Personalizing Two Interdependent Treatments: Structural Estimation and Evidence from Social E-Commerce

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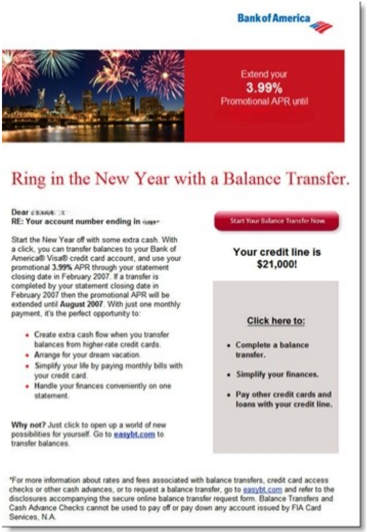
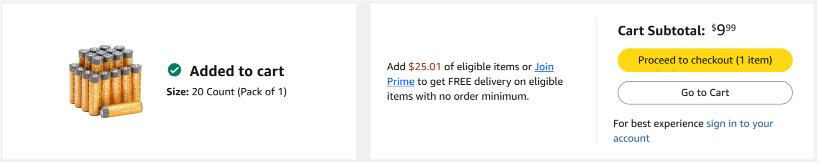
Interdependent Personalization is Common



- APR + credit line

Interdependent Personalization is Common



- Product recommendations + free delivery threshold

Interdependent Personalization is Common

Examples:

- APR + credit line
- Product recommendations + free delivery threshold
- ...

Less studied despite increasing prevalence

Interdependent Personalization is Common

Examples:

- APR + credit line
- Product recommendations + free delivery threshold
- ...

Less studied despite increasing prevalence

This paper:

- How much profit lift can an **integrated** personalization yield, compared with isolated personalizations?
- Focus on the integrated personalization of
  - (Post-discount) price
  - "Broadcasting" requirement

Personalized Pricing: What Next If Not Working?

One of the most studied personalization variables

- Can take many forms
- Goal: align prices according to customer WTP
- Mixed empirical evidence
  - Some found substantial gains (e.g., Dubé and Misra 2023)
  - Some found modest gains or losses (e.g., Smith et al. 2023)
- Challenge: Variation in WTP alone may not be sufficient for effective price personalization

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- Challenge: Variation in WTP alone may not be sufficient for effective price personalization

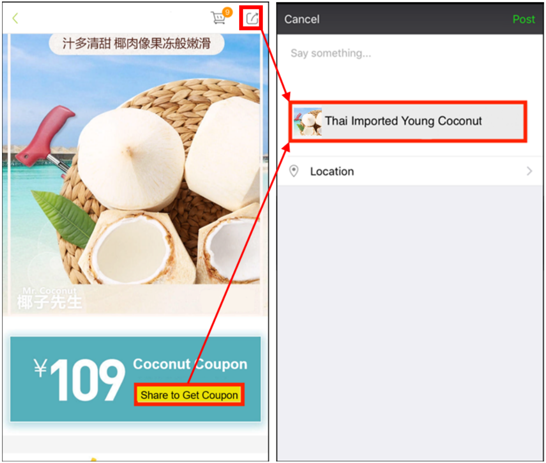
Idea of this paper: What if the firm can personalize the price along with a second marketing variable?

- Capture additional dimensions of customer heterogeneity
- Interdependent $\Rightarrow$ helps personalize prices

Social E-Commerce and Broadcasting Promotions

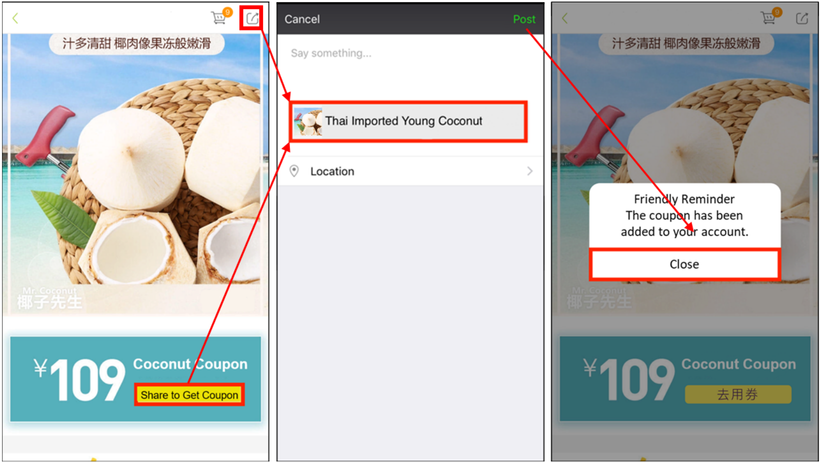
Sharing is related to additional dimensions of heterogeneity

