the policy-relevant welfare effect of participation, we introduce another measure, the *extensive margin*. It evaluates individual surplus S_i^l at consumers' actual return behavior q_i^l. We quantify this margin using the purchase-efficient gap, the purchase cutoff $\hat{\nu}^l$ minus the efficient cutoff ($S_i^l(\nu_i) = 0$). If the gap is positive, the seller underprovides by excluding buyers with $S_i^l \geq 0$. If the gap is negative, the seller overprovides by admitting buyers with $S_i^l < 0$. Section 7 applies this framework at estimated parameters to evaluate the optimal-refund benchmark, RI versus CI, and counterfactual RPD menus.

5 Identification

The primitives to be identified are the coverage distribution $\Psi(\cdot)$, category-specific ex-ante heterogeneity ω_j, mean ex-ante value μ_t, ex-post precision σ_t, and production cost θ_t^c. Net return handling cost h_t is calibrated in Section 6. As in Anderson et al. (2009), high uncertainty and low hassle cost both increase purchases and returns. We normalize hassle cost to 5 RMB so uncertainty is separated from hassle cost.[14]

[14]Normalizing $\kappa = 0$ would imply that, under RI, the purchase probability is always one.

Under RI, fully reimbursed shipping makes the purchase threshold independent of k_i, so purchase does not select on coverage and $\Psi(\cdot)$ is non-parametrically identified from the empirical coverage distribution.

Let $\bar{w}_t^r$ be mean willingness to pay. Under RI, the purchase probability is $\mathbb{E}[D_{it}^r(k_i, p_t)] = 1 - \Phi\left(\frac{p_t - \bar{w}_t^r}{\omega_j}\right)$. Given a price instrument, variation in p_t across category-months traces out this purchase schedule. How fast the purchase probability falls in price identifies ex-ante heterogeneity ω_j, and where the schedule lies identifies mean willingness to pay $\bar{w}_t^r$. $\bar{w}_t^r$ decomposes into intrinsic value and return option value:

$$\bar{w}_t^r \equiv \underbrace{\mu_t + \xi_t}_{\text{Intrinsic value}} + \underbrace{\left[-\frac{1}{\sigma_t}\ln(1 - e^{-\sigma_t \kappa})\right]}_{\text{Return option value}}.$$

While purchase variation identifies $\bar{w}_t^r$, it cannot separate intrinsic value from return option value. Expected returns provide the additional identification that separates them. Holding purchase probability (and thus $\bar{w}_t^r$) fixed, expected returns strictly increase in uncertainty, so joint variation in purchases and returns across markets identifies σ_t, which backs out the option value and isolates intrinsic value $\mu_t + \xi_t$ (Online Appendix B). CI purchase, return, and insurance moments further restrict the same demand primitives through endogenous insurance selection under CI.

Finally, given calibrated net handling cost h_t, inverting the retailer's pricing first-order condition at observed prices maps estimated demand responses into marginal cost θ_t^c. Cross-market variation in cost shifters identifies cost parameters α^c and store-level cost shocks ζ_t^c via $\theta_t^c = X_t \alpha^c + \zeta_t^c$.

6 Estimation

We estimate the model by GMM, pooling moment conditions across categories j. The estimation sample contains 6 apparel categories and 313 category × month markets after smoothing, resampling, and the 5% purchase-probability screen described in Online Appendix A. Smoothing and resampling capture stable long-run demand. The screen keeps purchase probabilities away from zero to avoid the zero-share problem.[15] Market size is defined at the category × season level as twice the maximum monthly sales within that category-season, and monthly purchase probabilities equal smoothed sales divided by that size. Because the outside option is unobserved, absolute market size cannot be separately identified from the mean utility level. Setting market size to twice peak sales keeps purchase probabilities interior and comparable across seasons. Category-specific ex-ante heterogeneity ω_j is fixed over time.

Each category-month market has a single list price and a single net handling cost, including months in

[15] A low purchase probability makes the purchase-probability inversion numerically unstable.

which RI and CI both appear. Purchase, return, and insurance-purchase counts under each scheme are scaled by the time share of that scheme, so each scheme is treated as if it had operated for the full month at that common price. That price balances the seller's pricing incentives under both schemes in that category-month.

6.1 Return-handling calibration

Net return handling cost is h_t = gross handling − scrap value$_t$. We set gross handling to 15 RMB per return, consistent with industry reports indicating that each apparel return costs sellers approximately 15 RMB in sunk marketing, packaging, and reverse logistics.[16] For scrap value, we calibrate a three-way disposition of returned inventory using industry surveys. About one-half of returned apparel units are resold at full retail price (e.g., 48%). Condition grading assigns roughly 20–30% of units to discount or outlet channels and 20–30% to secondary liquidation; we combine these into a 40% markdown tail. Roughly 10% of returns are written off.[17] Weighting across these channels yields an average net scrap value of $0.5\,p_t + 0.4\times(0.5\text{–}0.7)\,p_t \approx 0.75\,p_t$, implying baseline net handling cost $h_t = 15 - 0.75\,p_t$ (RMB). Online Appendix E reports robustness checks under alternative scrap shares of $0.65\,p_t$ and $0.85\,p_t$.

6.2 Demand Side

We estimate demand parameters following the nested fixed-point approach of Berry et al. (1995). The nonlinear parameters $\Theta = (\beta^\omega, \beta^\sigma)$ determine ex-ante heterogeneity, $\omega_j = C_j'\beta^\omega$ for a category-indicator vector C_j, and ex-post precision, $\sigma_t = X_t^\sigma \beta^\sigma$ for a market-covariate vector X_t^σ. Mean utility is $\mu_t = X_t\beta^\mu$, where X_t contains category-month demand shifters: assortment size, in-season share, newly published share, category indicators, and garment style attributes (length, cut, and material texture). Because β^σ is identified from cross-market variation in σ_t, we keep X_t^σ parsimonious, with only category indicators and newly published share. Assortment size and in-season share shift ex-ante value and production cost (μ_t and θ_t^c) rather than uncertainty, and are therefore excluded.

For each candidate Θ, we recover the mean-utility index $\delta_t(\Theta) = \mu_t + \xi_t$ by inverting model purchase

[16] China Venture News and Zhou Jiabao (2025), reprinting *Times Finance*, cite Yinman founder Fang Jianhua on per-return seller costs for Chinese e-commerce apparel. Yinman operates reverse-logistics services for online retailers; the 15 RMB figure is described as the cost of a return that generates no resale revenue, net of any recovery. We treat this as a per-unit processing charge (reverse shipping, inspection, repackaging, and a share of customer-acquisition and fulfillment costs allocated to the return event) and hold it fixed across categories and months.

[17] 48% full-price resale: Eightx (2026, Average eCommerce Return Rate by Category), a U.S. e-commerce apparel benchmark. SELVANE (2024, The hidden cost of fast fashion returns) sorts returns into full-price, discount or outlet (about 20–30%), and secondary liquidation (about 20–30%), with 25–30% never returning at list price; we map the last two channels into the 40% markdown tail. McKinsey & Company (2020, Returning to order) estimates that about 10% of apparel returns are discarded; remaining units that fail full-price resale enter the markdown tail and recover 50–70% of list price. The same shares apply in every category, so h_t varies only through p_t.

probabilities. In single-policy markets, the inversion matches observed coverage-weighted purchase probabilities. When RI and CI coexist within a market, a single δ_t minimizes the sum of squared discrepancies in coverage-weighted purchase probabilities across both policies. We estimate $\beta^\mu(\Theta)$ by IV regression of $\delta_t(\Theta)$ on X_t and define structural demand shocks $\xi_t(\Theta) = \delta_t(\Theta) - X_t\beta^\mu(\Theta)$.

The instrument vector Z_t includes X_t and a Hausman-style cost instrument: the contemporaneous average price of other apparel categories sold by the retailer. Common input costs (textiles, labor, warehousing, and platform logistics) induce joint price variation across categories. Normalizing purchase probabilities by category-season market size removes the common seasonal demand shock across categories, and averaging prices within a category lessens the demand-shock links between individual garments.[18] With these adjustments, category-specific demand shocks ξ_{jt} remain largely orthogonal to demand shocks in other categories, so other-category prices pick up little own-category demand. The first-stage partial F-statistic of this instrument for own price is 100.15 ($p = 0.000$; $N = 313$), well above conventional thresholds for weak instruments.

Given candidate Θ, we form two sets of GMM moments: orthogonality conditions $E[Z_t\xi_t(\Theta)] = 0$ and squared prediction errors $m_t(\Theta)^2$ matching sample return and insurance rates to their model-implied counterparts, where $m_t(\Theta)$ is the coverage-weighted gap.[19] We choose $\hat{\Theta}$ to minimize $\bar{g}_n(\Theta)'W\bar{g}_n(\Theta)$, iterating the weighting matrix W to convergence, and set $\hat{\beta}^\mu = \beta^\mu(\hat{\Theta})$.

6.3 Supply Side

Given $\hat{\Theta}$, we compute model-implied demand and its price derivative under each policy in each market. Substituting these and the observed price into the retailer's pricing first-order condition gives one linear equation in θ_t^c, which we solve to recover the marginal production cost. When only one policy is observed in a market, inversion directly recovers θ_t^c. When both policies coexist, we invert each first-order condition and set θ_t^c to the weighted average of the two implied costs that minimizes the sum of squared pricing residuals.[20] This yields 309 implied cost observations.[21] Regressing θ_t^c on X_t and time fixed effects without an intercept

[18] A pair of pants may go especially well with a certain shirt, which links the demand shocks for those two garments. Averaging prices within each category lessens those links. Market size equals twice peak monthly sales in the category-season and is held fixed within that season, so a larger season raises the denominator and the common seasonal scale does not enter purchase probabilities or ξ_{jt}.

[19] Squaring each market's return- and insurance-rate errors prevents large positive and negative errors from canceling across markets. At the true parameter vector Θ_0 under correct specification, each $m_t(\Theta_0)$ equals zero.

[20] The weights are $(dD_t^r/dp_t)^2$ and $(dD_t^c/dp_t)^2$, because each first-order condition is linear in θ_t^c with slope dD_t^l/dp_t.

[21] All 313 category-month markets enter demand estimation; supply inversion drops four cells where $|\partial D^l/\partial p| < 10^{-5}$, where dividing by a near-zero derivative is numerically unstable.

recovers cost parameters $\hat{\alpha}^c$ and store-level cost shocks $\hat{\zeta}_t^c$ from $\theta_t^c = X_t\alpha^c + \zeta_t^c$.

6.4 Parameter Estimates

Table 2 reports selected estimates associated with ex-ante heterogeneity β^ω, ex-post uncertainty β^σ, mean value β^μ, and production cost α^c. Standard errors and 95% percentile confidence intervals are computed from $B = 500$ transaction-level bootstrap replicates. Each draw resamples transactions with replacement and re-estimates the model, recentering GMM moment conditions at their full-sample values evaluated at $\hat{\Theta}$. Bootstrap distributions of the main demand and cost parameters appear in Online Appendix F.1.

Ex-ante heterogeneity ω_j is widest for dresses (59.125) and narrowest for tops (18.401). Ex-post uncertainty follows the same order: it is highest for dresses ($\sigma_t = 0.003$) and lowest for tops ($\sigma_t = 0.089$). A one-percentage-point increase in the newly published share raises mean utility μ_t by about 1.6 RMB. On the supply side, in-season listings have higher marginal production costs (13.704).

Table 2: Selected parameter estimates.

Parameter	Estimate	SE	95% CI
β^ω (dress)	59.125	27.485	[58.756 , 72.342]
β^ω (two-piece)	46.162	5.638	[33.979 , 55.141]
β^ω (outerwear)	45.050	13.794	[22.434 , 63.008]
β^ω (pants)	34.611	12.883	[28.793 , 46.593]
β^ω (sweater)	23.447	6.386	[16.540 , 29.890]
β^ω (tops)	18.401	7.964	[2.602 , 34.680]
β^σ (newly published share)	0.073	0.006	[0.065 , 0.081]
β^σ (dress)	0.003	0.000	[0.002 , 0.003]
β^σ (two-piece)	0.051	0.006	[0.044 , 0.071]
β^σ (outerwear)	0.040	0.009	[0.031 , 0.065]
β^σ (pants)	0.048	0.005	[0.039 , 0.053]
β^σ (sweater)	0.050	0.006	[0.042 , 0.060]
β^σ (tops)	0.089	0.037	[0.050 , 0.203]
β^μ (Assortment size)	-0.056	0.052	[-0.185 , 0.001]
β^μ (Newly published share)	155.304	21.784	[152.345 , 201.149]
β^μ (In-season share)	2.835	5.874	[-6.991 , 6.855]
α^c (Assortment size)	-0.115	0.020	[-0.151 , -0.073]
α^c (Newly published share)	-2.035	9.387	[-27.202 , 1.457]
α^c (In-season share)	13.704	1.644	[12.117 , 18.577]

6.5 Model Fit

Table 3 compares model-implied and sample values of prices, purchase probabilities, and return and insurance rates at the category × month level. Panel A reports unconditional rates per potential consumer, counting

both purchasers and non-purchasers in the denominator. These are the moments targeted in estimation,[22] while Panel B reports the corresponding rates per purchase. Each entry is an unweighted mean or standard deviation across the 313 category × month markets.

Table 3: Model vs. sample at $\hat{\Theta}$ (category × month cell means and SDs).