Social E-Commerce and Broadcasting Promotions



Sharing is related to additional dimensions of heterogeneity

Social E-Commerce and Broadcasting Promotions



Sharing is related to additional dimensions of heterogeneity

- “Cost” of sharing Example
- Capacity for generating referrals Example

Research Questions

1. How much heterogeneity is there in sharing costs and referral generation capacities? How does this heterogeneity compare to heterogeneity in willingness to pay and price sensitivity?

2. How much profit lift can integrated personalization yield compared with isolated personalization?

What We Do

Develop a structural model

- Two-stage model with forward-looking consumers:
  1. Sharing (broadcasting) decision
  2. Purchasing decision
- Allow for heterogeneity in primitives underlying sharing and purchasing decisions

Estimate the model on a large-scale field experiment

- The firm did not personalize pricing or broadcasting requirements (randomized)

Conduct counterfactual analyses based on the model

- Characterize optimal integrated personalization
- Compare profits: integrated v. isolated personalizations

Preview of Results

1. How much heterogeneity is there in sharing costs and referral generation capacities? How does this heterogeneity compare to heterogeneity in willingness to pay and price sensitivity?
   - We found greater heterogeneity in sharing costs and referral generation capacities, compared with the heterogeneity in purchasing primitives Details

2. How much profit lift can integrated personalization yield compared with isolated personalization?
   - Price personalization improves profit by 2.4%
   - Personalizing broadcasting requirements improves profit by 27%
   - Integrated personalization improves profit by 40.3% Details