		Mean		SD	
		Model	Sample	Model	Sample
Price	RI (RMB)	106.76	99.83	53.55	39.56
	CI (RMB)	98.18	95.22	49.32	33.12
Purchase	RI (%)	18.90	26.20	19.59	15.51
	CI (%)	15.11	23.04	17.68	12.83
Panel A: Per potential consumer (targeted moments)					
Return	RI return (%)	6.63	7.69	9.47	6.27
	CI return (%)	2.94	5.55	8.48	4.65
	CI insurance (%)	1.55	0.55	8.83	0.79
Panel B: Per purchase (conditional)					
Return	RI return (%)	37.21	29.33	16.54	15.29
	CI return (%)	17.72	22.90	15.69	12.97
	CI insurance (%)	8.29	2.61	20.46	7.77

The model reproduces the key empirical patterns. Mean RI list prices, purchase probabilities, and return rates exceed their CI counterparts in both model and sample.[23] Purchase probabilities are underpredicted by about 7 percentage points under RI and about 8 under CI. This systematic underprediction can be due to the true valuation distribution having a heavier tail than the assumed normal.

At $\hat{\Theta}$, unconditional return rates average 6.6% under RI and 2.9% under CI in the model, compared with 7.7% and 5.6% in the sample. The implied RI-CI gap is 3.7 percentage points in the model and 2.1 percentage points in the sample, compared with 19.5 and 6.4 percentage points for the conditional gaps in Panel B. There, the model overpredicts RI returns and underpredicts CI returns. Return fit is therefore less poor than the conditional comparison alone suggests, although CI unconditional returns remain underpredicted by more than RI returns. Unconditional CI insurance rates are likewise closer than conditional take-up (1.6% vs. 0.6% in Panel A, against 8.3% vs. 2.6% in Panel B). Level fit remains imperfect. We still use the estimates to compare relative welfare across policies within each category, because welfare is determined mostly by the unconditional rates per potential consumer. The error in the unconditional purchase rate is large, but about the same under both policies, so it does not favor either one. The model overstates the unconditional return

[22] Estimation targets unconditional rates per potential consumer, which prevents markets with low purchase rates from destabilizing the moment conditions by dividing by near-zero denominators.

[23] In Table 1, pooled raw prices weight each transaction equally. RI transactions place more weight on lower-priced categories such as tops (31% of listings) and less on higher-priced categories such as outerwear than CI transactions do, so pooled CI prices exceed pooled RI prices even though RI prices are higher within every category except tops. Here, each category–month market contributes equally to the mean, downweighting the high-volume categories that drive the pooled ranking.

gap by about 1.6 percentage points, which slightly favors CI on the ex-post margin.

7 Counterfactual Simulations

We apply the welfare framework at the estimated parameters to evaluate return policies across categories. We first examine the category primitives and pricing forces. We then evaluate an optimal-refund benchmark to isolate the baseline market-structure distortion from monopoly pricing, compare the two observed policies, RI and CI, and evaluate an alternative return-penalty discount (RPD) mechanism. Section 7.5 examines the distribution of surplus across agents, and Section 7.6 conducts robustness checks.

For the welfare counterfactuals, we construct one *representative* snapshot per category. Covariates, premium-related inputs, demand shocks, and production-cost shocks are averaged across periods using consumer-count weights, and total market size is the sum of those counts. We then solve for equilibrium prices under each policy and evaluate purchase probabilities, return rates, and welfare by aggregating over valuations and coverage. Averaging primitives first, rather than averaging period-by-period welfare, targets long-run performance and keeps noisy thin months from dominating a highly nonlinear welfare functional.

7.1 Category Primitives

Welfare depends on the social value of a purchase and whether the consumer buys the product to realize that value. The social value of a purchase reflects the values when kept and when returned, weighted by the return probability, as well as the option value created by ex-post uncertainty. How much higher the return probability is under RI than under CI depends on the price, reimbursement, and this uncertainty. Finally, whether the purchase is realized depends on the price and the leniency of the return policy. Table 4 reports the category primitives affecting these factors and the implied prices, purchase probabilities, and return probabilities under RI and CI.

Table 4: Category primitives

						Purchase probability		Return probability	
Category	Production cost	Net scrap value	Ex-post SD	RI price	CI price	RI	CI	RI	CI
dress	42.22	48.85	29.84	71.64	67.97	0.11	0.07	0.56	0.35
outerwear	81.76	76.36	17.65	120.29	115.43	0.28	0.23	0.32	0.12
pants	66.26	59.65	17.92	100.18	94.43	0.33	0.28	0.37	0.14
sweater	88.17	71.95	17.32	120.79	112.13	0.41	0.37	0.42	0.15
top	35.39	25.52	10.05	54.06	49.05	0.20	0.21	0.28	0.06
twopiece	72.08	66.14	16.55	108.83	103.91	0.22	0.19	0.31	0.11

Notes: Return probabilities are conditional on purchase.

The value when kept is related to the margin, $(p - \theta^c)/p$. Economically, a higher margin reflects a wider wedge between ex-ante consumer valuations and production costs, so the gains from expanding participation

are larger where the margin is high.[24] The dress category has the highest margin (38%–41%), which raises the social value of a purchase, whereas sweaters have the lowest (21%–27%), where a kept purchase adds much less value. The other categories (tops, outerwear, pants, and two-piece sets) are about 28%–35%.

The value when returned depends on the net scrap value ($-h_t$), which captures salvage value net of shipping and processing frictions. In the dress category, net scrap value is 48.85 RMB, preserving 68%–72% of the retail price, so the social cost of a return is relatively low and an increase in the return probability reduces the social value of a purchase less. For tops, net scrap value is 25.52 RMB, which covers 47%–52% of the price, so the social cost of a return is much higher and an increase in the return probability reduces the social value of a purchase more. For sweaters, outerwear, pants, and two-piece sets, net scrap value covers about 60%–66% of the retail price.

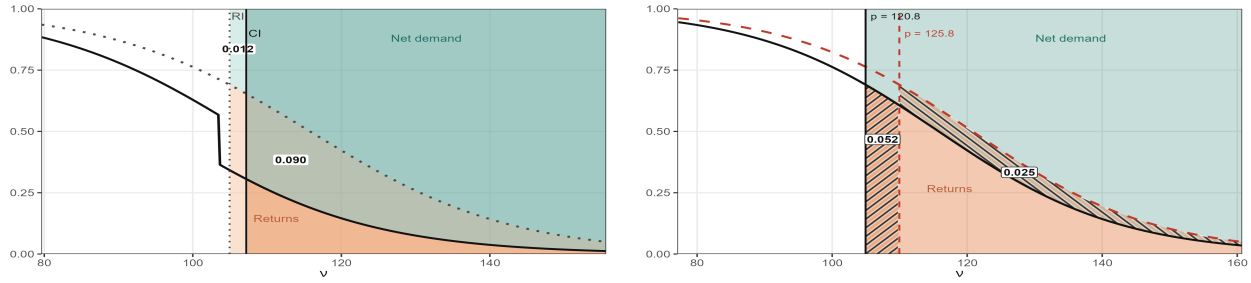
Ex-post uncertainty plays two roles. First, if a buyer could not choose between keeping and returning, greater dispersion in ex-post shocks would not affect the expected value of a purchase. Because the buyer observes the shocks and selects the option with the higher realization, greater uncertainty creates option value that raises the social value of a purchase and makes expanding purchases more valuable. Second, ex-post uncertainty governs how strongly price and reimbursement shift probability from keeping to returning, and thus how much higher the return probability conditional on purchase is under RI than under CI across all categories. When uncertainty is low, mean payoffs dominate idiosyncratic shocks, amplifying that shift.[25] Tops have low uncertainty (about 10 RMB), so option value is small and the return probability is highly sensitive to price and reimbursement. Dresses have high uncertainty (about 30 RMB), so option value is large and the return probability is much less sensitive. Outerwear, pants, sweaters, and two-piece sets have medium uncertainty (about 17 RMB).

The equilibrium price is higher under RI in every category. We explain it by revisiting the surplus-extraction and return-mitigation forces, using sweaters as an illustration. The other categories are in Appendix C. In Figure 5a, the return probability is lower under CI even among insured buyers, because CI's price is lower. Weaker reimbursement under CI excludes net demand of 0.012 (with market size normalized to 1) despite a lower price, while its lower return probability adds net demand of 0.090. Combined, net demand is higher under CI, which raises the surplus-extraction incentive. The same pattern holds in the other

[24] Online Appendix C (Figure 10) verifies that, holding production cost and other primitives fixed at their category estimates, shifting mean ex-ante valuation upward weakly raises the equilibrium margin $(p - \theta^c)/p$ under both RI and CI in every category.

[25] Equations (5) and (8) imply that reimbursement changes return odds $q_i/(1 - q_i)$ by a factor of $e^{\sigma k_i}$, and higher uncertainty lowers σ and therefore attenuates this shift.

categories except dresses, where net demand is slightly higher under RI. For return mitigation, Figure 5b shows that selection is stronger than the behavior effect. When the price rises by 5 RMB, the mass of low-valuation frequent returners screened out is 0.052, while the higher return probability among remaining buyers raises return volume by 0.025. The seller mitigates returns by raising the price to screen out frequent returners. This effect is stronger under RI, and the same ranking holds in every category. In summary, the higher price under RI is attributed to stronger pass-through and return mitigation, which dominate the surplus-extraction effect.



(a) Surplus Extraction (Sweater) (b) Return Mitigation (Sweater)

Notes: Coverage is set to the median of Ψ.

Finally, the purchase probability, which reflects both the equilibrium price and the leniency of the return policy, is higher under RI than under CI in every category except tops, where it is about 1 percentage point lower. Because this reversal for tops differs from the sample pattern (Table 3),[26] we discuss how it affects the welfare comparison below.

7.2 Optimal-Refund Benchmark

In our model, marginal cost pricing ($p = \theta^c$) and a return refund equal to net scrap value ($-h$) implement the first best. Because the buyer receives net scrap value instead of p on return, the buyer internalizes the seller's net return loss.[27] Return policy can improve ex-ante and ex-post efficiency, but once returns are efficient the remaining distortion is monopoly pricing above the production cost, which stems from market structure.

To isolate this residual market-structure distortion (a loss that return policy design itself cannot correct), we evaluate an *optimal-refund benchmark* (Online Appendix D.2). Setting the consumer refund equal to net scrap value eliminates ex-post return inefficiency, as return probabilities coincide with the first-best rule q_i^*. The remaining gap to the first best is entirely ex-ante inefficiency from monopoly pricing. Neither RI nor CI attains this benchmark, because both refund p on return.

[26] In the sample, the purchase probability for tops is higher under RI in 7 of the 9 months observed under both policies, and it averages about 23% in the 16 RI-only months against about 15% in the 11 CI-only months.

[27] Expected seller profit from consumer i is then zero on every path, so $S_i^* = CS_i^*$ and efficient purchase and return decisions maximize consumer surplus as well as social surplus.

This benchmark is a welfare diagnostic rather than a direct policy prescription. Net handling cost h combines logistics, inspection, and resale value that vary across sellers and categories and are imperfectly observed, so mandating refund $-h$ listing by listing is impractical. Furthermore, distance-selling laws generally mandate full product-price reimbursement on no-reason returns, as under China's seven-day no-reason return rules and the EU Consumer Rights Directive.[28] Product-refund forfeiture beyond these statutory floors raises consumer-protection concerns, although restocking fees and partial refunds are tolerated when disclosed at checkout and tied to processing costs.

Table 5 reports the optimal-refund benchmark across the six apparel categories. Efficient returns set $\Delta^{ex\text{-}post} = 0$ by construction, so the remaining welfare shortfall is entirely ex-ante, at about 29.4% of first-best welfare for dresses and 23.8%–25.6% in the other five categories, with welfare under this benchmark attaining 70.7% to 76.2% of first best.

Table 5: Optimal-refund benchmark: welfare decomposition and extensive-margin cutoffs

Category	Welfare (% FB)	$\Delta^{ex\text{-}ante}$ (% FB)	Purch. cutoff	Eff. cutoff	Marg. SS
dress	70.65	29.35	55.48	15.38	20.84
outerwear	74.59	25.41	113.55	78.36	32.09
pants	74.94	25.06	91.98	63.05	26.17
sweater	76.22	23.78	109.18	86.81	21.28
top	75.06	24.94	48.37	35.07	13.04
twopiece	74.36	25.64	102.31	69.36	30.47

Columns 4–6 report the purchase cutoff, the first-best efficient cutoff, and marginal social surplus at the purchase cutoff. Marginal social surplus is strictly positive in every category, ranging from 13.04 RMB for tops to 32.09 RMB for outerwear. This confirms that the ex-ante shortfall is monopoly underprovision on the extensive margin. The seller's market power pushes the purchase cutoff above the efficient cutoff, excluding marginal buyers whose purchase would generate positive social surplus. The purchase-efficient gap is largest for dresses (about 40.1) and smallest for tops (about 13.3).

7.3 RI vs. CI

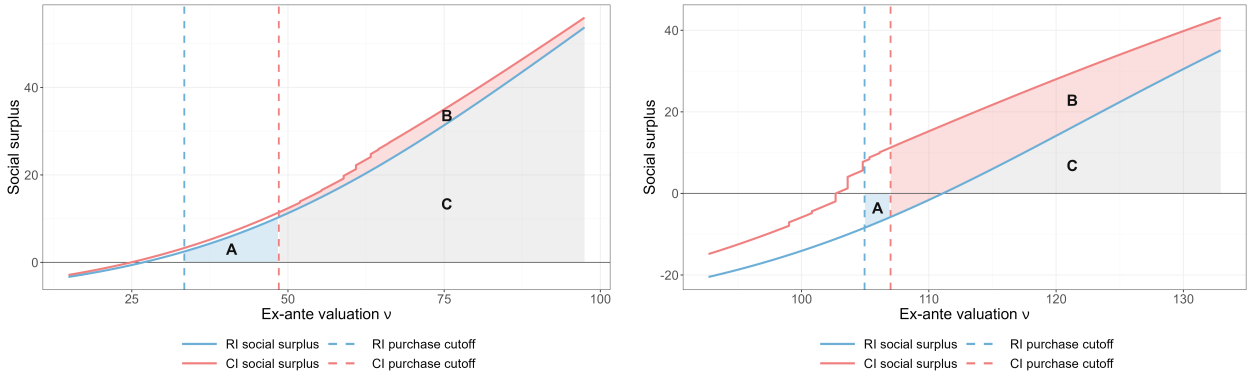
7.3.1 Extensive versus ex-post margin trade-off

On the ex-post margin, both RSI schemes refund p on return and are therefore more lenient than the optimal-refund benchmark. On return, the seller incurs net cost $p + h$ (refunding p and absorbing net handling cost h), and the insurer bears return shipping k_i when reimbursed. Because the buyer does not face these costs

[28] China's *Law on Protection of Consumer Rights and Interests* (Art. 25) and *Interim Measures for Seven-Day No-Reason Returns on Online Purchases*. EU Directive 2011/83/EU, Art. 13. Exceptions and prior buyer confirmation narrow these rights.

when deciding to return, the uninternalized loss is $p + h + k_i$ under RI and for insured CI purchasers, but only $p + h$ for uninsured purchasers who bear k_i themselves. CI therefore achieves better ex-post return discipline than RI. On the extensive margin, however, automatic coverage under RI encourages more consumers to buy, which can reduce the monopoly underprovision in Table 5 more than CI does.

Figure 6 illustrates the resulting trade-off between the extensive and ex-post margins for dresses and sweaters at estimated equilibria. Solid curves plot the individual social surplus of a consumer with valuation v evaluated at the equilibrium price, and dashed vertical lines mark purchase cutoffs where consumer surplus is zero. Region A is the social surplus of marginal buyers who purchase under RI but not under CI, Region B is the ex-post social surplus gain of CI over RI among buyers who purchase under both policies, and Region C is the social surplus common to both policies (so total social surplus is $A + C$ under RI and $B + C$ under CI, weighted by the valuation density). Curves and cutoffs average across empirical coverage masses.[29]



(a) Dress. (b) Sweater.

Figure 6: Social surplus and purchase cutoffs under RI and CI.

Relative to CI, whether RI performs better depends on whether the extensive-margin region A outweighs the ex-post region B. In Figure 6, the vertical difference between the solid curves of CI and RI (Region B) captures the combined effect of equilibrium pricing and the reduction in ex-post return inefficiency under CI when buyers remain uninsured. For dresses, CI's solid curve lies only modestly above RI's, so the ex-post margin gain from having uninsured buyers bear return shipping is small. This is because reimbursement shifts less probability between keeping and returning when uncertainty is high (Table 4). Against that small ex-post gain B, RI's extensive-margin gain A dominates, as the wide band of socially valuable buyers between the two purchase cutoffs raises welfare relative to CI. The purchase cutoffs differ substantially because high return rates make shipping coverage especially valuable for dresses.[30] RI provides this coverage automatically,

[29] Under CI, social surplus jumps at insurance cutoffs because coverage lowers private return cost.

[30] Price affects consumer surplus only when the item is kept (probability $1 - q_i$), whereas coverage matters only when it is returned (probability q_i), so coverage shifts the purchase cutoff in proportion to $q_i/(1 - q_i)$.

whereas CI requires consumers to pay a separate premium.

For sweaters, the trade-off reverses. Across consumers' valuations, CI's solid curve lies well above RI's, making Region B large. This is because reimbursement shifts more probability between keeping and returning when uncertainty is lower, so having uninsured buyers bear return shipping greatly improves ex-post efficiency. On the other hand, the RI–CI difference in purchase cutoffs is narrow, and the buyers RI admits between the two purchase cutoffs lie below zero in Region A, generating negative social surplus. Return discipline under CI therefore dominates. Under RI, such overprovision can arise because the seller does not fully internalize insurer claim losses, admitting marginal, return-prone consumers whose transactions generate negative social surplus.

Table 6 reports the purchase cutoff, the efficient cutoff, and the social surplus generated by the marginal consumer under RI and CI, with RPD included for completeness and easy comparison.[31] CI underprovides in every category. RI underprovides for dresses, slightly underprovides for outerwear and two-piece sets, and overprovides for pants, sweaters, and tops. Relative to the gaps under the optimal-refund benchmark in Table 5 (about 13 to 40), RSI softens underprovision on the extensive margin, and RI softens more than CI and can overshoot. The RI purchase-efficient gap is about 7 for dresses and ranges from about -6 to about 0.6 for the other five categories, while the CI purchase-efficient gap always stays positive (about 24 for dresses and 4 to 10 for the other five categories).

Table 6: Purchase cutoffs, efficient cutoffs, and marginal social surplus by category

	Purchase cutoff			Efficient cutoff			Marginal social surplus		
Category	RI	CI	RPD	RI	CI	RPD	RI	CI	RPD
dress	33.41	48.53	66.19	26.49	24.54	34.59	2.49	11.44	26.07
outerwear	103.94	110.03	114.25	103.36	99.84	81.68	0.62	21.02	32.49
pants	83.41	88.83	89.38	85.04	81.04	74.62	-1.83	16.72	17.09
sweater	104.95	106.96	109.22	111.08	102.98	89.87	-8.42	11.23	19.70
top	48.17	47.87	48.48	49.31	40.04	35.34	-2.00	10.39	13.09
twopiece	94.19	99.29	102.89	93.67	90.09	71.99	0.59	20.49	30.82

Notes: Entries average across coverage types. Efficient cutoffs use each scheme's equilibrium return behavior.

The larger purchase-efficient gap under CI reflects shifts in both the efficient and purchase cutoffs. On the one hand, more purchases are socially efficient under CI (a lower efficient cutoff) because stronger ex-post return discipline among uninsured buyers raises the social surplus of a purchase relative to RI. On the other

[31] The purchase-efficient gap measures extensive-margin distortion. In a textbook single-product monopoly without returns, the degree of underprovision increases with the margin and the price. Across return schemes, however, posted price and margin poorly measure extensive-margin distortions. RI and CI attach different return benefits and insurance costs for buyers and shift costs differently for sellers, so they are effectively different products rather than the same good. The gap is therefore a better metric for comparing extensive-margin underprovision across policies.

hand, fewer of these efficient purchases are enabled under CI (a higher purchase cutoff) despite a lower price, because CI does not automatically reimburse return shipping and the seller's stronger surplus-extraction incentive keeps the price reduction small. For tops, the two policies enable nearly the same set of purchases (cutoffs of about 48), so the larger CI gap comes entirely from having more socially efficient purchases.

7.3.2 Welfare decomposition

Integrating individual social surplus over purchasers yields aggregate welfare. Figure 7 shows how the extensive- and ex-post-margin forces aggregate into welfare across categories. Each stacked bar expresses welfare and the shortfalls from ex-post and ex-ante inefficiency as percentages of first-best welfare.[32] Ex-post inefficiency is larger under RI than under CI in every category, consistent with the lower return probabilities under optional insurance. Full-forfeiture RPD is included for later comparison.



Figure 7: Welfare decomposition by category, normalized as a share of first-best welfare.

For dresses, where the margin, net scrap value, and uncertainty are all high, RI attains a larger share of first-best welfare than CI (76% vs. 74%) because the ex-ante gain from broader participation (Region A) outweighs the incremental ex-post loss from returns (Region B).

Outside the dress category, the ranking reverses. For outerwear, pants, sweaters, and two-piece sets, where margins are low to medium and net scrap value and uncertainty are medium, CI outperforms RI because the ex-post gain from curbing over-return dominates. For sweaters, for example, CI outperforms RI by about 33 percentage points of first-best welfare ex post while losing only about 4 percentage points ex ante, as RI dissipates about 58% of first-best welfare. For tops, where the margin is intermediate but net scrap value and uncertainty are both low, RI underperforms CI on both margins, dissipating about 51% of

[32] In Table 6, extensive-margin cutoffs use each scheme's private return behavior q_i^l. The first-best efficient cutoff under the optimal-refund benchmark, evaluated at q_i^*, remains below every q_i^l-efficient cutoff, so the first-best residual $\Delta^{ex\text{-}ante}$ in Figure 7 still reflects underprovision relative to first best even where RI overprovides on the extensive margin (Table 5).

first-best welfare through poor ex-ante screening and ex-post over-return.

Because the model overstates the RI–CI return gap relative to the sample (Table 3), CI's estimated advantage outside dresses is, if anything, overstated, while RI's advantage in dresses is conservative. For tops, however, purchase probability is higher under CI than under RI in the counterfactual (Table 4) yet lower in the sample, so CI's ex-ante advantage from screening out inefficient purchases is likely understated.

7.4 Return-Penalty Discount (RPD)

Under return-penalty discount (RPD), each consumer chooses either a full price with full refund rights, or a discounted price with no or partial product refund on return, as in common "final sale" or restocking-fee menus.[33] RPD preserves a full-refund option while adding a second branch with stricter refund terms. On the discount branch, share $\phi \in (0, 1]$ of the discounted price is forfeited on return. Equilibrium conditions and the explicit expressions for the welfare objects appear in Online Appendix D.1.

Relative to RSI, RPD is an alternative for correcting excessive returns, especially when the margin, net scrap value, and uncertainty are low. RSI expands low-end participation by subsidizing returns, thereby creating adverse selection ex-ante and over-return ex-post. In contrast, RPD makes the discount attractive to high-valuation keepers rather than to buyers who expect to return, so it does not expand low-end participation through return subsidies. On that branch, forfeiture also lowers the return probability ex-post.

RPD also places screening with the party that holds product-level information. Under CI, the insurer sets standardized premiums while the seller chooses only product price. Even when the return rate is low, a premium set from return probability can be too low if net scrap value is low, so optional coverage underprices the social cost of returns. Cheap coverage can then generate additional purchases and returns that impose a large negative externality on the seller, which cannot be corrected through product price alone. In contrast, under RPD the platform sets the refund terms, and the seller chooses both the list price and the discount. These two instruments let the seller incorporate private information about return costs into the menu, which can improve welfare relative to CI. Nevertheless, the additional instruments can also strengthen the seller's ability to extract surplus and enlarge the purchase-efficient gap.

7.4.1 Full-forfeiture RPD

We first report full-forfeiture RPD ($\phi = 1$), the leading case that delivers the strictest return discipline and is straightforward to implement. Ex ante, stricter refund terms can exclude socially valuable marginal buyers.

[33] Amazon allows a restocking fee of up to 20 percent after the return window.

Ex post, no product refund narrows the return subsidy to an externality gap of $-h$ alone. When net scrap value is positive ($-h > 0$), this gap is positive, so full forfeiture can overshoot into under-return because consumers do not internalize the positive externality that net scrap value confers on the seller. Table 7 reports the list price, discount d, effective price, and segment-level purchases and returns.

Depending on the wedge between the purchase cutoff and the cutoff that is indifferent between the discount and the full price, buyers may end up only on the discount branch. In most categories full-price demand is negligible, purchases concentrate on the discount branch, and the return probability there is about zero. Pants are the exception: the full-price purchase probability is 0.15, against 0.12 on the discount branch, and the full-price return probability is 0.21. In contrast to RSI, ex-post inefficiency on the discount branch takes the form of under-return rather than over-return. Ex-post inefficiency is nevertheless smaller under full-forfeiture RPD than under either RSI policy (Figure 7).

Table 7: RPD counterfactual: prices and segment-level purchase probabilities, returns, and return probabilities by category

				Discount option			Full price		
Category	Price	Discount	Effective price	Purchase prob.	Return	Return prob.	Purchase prob.	Return	Return prob.
dress	104.85	37.98	66.88	0.04	0.00	0.01	0.00	0.00	
outerwear	196.74	82.49	114.25	0.20	0.00	0.00	0.00	0.00	
pants	94.98	1.56	94.29	0.12	0.00	0.00	0.15	0.03	0.21
sweater	115.72	6.49	109.22	0.34	0.00	0.00	0.00	0.00	0.00
top	83.91	35.43	48.48	0.20	0.00	0.00	0.00	0.00	
twopiece	174.98	72.09	102.89	0.17	0.00	0.00	0.00	0.00	

Notes: Effective price is $p - d$. Full-price return probabilities are left blank for segments with negligible full-price volume.

Participation, on the other hand, is weaker. By driving return probabilities on the discount branch close to zero, refund forfeiture leaves the seller with a pool of confident keepers who rarely return, sharpening the surplus-extraction incentive. For dresses, the RPD purchase cutoff is about 66, against about 49 under CI and 33 under RI, even though RPD's effective price (about 67) lies slightly below the CI price (about 68). Forfeiting the product payment on return removes the implicit full-refund subsidy, so the purchase cutoff can rise above the CI cutoff even when the demand-weighted price paid is lower.

Relative to the RI and CI purchase-efficient gaps above, full-forfeiture RPD underprovides by more. For dresses the gap rises to about 32 and marginal social surplus to about 26 (Table 6). Outside dresses, RPD's gap exceeds CI's in every category.

Relative to RI, this stronger screening raises welfare in every category other than dresses. Relative to CI, it raises welfare for sweaters, where the margin is thin. For tops, outerwear, pants, and two-piece sets, welfare is almost indistinguishable from CI, with tops about one percentage point higher, outerwear and two-piece sets about one percentage point lower, and pants tied. In the dress category, where the extensive

margin is especially valuable, RPD underperforms both RI and CI. Marginal entrants often have relatively low valuations and high return propensity, yet many such purchases remain socially worth encouraging because kept sales generate high surplus. RSI preserves a channel for those buyers. The discount branch under full-forfeiture RPD largely shuts it down, so the participation loss outweighs the ex-post gain and welfare falls to about 56% of first best.

7.4.2 Partial forfeiture and restocking fees

Full forfeiture is extreme. Softening the return penalty on the discount branch to a partial forfeiture $\phi \in (0, 1)$ restores some participation while retaining most of the return discipline. A natural retail implementation is a restocking fee. On return the buyer pays $\phi(p - d)$ and recovers share $1 - \phi$ of the discounted payment. We focus on restocking fees in the 10–15% range, which are common in retail practice on eligible returns. Figure 8 shows the welfare decomposition across categories as ϕ varies over $\{0.05, 0.10, 0.15, 0.20\}$.

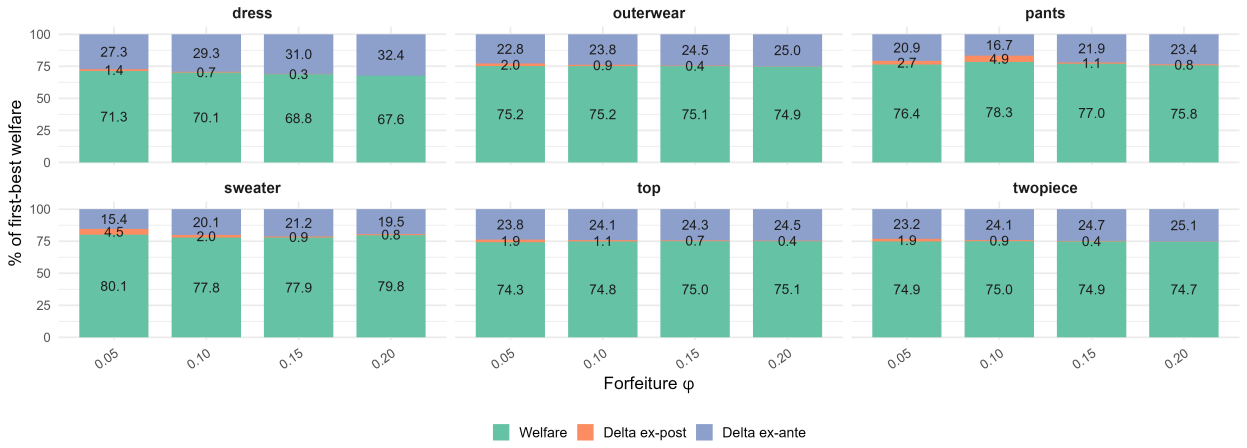


Figure 8: Partial-forfeiture RPD: welfare decomposition by category and $\phi \in \{0.05, 0.10, 0.15, 0.20\}$, normalized within each cell.

A lower ϕ reduces under-return, softens the seller's surplus-extraction incentive, and raises participation relative to full forfeiture while retaining most of the return discipline. Outside dresses, welfare at a 10%–15% restocking fee is about 75–78% of first best. Partial-forfeiture RPD exceeds both RSI policies and full-forfeiture RPD at these fees. It matches or exceeds the optimal-refund benchmark, except for tops, where partial-forfeiture RPD at a 10%–15% restocking fee underperforms the optimal-refund benchmark by about 1 percentage point (about 75% versus about 76%). The advantage over RI is large, about 9–36 percentage points of first best. The advantage over CI is small, about 0.5–4 percentage points, except for sweaters, where the margin is lowest and the advantage is about 6 percentage points. For dresses, welfare at a 10%–15% restocking fee is about 69%–70% of first best. It remains below RI (about 76%), CI (about 74%), and the

optimal-refund benchmark (about 71%), and lies well above full-forfeiture RPD (about 56%).

7.5 Welfare across agents

The decompositions above split efficiency losses relative to first best. Figure 9 instead shows how expected social surplus divides among consumers, the seller, and the insurer, as shares of first-best welfare. Partial-forfeiture RPD uses a 10%–15% restocking fee. Expected consumer surplus and seller profit lie above zero. Insurer profit is zero under RPD, which has no insurance, and under CI outside dresses, where no one buys coverage. It is negative under RI or CI when buyers are insured, because expected claims exceed the observed premiums.[34] The three components sum to welfare.

Welfare, expected consumer surplus, and seller profit largely follow the same ranking in every category. The exception is pants, where welfare and expected consumer surplus rank partial-forfeiture RPD, then CI, then full-forfeiture RPD, while seller profit under full-forfeiture RPD and CI is slightly above partial-forfeiture RPD (42.2% and 42.1% versus 41.9%). Outside dresses, partial-forfeiture RPD ranks first. Full-forfeiture RPD and CI are about the same (except for sweaters, where full-forfeiture RPD exceeds CI), and both rank above RI. For dresses, the ranking is RI, then CI, then partial-forfeiture RPD, then full-forfeiture RPD.

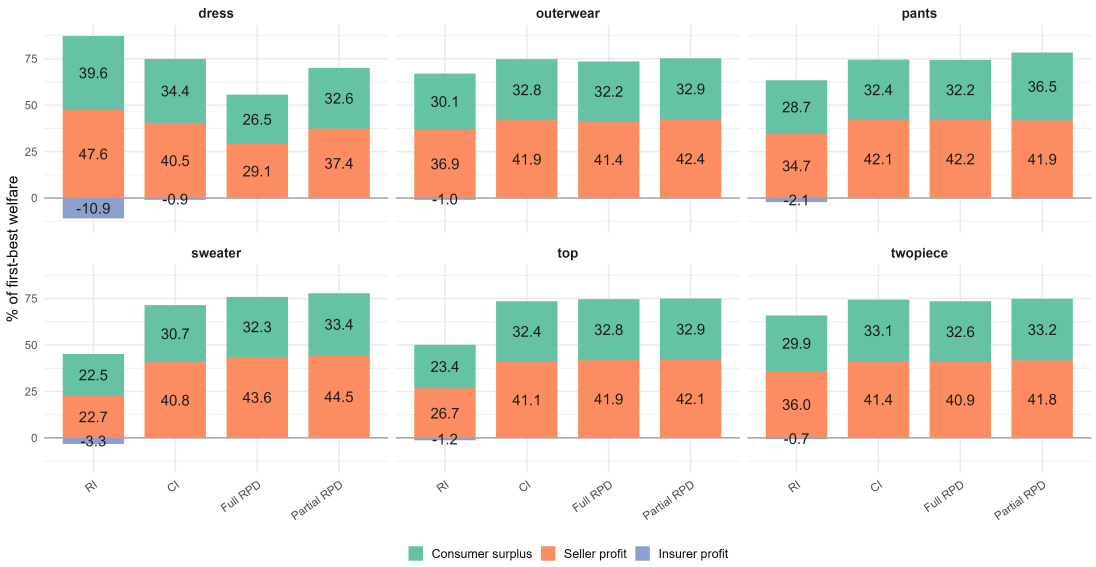


Figure 9: Welfare across agents by category and return policy.

[34] Negative insurer profit for a single apparel seller is consistent with reported underwriting losses on Taobao return-shipping insurance (Huatai in 2012; Wang Liangdi, 2017, Peking University).

7.6 Robustness check

7.6.1 Scrap-value sensitivity

The baseline decomposition uses the scrap calibration in Section 6.1 (about 75% of price on average). Because $h_t = 15 -$ scrap value, alternative scrap shares shift net scrap value and can reorder counterfactuals even when demand primitives are fixed. Online Appendix E gives a table of welfare for each policy at scrap shares of $0.65\,p_t$ and $0.85\,p_t$, and the welfare decomposition.

The RI–CI tradeoff and the advantage of partial forfeiture largely remain intact, with two exceptions. Outside dresses, CI remains above RI at both scrap shares. For dresses, RI still ranks above CI at 85% scrap, but lies about 6 percentage points below CI when scrap is 65% of price (about 68% versus about 74%). A 10%–15% restocking fee still beats both RSI policies outside dresses at 65% scrap and, at 85% scrap, for sweaters and tops. For outerwear, pants, and two-piece sets, partial RPD beats RI by about 2, 6, and 3 percentage points at 85% scrap and falls short of CI by about 0.5–1.5 percentage points.

7.6.2 Inference on welfare ranking and decomposition

Online Appendix F shows the bootstrap distributions of welfare and its decomposition by policy within each category. The interpretations below are based on a visual reading of those distributions and on the pairwise win rates, which count the share of draws in which one policy ranks above another.

The results on how the welfare ranking differs between dresses and the other categories, and on the ex-ante and ex-post efficiency tradeoff, are stable. RI ranks above the other policies for dresses. Outside dresses, partial-forfeiture RPD, evaluated at the welfare-maximizing restocking fee over $\phi \in \{0.10, 0.15\}$, ranks above the other policies for two-piece sets, outerwear, pants, and sweaters, as in Figure 9. For tops, it ranks above RI and CI, while full RPD and partial RPD are close. Relative to CI, RI has lower ex-ante inefficiency and higher ex-post inefficiency in every category except tops, where it is worse on both margins. Relative to full forfeiture, partial RPD lowers ex-ante inefficiency. Its ex-post inefficiency is lower for dresses, similar for pants, and higher for the other categories.

Overall, the bootstrap evidence corroborates the welfare rankings and decomposition patterns discussed above.

8 Conclusion

This paper studies the welfare consequences of RSI and RPD in online retail. Using transaction-level data from an apparel retailer on Taobao that repeatedly switched between RI and CI, we estimate a structural

model of purchase, return, and insurance decisions under monopoly pricing across six garment categories. The welfare ranking among return policies is category-specific, governed by the trade-off between ex-ante efficiency and ex-post efficiency.

For categories in which the margin, net scrap value, and uncertainty are high, a generous return policy (RI) performs better by greatly improving ex-ante efficiency at the cost of ex-post efficiency, as for dresses. For categories in which the margin, net scrap value, and uncertainty are lower, a stricter return policy (CI) performs better by greatly improving ex-post efficiency at the cost of ex-ante efficiency, as for sweaters. When net scrap value and uncertainty are both low, as for tops, a generous return policy strongly shifts the return rate and makes many purchases inefficient to begin with. A stricter return policy then improves both ex-ante efficiency and ex-post efficiency by screening out inefficient purchases and curbing inefficient returns.

The platform should set the return policy according to these three category-specific primitives. When the platform does not observe these primitives, partial-forfeiture RPD with a moderate restocking fee (10%–15%) outperforms both RSI policies outside dresses at the baseline and when net scrap value is low. When net scrap value is high, partial RPD still outperforms both RSI policies for sweaters and tops. For outerwear, pants, and two-piece sets, partial RPD beats RI but falls slightly short of CI. For dresses, partial RPD remains below RI at the baseline and when net scrap value is high.

These findings challenge prevailing e-commerce platform practices. Platforms frequently compel merchants to offer automatic return insurance indiscriminately, even on merchandise where the margin, net scrap value, and uncertainty are low, or require them to adopt RI in order to join major sales events such as Singles' Day. Mandatory RI is inefficient in categories with a low margin, low net scrap value, or low uncertainty, dissipating about 58% of first-best welfare for sweaters and about 51% for tops. The social cost of uniform reimbursement is larger under emerging practices such as refund-without-return policies, because net scrap value can fall below our baseline calibration.

8.1 Limitations and future research

We treat RSI as given when recovering demand and inverting seller pricing. Conditional on the observed scheme, endogenizing enrollment would leave demand estimation largely unchanged. Purchase, insurance, and return still identify the same primitives. The supply side would change, because optimality of the chosen scheme becomes an additional inequality constraint on total profit at the store level. Recovered costs would

have to rationalize both within-scheme pricing and the seller's preference for RI versus CI at the store level. We deliberately avoid that inequality.[35] Total profit at the store level depends on the relative market size of each category, whereas production cost recovered only from the observed price does not. The model treats each category on its own, and the welfare comparison is within a category, so relative market size should not enter the recovered costs.

Several extensions would change the policy ranking. First, under oligopoly, buyers screened out by a high price or a strict refund can divert to other products or sellers. That diversion mitigates the social cost of exclusion relative to our single-seller benchmark and therefore tilts welfare toward stricter return terms. Second, we study platform-regulated refund menus (RPD). Delegating refund choice to sellers adds a screening instrument that can expand participation for some types while strengthening surplus extraction, with an ambiguous net welfare effect. Third, our counterfactuals are risk-neutral; risk aversion would raise the value of automatic coverage. Fourth, we take insurer premiums as exogenous. Endogenizing them would reintroduce double marginalization between the insurer and the seller, with an ambiguous effect on the ranking across categories.[36] Fifth, on a two-sided platform, return policy also shifts cross-network externalities between buyers and sellers; characterizing the platform-optimal refund then requires modeling both sides jointly, which we leave for future research.

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[35] Both schemes are observed in 18 of 73 months. In those months the store changes scheme while category fundamentals are expected to be relatively unchanged, so a ranking of total profit cannot justify the observed scheme.

[36] Double marginalization pushes the retail price above the vertically integrated benchmark. The wedge is weaker than in a fixed-cost insurance model because expected claims scale with the return probability, so the insurer sets a lower premium than when claims are a fixed cost. Remaining pass-through can still widen the private-social gap in return costs. Ex ante, higher prices are costly when marginal purchases have positive social surplus (as for dresses) but can help in thin-margin categories where RSI already overprovides. Ex post, a higher price can worsen over-return.

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Online Appendix

A Data Construction

This appendix constructs the analysis sample from raw transactions in three steps: filters, RSI classification and CI imputation, and aggregation.

A.1 Sample Filtering

We keep 2017–2023 transactions and drop multi-item or multi-quantity orders (complementarity and lower marginal return cost), orders without a logistic ID (typically cancelled before shipment), orders with buyer-paid premium shipping services (a separate surcharge outside the product price), partial refunds for minor defects, and non-product listings. We also drop single-day RSI switches for promotions such as Singles' Day, so the sample reflects the store's usual scheme.

A.2 RSI Scheme Classification and CI Imputation

Missing insurance fields are ambiguous (RI ineligibility versus CI non-purchase). Complete records with premium and coverage are RI. Coverage only is CI. We propagate the day-level majority label, treat long runs of missing records as CI, and drop remaining ambiguous cases and confirmed RI ineligibility (1.8% of RI transactions).

CI coverage is imputed from the nearest same-province observation by date. Premiums are not recorded in 2017–2023, so we impute $I^c(k_i) = ak_i + b$ from 2025 Taobao data. Agents do not internalize current returns into future premiums.[37]

A.3 Aggregation, Filtering and Smoothing

We aggregate the cleaned transactions to category × month cells, counting sales and averaging transaction prices within each cell. We keep categories whose average monthly sales over the sample reach at least fifty transactions. The six qualifying categories are dress, tops, pants, sweater, two-piece, and outerwear.

Monthly sales and prices are smoothed with a five-month centered moving average that combines the current month with the two adjacent months on each side, using the available months only at the ends of the sample. Each category-month is then resampled to its smoothed sales count, drawing from the month's observed transactions without replacement when observed sales exceed the smoothed count and

[37] We treat the 2025 premium-coverage slope as stable. It implies premiums of roughly 60% of coverage, consistent with older public documentation (e.g. Zhihu).

with replacement otherwise. Every resampled transaction in a category-month is assigned the smoothed price, so RI and CI transactions in the same month share one list price and therefore one net handling cost $h_t = 15 - 0.75\, p_t$.

Market size is twice the peak smoothed monthly sales within the category-season, with seasons defined as March–May, June–August, September–November, and December–February. Monthly purchase probabilities equal smoothed sales divided by market size. We drop category-months with purchase probability below 5% to avoid the zero-share problem.

When both schemes appear within a month, we compute each scheme's time share as the share of the month's transaction-active hours during which the scheme was in effect, common across categories. The observed purchase, return, and insurance-purchase counts under each scheme are divided by that time share, converting them into full-month counts at the common smoothed price. The scale factor is capped at the market size divided by twice the scheme's observed transaction count, so no scheme's full-month volume exceeds half the market size and purchase probabilities remain interior. Because a single factor multiplies every coverage × purchase × return (× insurance) cell of the scheme-month, the scaling preserves the return rate per purchase and the insurance take-up rate within the scheme-month.

B Identification of Ex-Post Precision

This appendix derives the expression for expected returns under RI and proves that, holding the purchase schedule fixed, expected returns are strictly decreasing in ex-post precision σ_t.

Under RI, return shipping is fully reimbursed up to k_i, yielding mean return utility $\overline{u}_{it}^{\text{return}} = -\kappa$. A consumer purchases if and only if $\nu_{it} \geq \hat{\nu}_t^r \equiv p_t + \frac{1}{\sigma_t}\ln(1 - e^{-\sigma_t\kappa})$. Defining willingness to pay as $w_{it}^r \equiv \nu_{it} - \frac{1}{\sigma_t}\ln(1-e^{-\sigma_t\kappa})$, the purchase condition is equivalent to $w_{it}^r \geq p_t$. Because $\nu_{it} \sim \mathcal{N}(\mu_t + \xi_t, \omega_j^2)$, w_{it}^r is normally distributed with mean $\bar{w}_t^r = \mu_t + \xi_t - \frac{1}{\sigma_t}\ln(1 - e^{-\sigma_t\kappa})$ and standard deviation ω_j.

Conditional on purchase, the probability of return is

$$q_{it}^r(\nu_{it}) = \frac{e^{-\sigma_t\kappa}}{e^{\sigma_t(\nu_{it}-p_t)} + e^{-\sigma_t\kappa}}.$$

Substituting $\nu_{it} - p_t = (w_{it}^r - p_t) + \frac{1}{\sigma_t}\ln(1 - e^{-\sigma_t\kappa})$ into the denominator and dividing both numerator and denominator by $e^{-\sigma_t\kappa}$ simplifies the individual return probability to

$$q_{it}^r(w_{it}^r) = \frac{1}{1 + (e^{\sigma_t\kappa} - 1)e^{\sigma_t(w_{it}^r - p_t)}}. \tag{14}$$

Integrating over the distribution of w_{it}^r yields the unconditional expected return rate per potential buyer:

$$\mathbb{E}[R_{it}^r(p_t)] = \mathbb{E}_{w_{it}^r}\left[\frac{1}{1+(e^{\sigma_t\kappa}-1)e^{\sigma_t(w_{it}^r-p_t)}}\,\mathbf{1}\big(w_{it}^r \geq p_t\big)\right]. \tag{15}$$

The return rate conditional on purchase is simply $\mathbb{E}[R_{it}^r(p_t)]/\mathbb{E}[D_{it}^r(p_t)]$.

As shown in Section 5, price variation identifies ω_j and $\bar{w}_t^r$, holding the distribution of w_{it}^r and the purchase probability $\mathbb{E}[D_{it}^r(p_t)] = 1 - \Phi\big(\frac{p_t-\bar{w}_t^r}{\omega_j}\big)$ fixed. For every purchaser ($w_{it}^r \geq p_t$), $w_{it}^r - p_t \geq 0$. Because $\kappa > 0$, the term $e^{\sigma_t\kappa} - 1 > 0$ is strictly increasing in σ_t, while $e^{\sigma_t(w_{it}^r-p_t)} \geq 1$ is weakly increasing in σ_t. The denominator of (14) is therefore strictly increasing in σ_t, so each purchaser's return probability is pointwise strictly decreasing in σ_t. Because the distribution of w_{it}^r and the purchase region $w_{it}^r \geq p_t$ are held fixed, the expected return rate (15) (as well as the return rate conditional on purchase) is strictly decreasing in σ_t. Consequently, σ_t is uniquely identified by the return rate, after which intrinsic mean valuation $\mu_t + \xi_t = \bar{w}_t^r + \frac{1}{\sigma_t}\ln(1 - e^{-\sigma_t\kappa})$ is uniquely recovered.

C Surplus Extraction and Return Mitigation by Category

Figure 10 plots the equilibrium margin $(p - \theta^c)/p$ under RI and CI across demand-shock shifts in mean ex-ante valuation, holding production cost and other primitives at their category estimates. Figure 11 pairs surplus extraction and return mitigation for the categories other than sweaters. In each row the left panel is surplus extraction at equilibrium prices and the right panel is return mitigation under RI.

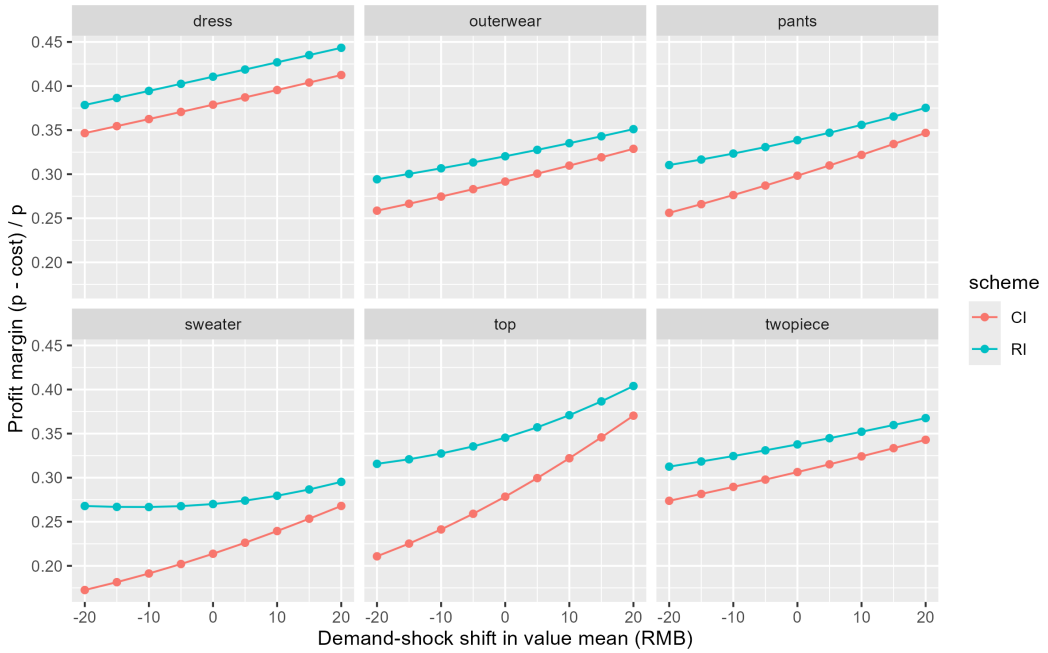
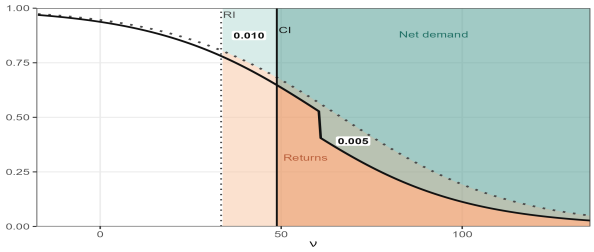
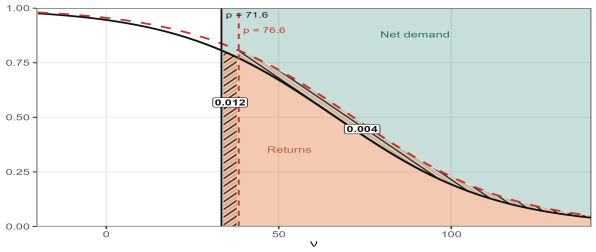


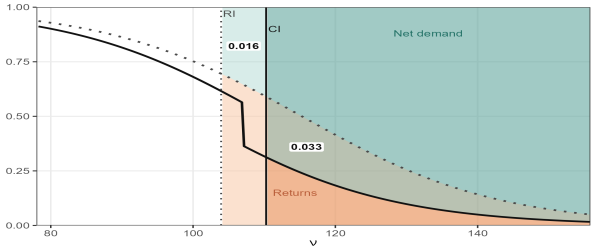
Figure 10: Equilibrium margin $(p - \theta^c)/p$ under RI and CI across demand-shock shifts in mean valuation.



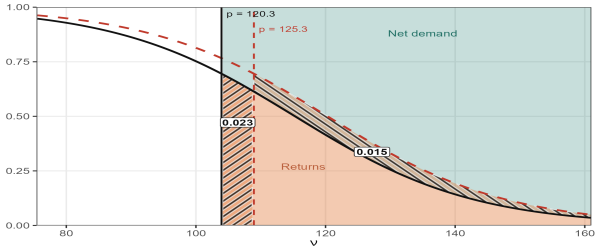
(a) Surplus Extraction (Dress)



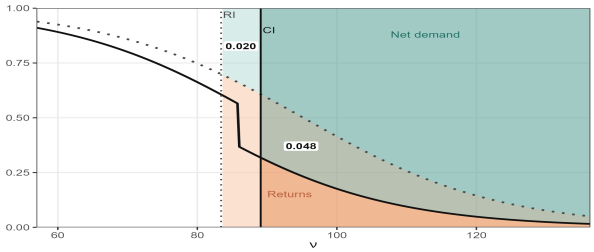
(b) Return Mitigation (Dress)



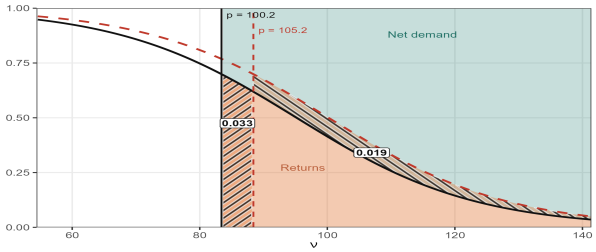
(c) Surplus Extraction (Outerwear)



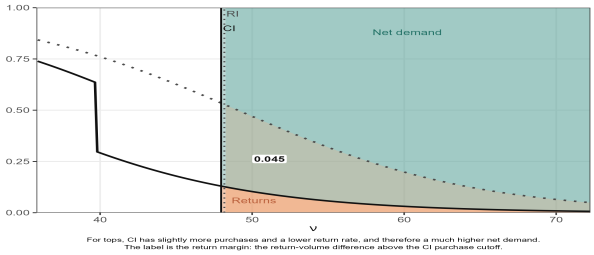
(d) Return Mitigation (Outerwear)



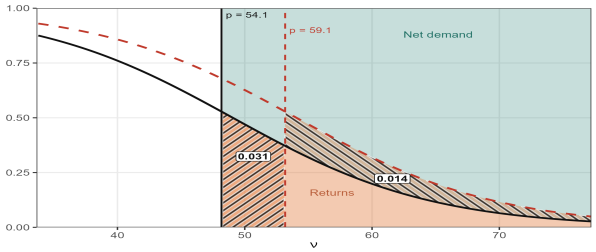
(e) Surplus Extraction (Pants)



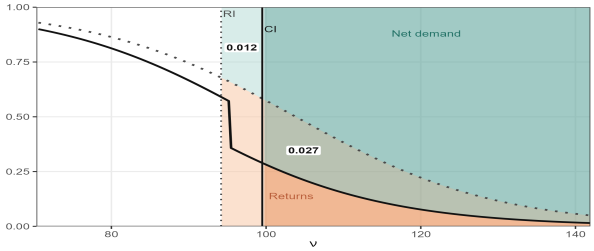
(f) Return Mitigation (Pants)



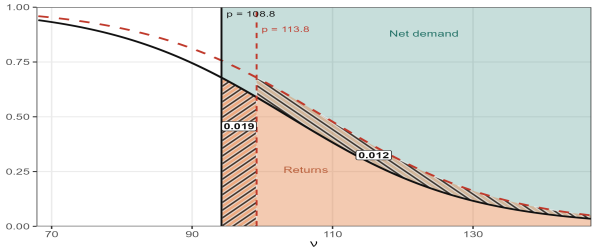
(g) Surplus Extraction (Tops)



(h) Return Mitigation (Tops)



(i) Surplus Extraction (Two-piece)



(j) Return Mitigation (Two-piece)

Figure 11: Left panels are surplus extraction at equilibrium prices; dotted lines are RI and solid lines are CI. Right panels are return mitigation under RI.

D Return-Policy Extensions

D.1 Return-Penalty Discount: Equilibrium

RPD offers a discount branch at $p - d$ with forfeiture share $\phi \in [0, 1]$ of $p - d$ on return, or a full-price branch at p with a full product refund. The buyer bears $\kappa + k_i$ on either return; the discount branch recovers $(1 - \phi)(p - d)$.

Expected surplus on the two branches is

$$CS_i^f = \frac{1}{\sigma} \ln \left(e^{\sigma(\nu_i - p)} + e^{-\sigma(\kappa + k_i)} \right), \tag{16}$$

$$CS_i^d = d - p + \frac{1}{\sigma} \ln \left(e^{\sigma \nu_i} + e^{\sigma[(1-\phi)(p-d) - (\kappa + k_i)]} \right). \tag{17}$$

The consumer prefers the discount branch when $CS_i^d \geq CS_i^f$, which defines

$$\tilde{\nu}^{RPD} = -(\kappa + k_i) + \frac{1}{\sigma} \ln \left(\frac{e^{\sigma(p-d)} - e^{\sigma(1-\phi)(p-d)}}{1 - e^{-\sigma d}} \right). \tag{18}$$

Purchase thresholds are

$$\hat{\nu}^d = \frac{1}{\sigma} \ln \left(e^{\sigma(p-d)} - e^{\sigma[(1-\phi)(p-d) - (\kappa + k_i)]} \right), \tag{19}$$

$$\hat{\nu}^f \equiv p + \frac{1}{\sigma} \ln \left(1 - e^{-\sigma(\kappa + k_i)} \right). \tag{20}$$

The consumer purchases when $\max\{CS_i^d, CS_i^f\} \geq 0$. Both branches are active when $\tilde{\nu}^{RPD} \geq \hat{\nu}^f$, or equivalently (when $1 - e^{-\sigma d} > 0$)

$$\frac{e^{\sigma(p-d)} - e^{\sigma(1-\phi)(p-d)}}{1 - e^{-\sigma d}} \geq e^{\sigma p} \left(e^{\sigma(\kappa + k_i)} - 1 \right). \tag{21}$$

Conditional on purchase,

$$q_i^d = \frac{e^{\sigma[(1-\phi)(p-d) - (\kappa + k_i)]}}{e^{\sigma \nu_i} + e^{\sigma[(1-\phi)(p-d) - (\kappa + k_i)]}}, \tag{22}$$

$$q_i^f = \frac{e^{-\sigma(\kappa + k_i)}}{e^{\sigma(\nu_i - p)} + e^{-\sigma(\kappa + k_i)}}. \tag{23}$$

With branch indicators D_i^d, D_i^f and aggregates D^d, R^d, D^f, R^f, the seller chooses (p, d) to maximize $\pi^{RPD} = \pi^d + \pi^f$, where $\pi^d = (p - d - \theta^c) D^d - [(1 - \phi)(p - d) + h] R^d$ and $\pi^f = (p - \theta^c) D^f - (p + h) R^f$. Individual social surplus on each branch is

$$S_i^d \equiv CS_i^d + (p - d - \theta^c) - q_i^d \left[(1 - \phi)(p - d) + h \right], \tag{24}$$

$$S_i^f \equiv CS_i^f + (1 - q_i^f)(p - \theta^c) - q_i^f (\theta^c + h). \tag{25}$$

Define $CS^{RPD} \equiv \mathbb{E}_{\nu_i,k_i}[D_i^d\, CS_i^d + D_i^f\, CS_i^f]$ and $W^{RPD} \equiv \mathbb{E}_{\nu_i,k_i}[D_i^d\, S_i^d + D_i^f\, S_i^f]$. The main-text full-forfeiture case is $\phi = 1$; partial forfeiture varies ϕ.

D.2 Optimal Refund Policy

With list price p and return refund $-h$,

$$CS_i^{\text{rs}} = -p + \frac{1}{\sigma}\ln\left(e^{\sigma\nu_i} + e^{-\sigma(h+\kappa+k_i)}\right), \tag{26}$$

$$\hat{\nu}^{\text{rs}} = \frac{1}{\sigma}\ln\left(e^{\sigma p} - e^{-\sigma(h+\kappa+k_i)}\right), \tag{27}$$

where $\hat{\nu}^{\text{rs}}$ solves $CS_i^{\text{rs}} = 0$ when $e^{\sigma p} > e^{-\sigma(h+\kappa+k_i)}$. The consumer purchases when $\nu_i \geq \hat{\nu}^{\text{rs}}$ and returns with $q_i^{\text{rs}} = q_i^*$ from (11). Aggregates are

$$D^{\text{rs}} \equiv \mathbb{E}_{\nu_i,k_i}\left[\mathbf{1}\left(\nu_i \geq \hat{\nu}^{\text{rs}}\right)\right], \tag{28}$$

$$R^{\text{rs}} \equiv \mathbb{E}_{\nu_i,k_i}\left[\mathbf{1}\left(\nu_i \geq \hat{\nu}^{\text{rs}}\right) q_i^{\text{rs}}\right], \tag{29}$$

and the seller chooses p to maximize $\pi^{\text{rs}}(p) = (p - \theta^c)D^{\text{rs}}$, with $S_i^{\text{rs}} = CS_i^{\text{rs}} + (p - \theta^c)$.

E Scrap-Value Sensitivity

The main text varies scrap to $0.65\, p_t$ and $0.85\, p_t$. Each panel reports welfare as a percent of first best, then repeats the normalized policy decomposition and the partial-RPD ϕ grid.

E.1 Scrap value 0.65 p_t

Table 8: Welfare as a percent of first best. Scrap 0.65 p_t.

				Partial forfeiture ϕ			
Category	RI	CI	Full RPD	0.05	0.10	0.15	0.20
dress	68.3	74.2	61.6	73.8	73.3	72.5	71.8
outerwear	59.6	73.3	74.6	74.6	75.1	75.3	75.3
pants	53.6	72.7	76.8	74.4	77.4	75.5	79.3
sweater	31.5	68.4	76.4	73.6	77.5	78.0	76.5
top	42.9	72.4	75.0	73.6	74.3	74.7	75.0
twopiece	59.1	73.1	74.3	74.2	74.8	75.0	75.0

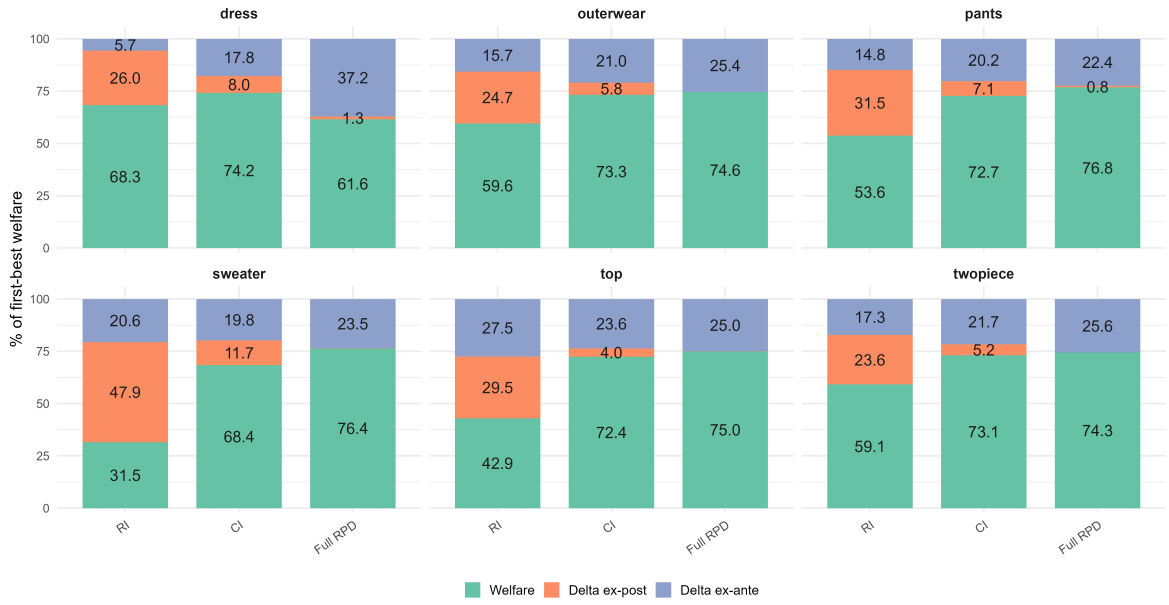


Figure 12: Welfare decomposition as a share of first best. Scrap 0.65 p_t.

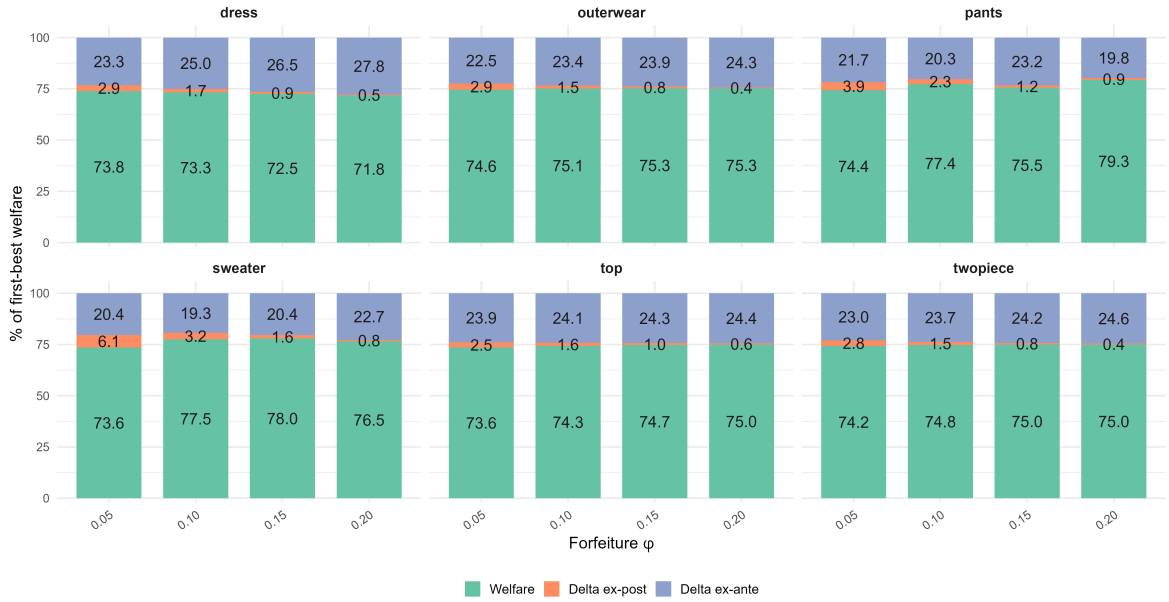


Figure 13: Partial-forfeiture RPD by ϕ. Scrap 0.65 p_t.

E.2 Scrap value 0.85 p_t

Table 9: Welfare as a percent of first best. Scrap 0.85 p_t.

				Partial forfeiture ϕ			
Category	RI	CI	Full RPD	0.05	0.10	0.15	0.20
dress	79.1	68.8	46.7	64.2	62.4	60.7	59.2
outerwear	72.1	75.2	71.5	74.8	74.2	73.7	73.2
pants	68.8	75.5	71.3	75.4	75.0	74.5	74.0
sweater	53.7	74.4	74.4	76.6	77.0	77.0	75.8
top	55.4	74.5	74.1	74.9	75.1	75.1	75.1
twopiece	71.1	74.9	71.8	74.7	74.2	73.8	73.4

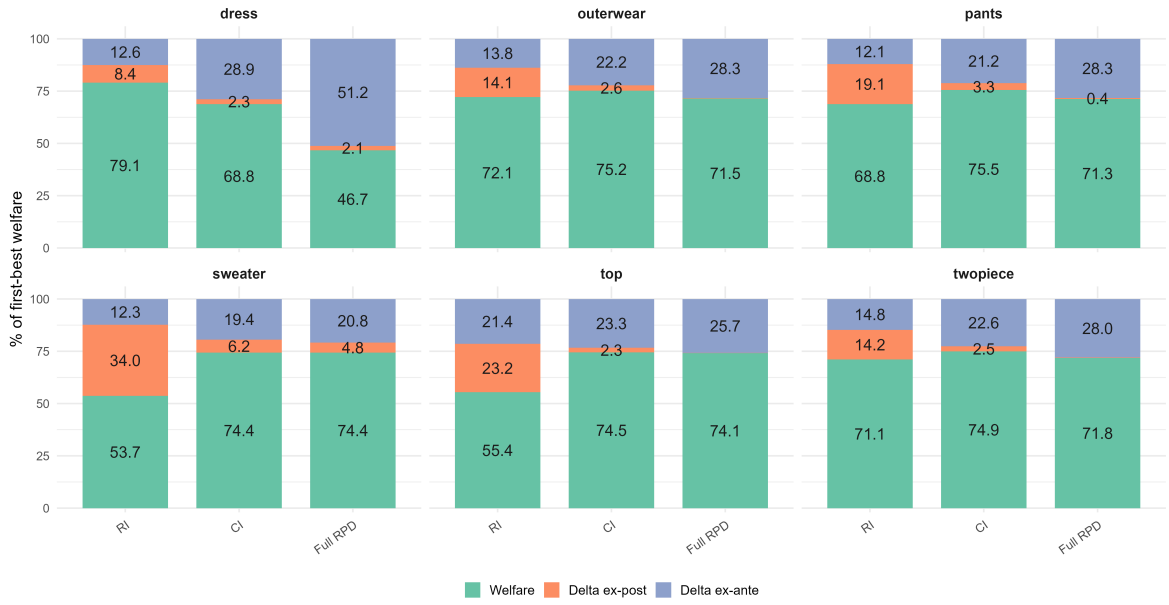


Figure 14: Welfare decomposition as a share of first best. Scrap 0.85 p_t.

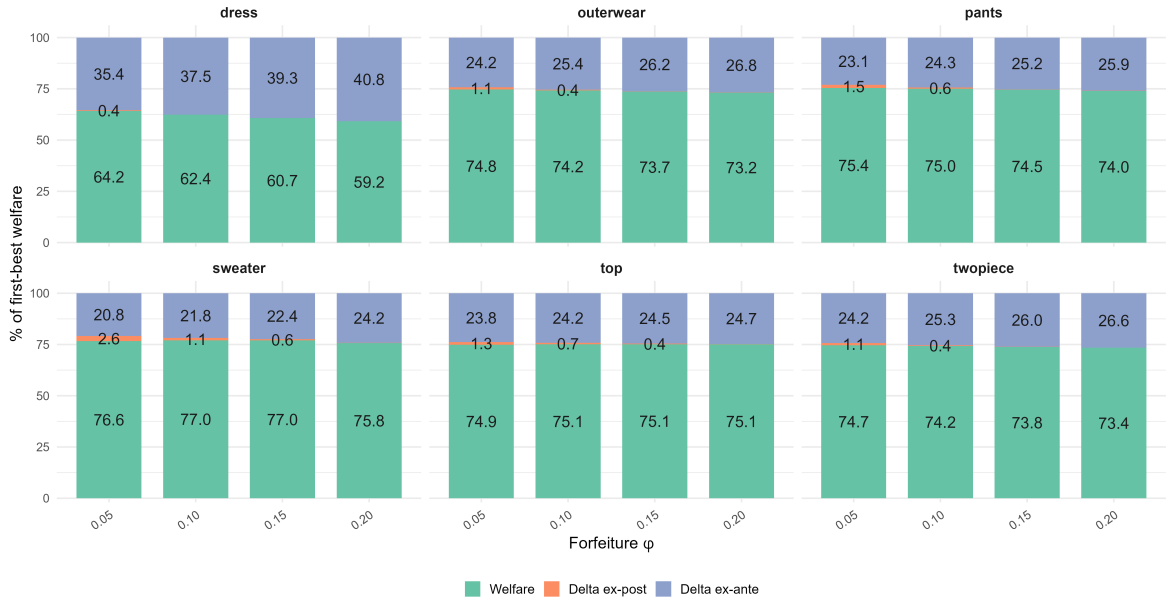
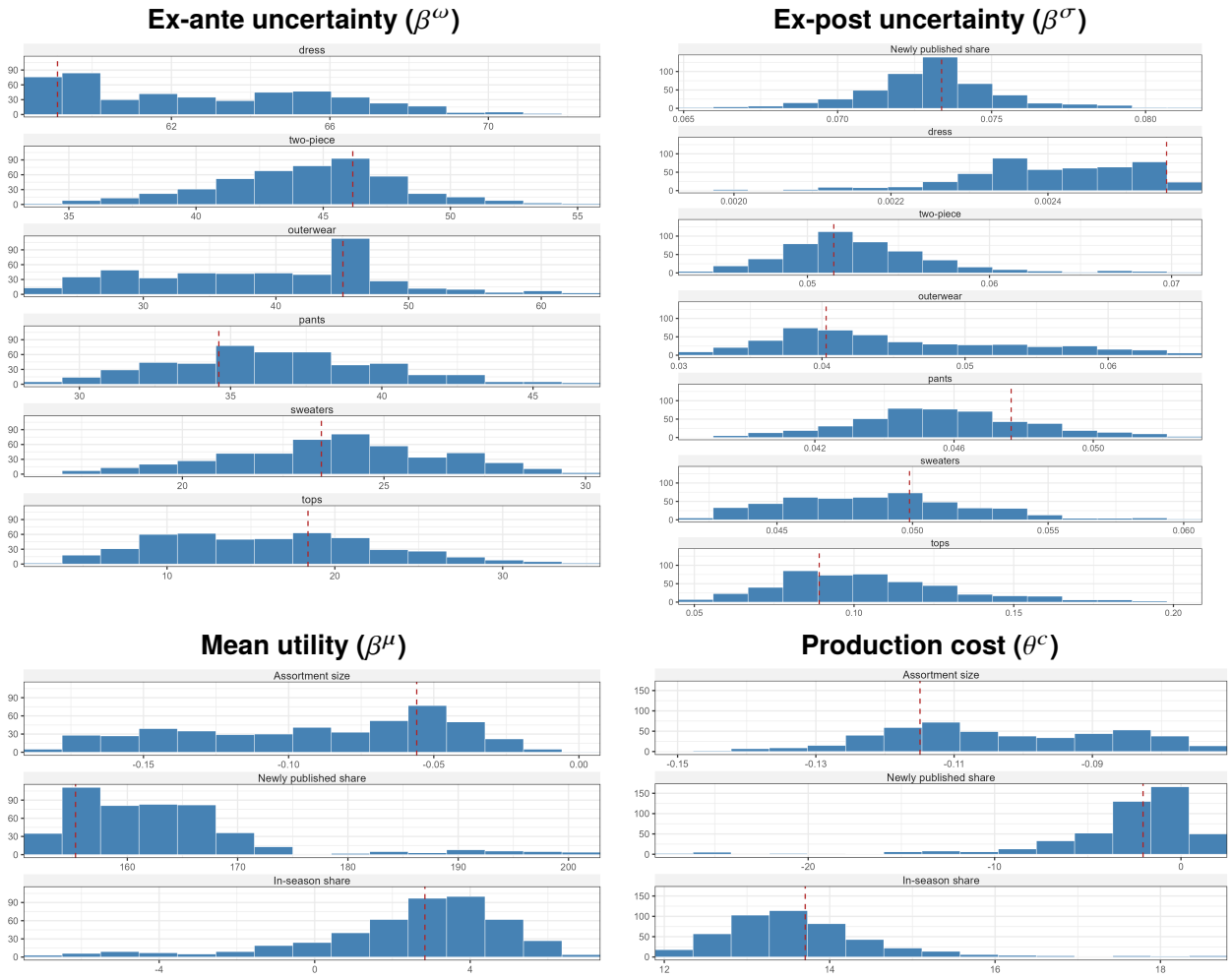


Figure 15: Partial-forfeiture RPD by ϕ. Scrap 0.85 p_t.

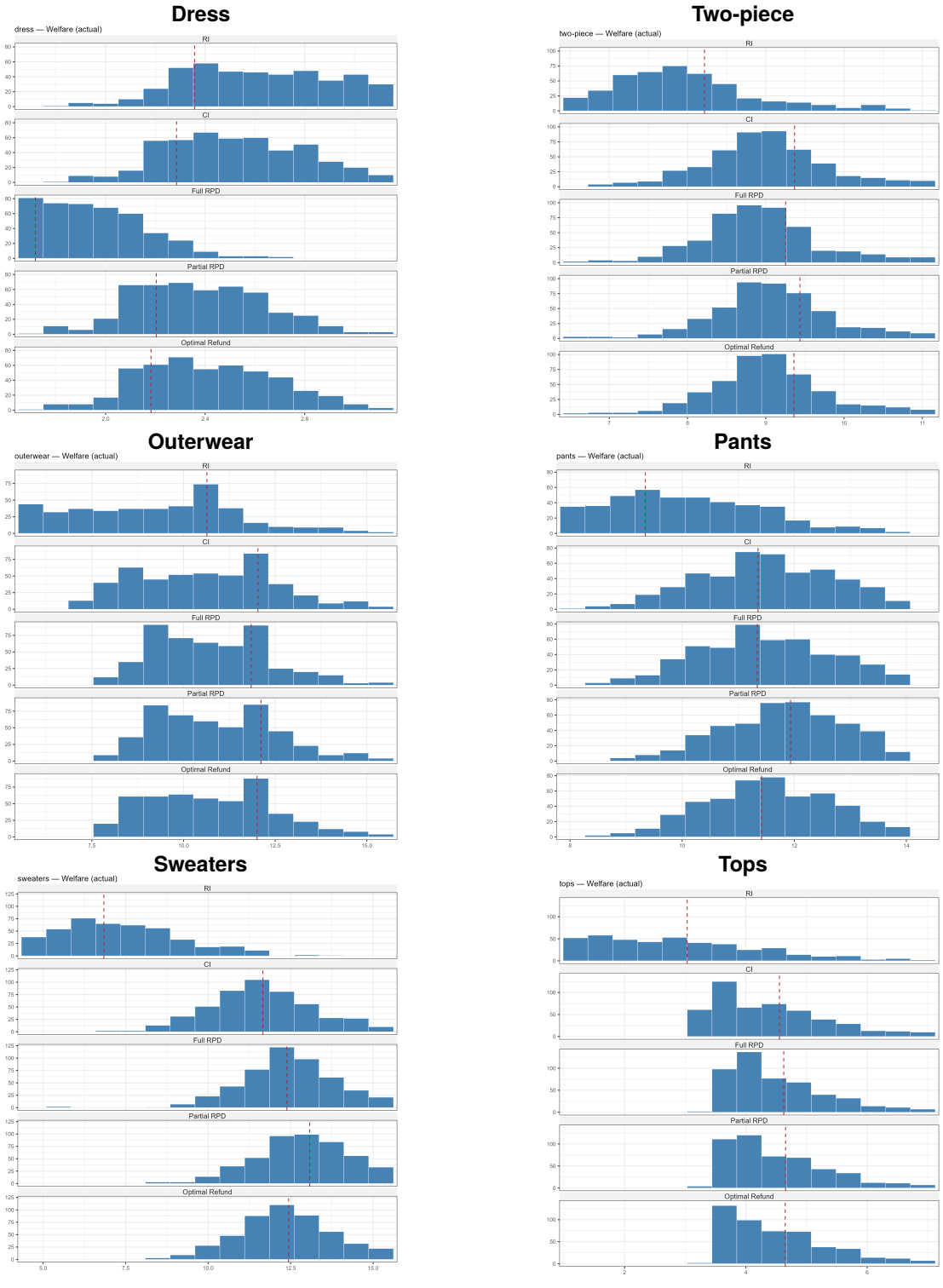
F Bootstrap Inference

Each panel plots bootstrap replicates in 15 bins. Axes span the 2.5th–97.5th percentile of the displayed draws (by coefficient for parameters; pooled across policies within a category for welfare, scaled to first best). The dashed line is the full-sample point estimate. Main-text standard errors use all replicates.

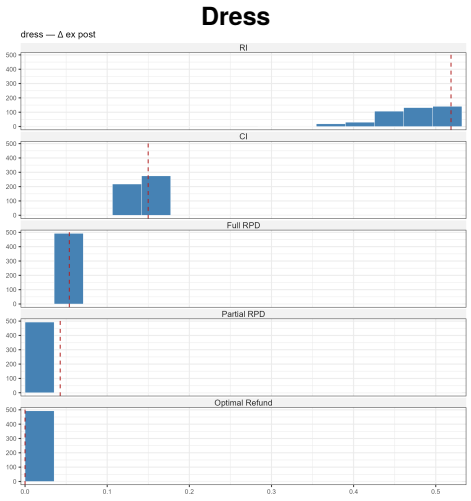
F.1 Point estimates

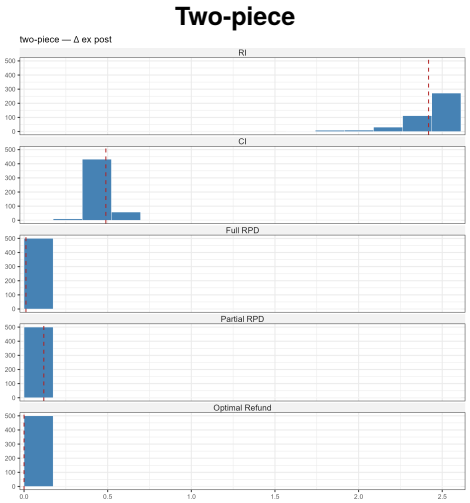


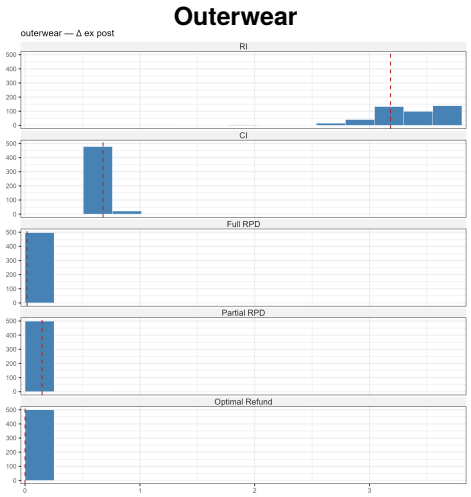
F.2 Actual welfare

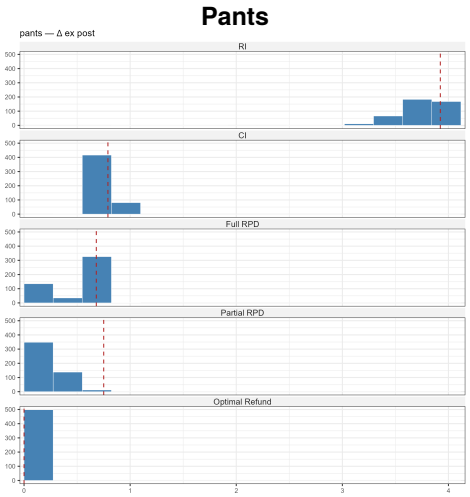


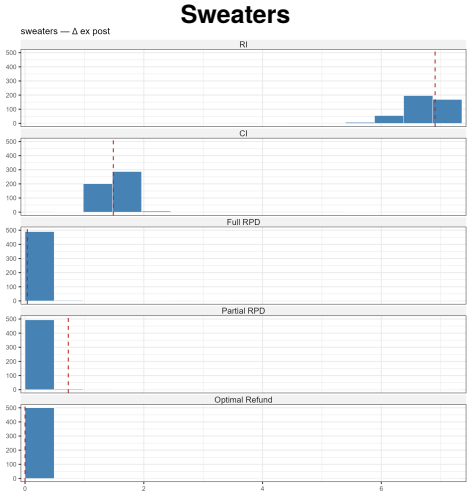
F.3 Δ ex-post

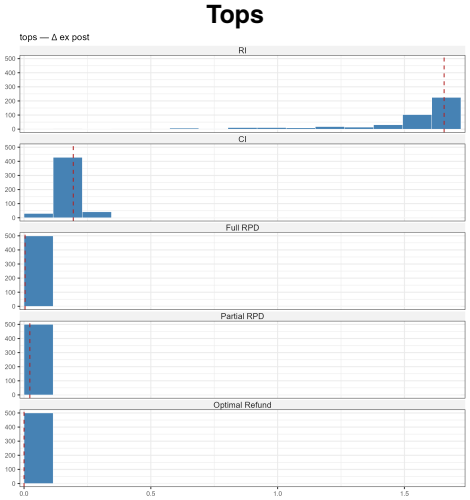

Dress
dress — Δ ex post
RI
CI
Full RPD
Partial RPD
Optimal Refund


Two-piece
two-piece — Δ ex post
RI
CI
Full RPD
Partial RPD
Optimal Refund

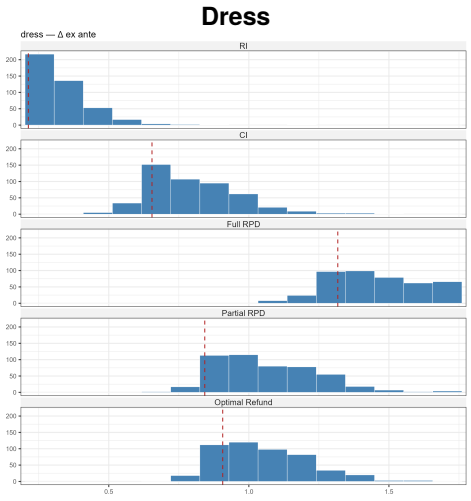

Outerwear
outerwear — Δ ex post
RI
CI
Full RPD
Partial RPD
Optimal Refund

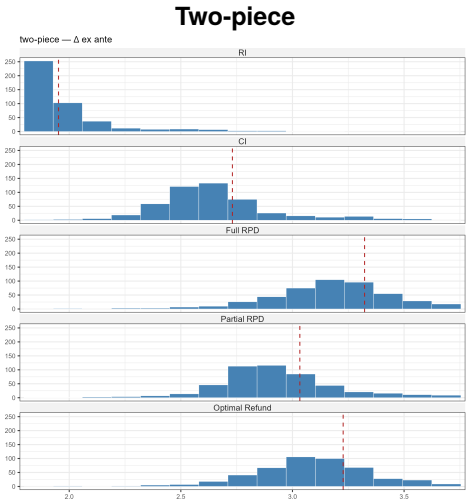

Pants
pants — Δ ex post
RI
CI
Full RPD
Partial RPD
Optimal Refund

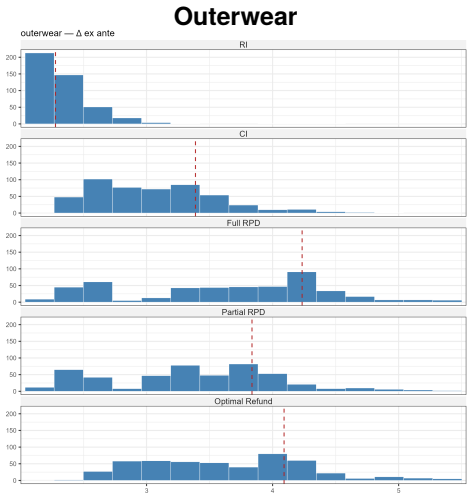

Sweaters
sweaters — Δ ex post
RI
CI
Full RPD
Partial RPD
Optimal Refund

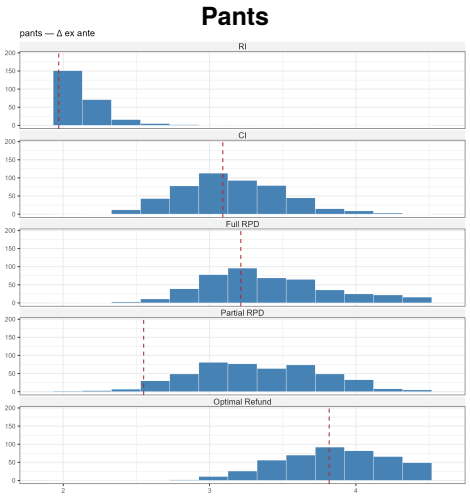

Tops
tops — Δ ex post
RI
CI
Full RPD
Partial RPD
Optimal Refund

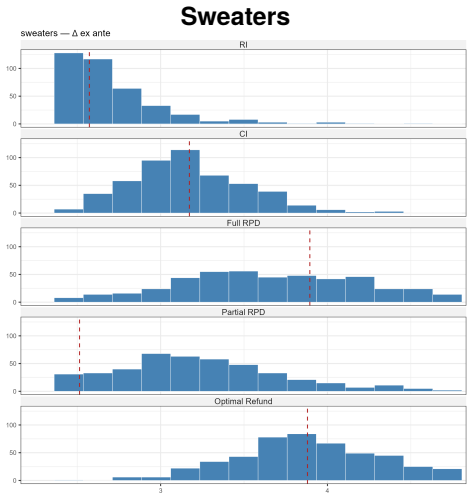
F.4 Δ ex-ante

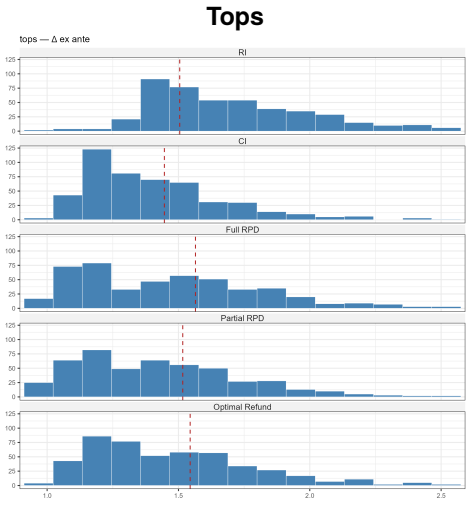

Dress
dress — Δ ex ante
RI
CI
Full RPD
Partial RPD
Optimal Refund


Two-piece
two-piece — Δ ex ante
RI
CI
Full RPD
Partial RPD
Optimal Refund


Outerwear
outerwear — Δ ex ante
RI
CI
Full RPD
Partial RPD
Optimal Refund


Pants
pants — Δ ex ante
RI
CI
Full RPD
Partial RPD
Optimal Refund


Sweaters
sweaters — Δ ex ante
RI
CI
Full RPD
Partial RPD
Optimal Refund


Tops
tops — Δ ex ante
RI
CI
Full RPD
Partial RPD
Optimal Refund

F.5 Pairwise win rates

Table 10: Pairwise bootstrap win rates for actual welfare.

Dress

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.99	1.00	1.00	1.00
CI	0.01	—	1.00	1.00	1.00
Full RPD	0.00	0.00	—	0.00	0.00
Partial RPD	0.00	0.00	1.00	—	0.01
Optimal Refund	0.00	0.00	1.00	0.99	—

Two-piece

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.00	0.01	0.01	0.01
CI	1.00	—	0.83	0.03	0.38
Full RPD	0.99	0.17	—	0.00	0.00
Partial RPD	0.99	0.97	1.00	—	1.00
Optimal Refund	0.99	0.62	1.00	0.00	—

Outerwear

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.02	0.04	0.02	0.03
CI	0.98	—	0.55	0.09	0.38
Full RPD	0.96	0.45	—	0.07	0.23
Partial RPD	0.98	0.91	0.93	—	0.99
Optimal Refund	0.97	0.62	0.77	0.01	—

Pants

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.01	0.01	0.01	0.00
CI	0.99	—	0.40	0.03	0.42
Full RPD	0.99	0.60	—	0.01	0.36
Partial RPD	0.99	0.97	0.99	—	0.99
Optimal Refund	1.00	0.58	0.64	0.01	—

Sweaters

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.01	0.01	0.01	0.01
CI	0.99	—	0.01	0.01	0.01
Full RPD	0.99	0.99	—	0.11	0.54
Partial RPD	0.99	0.99	0.89	—	0.97
Optimal Refund	0.99	0.99	0.46	0.03	—

Tops

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.00	0.00	0.00	0.00
CI	1.00	—	0.14	0.03	0.07
Full RPD	1.00	0.86	—	0.37	0.25
Partial RPD	1.00	0.97	0.63	—	0.56
Optimal Refund	1.00	0.93	0.75	0.44	—

Notes: Each off-diagonal cell is the share of bootstrap draws in which the row policy has higher actual welfare than the column policy (non-missing pairs only). Diagonal cells are blank.

Table 11: Pairwise bootstrap win rates for ex-post inefficiency.

Dress

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.00	0.00	0.00	0.00
CI	1.00	—	0.00	0.00	0.00
Full RPD	1.00	1.00	—	0.00	0.00
Partial RPD	1.00	1.00	1.00	—	0.00
Optimal Refund	1.00	1.00	1.00	1.00	—

Two-piece

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.00	0.00	0.00	0.00
CI	1.00	—	0.00	0.00	0.00
Full RPD	1.00	1.00	—	1.00	0.00
Partial RPD	1.00	1.00	0.00	—	0.00
Optimal Refund	1.00	1.00	1.00	1.00	—

Outerwear

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.00	0.00	0.00	0.00
CI	1.00	—	0.00	0.00	0.00
Full RPD	1.00	1.00	—	0.96	0.00
Partial RPD	1.00	1.00	0.04	—	0.00
Optimal Refund	1.00	1.00	1.00	1.00	—

Pants

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.00	0.00	0.00	0.00
CI	1.00	—	0.01	0.00	0.00
Full RPD	1.00	0.99	—	0.27	0.00
Partial RPD	1.00	1.00	0.73	—	0.00
Optimal Refund	1.00	1.00	1.00	1.00	—

Sweaters

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.00	0.00	0.00	0.00
CI	1.00	—	0.00	0.00	0.00
Full RPD	1.00	1.00	—	0.93	0.00
Partial RPD	1.00	1.00	0.07	—	0.00
Optimal Refund	1.00	1.00	1.00	1.00	—

Tops

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.00	0.00	0.00	0.00
CI	1.00	—	0.00	0.00	0.00
Full RPD	1.00	1.00	—	0.99	0.00
Partial RPD	1.00	1.00	0.01	—	0.00
Optimal Refund	1.00	1.00	1.00	1.00	—

Notes: Each off-diagonal cell is the share of bootstrap draws in which the row policy has lower ex-post inefficiency than the column policy. A higher number means the row policy is more efficient ex post. Diagonal cells are blank.

Table 12: Pairwise bootstrap win rates for ex-ante inefficiency.

Dress

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	1.00	1.00	1.00	1.00
CI	0.00	—	1.00	1.00	1.00
Full RPD	0.00	0.00	—	0.00	0.00
Partial RPD	0.00	0.00	1.00	—	0.28
Optimal Refund	0.00	0.00	1.00	0.72	—

Two-piece

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.99	1.00	1.00	1.00
CI	0.01	—	1.00	1.00	1.00
Full RPD	0.00	0.00	—	0.00	0.00
Partial RPD	0.00	0.00	1.00	—	1.00
Optimal Refund	0.00	0.00	1.00	0.00	—

Outerwear

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.93	0.91	0.89	0.97
CI	0.07	—	0.83	0.77	1.00
Full RPD	0.09	0.17	—	0.04	0.23
Partial RPD	0.11	0.23	0.96	—	1.00
Optimal Refund	0.03	0.00	0.77	0.00	—

Pants

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	1.00	0.99	0.99	0.99
CI	0.00	—	0.93	0.79	0.99
Full RPD	0.01	0.07	—	0.38	0.73
Partial RPD	0.01	0.21	0.62	—	0.99
Optimal Refund	0.01	0.01	0.27	0.01	—

Sweaters

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.88	0.91	0.79	0.95
CI	0.12	—	0.92	0.51	1.00
Full RPD	0.09	0.08	—	0.08	0.65
Partial RPD	0.21	0.49	0.92	—	1.00
Optimal Refund	0.05	0.00	0.35	0.00	—

Tops

	RI	CI	Full RPD	Partial RPD	Optimal Refund
RI	—	0.31	0.41	0.38	0.40
CI	0.69	—	0.69	0.67	0.89
Full RPD	0.59	0.31	—	0.19	0.26
Partial RPD	0.62	0.33	0.81	—	0.97
Optimal Refund	0.60	0.11	0.74	0.03	—

Notes: Each off-diagonal cell is the share of bootstrap draws in which the row policy has lower ex-ante inefficiency than the column policy. A higher number means the row policy is more efficient ex ante. Diagonal cells are blank.