Outline

Experimental Design and Data Sampling

Model and Estimation

Counterfactual Analysis

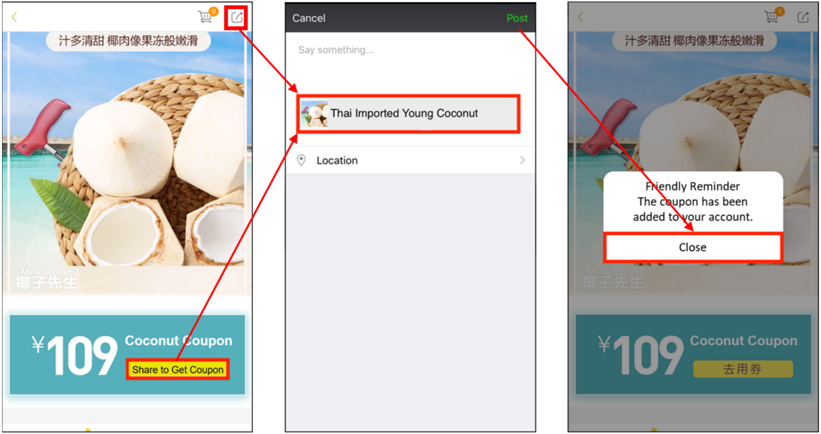
Summary

Experimental Design

Field experiment on an online grocery e-tailer in China

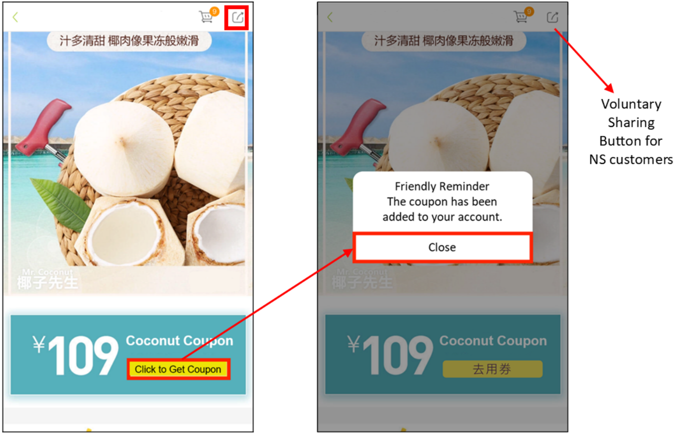
- Promotions on a signature product: a bundle of nine coconuts (hereafter **promoted product**)
  - Regular retail price: 188 CNY ($\sim$ 26 USD)
  - Post-discount price varies from 59–118 CNY ($\sim$ 8–17 USD) across promotion cycles and regions
    - 15 promotion cycles Overview
    - 3 regions: North, East, and South China
  - Define a **market** at the promotion cycle-region level
- Restrict the sample to customers who arrive organically (hereafter **focal customers**)
- Randomly assign each focal customer to the broadcasting (social, S) versus traditional (non-social, NS) condition Overview

Broadcasting (S) Condition: Requested to Share



Deal Page   Broadcast on News Feed   Coupon Obtained

Traditional (NS) Condition: Automatic Redemption



Deal Page

Coupon Obtained

Variables

Outcome variables:

- Indicator of sharing the deal
- Indicator of purchasing the promoted product
- Number of referred customers

Covariates: customer characteristics

- Past purchase behavior: RFM, etc.
- Reaction to past marketing activities: discounts, etc.
- Experiment-specific variables: new customer, etc.
- City characteristics
- Past sharing behavior

Other info: wholesale costs of the promoted product, etc.

Summary Statistics

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Overview of Customer Decisions

Customer i
receives
promotion
(discount c_i)

Overview of Customer Decisions

Traditional promotion

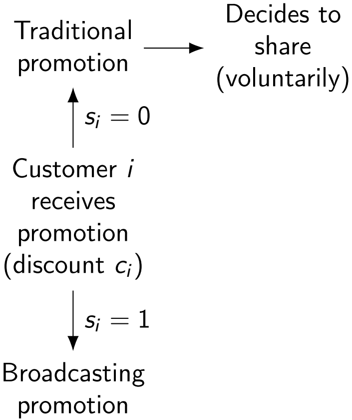
$\uparrow s_i = 0$

Customer i receives promotion (discount c_i)

$\downarrow s_i = 1$

Broadcasting promotion

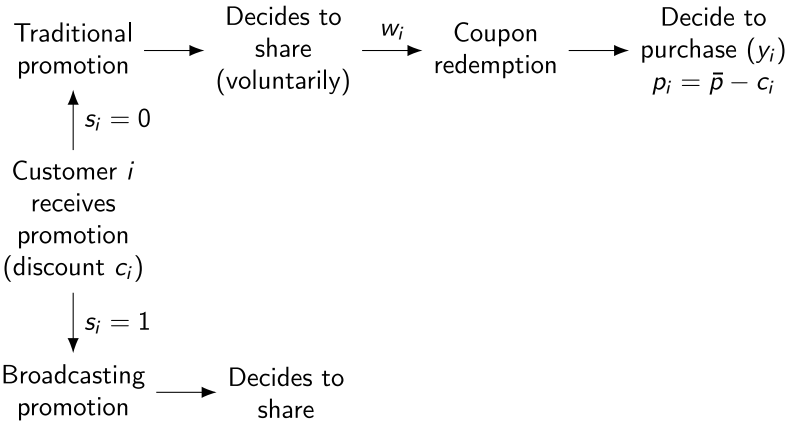
Overview of Customer Decisions



Overview of Customer Decisions

$$
\begin{tikzcd}
\text{Traditional promotion} \arrow[r] & \text{Decides to share (voluntarily)} \arrow[r, "w_i"] & \text{Coupon redemption} \arrow[r] & \begin{array}{c}\text{Decide to purchase } (y_i) \\ p_i = \bar{p} - c_i\end{array} \\
\begin{array}{c}\text{Customer } i \\ \text{receives promotion} \\ (\text{discount } c_i)\end{array} \arrow[u, "s_i = 0"'] \arrow[d, "s_i = 1"'] & & & \\
\text{Broadcasting promotion} & & &
\end{tikzcd}
$$

Overview of Customer Decisions



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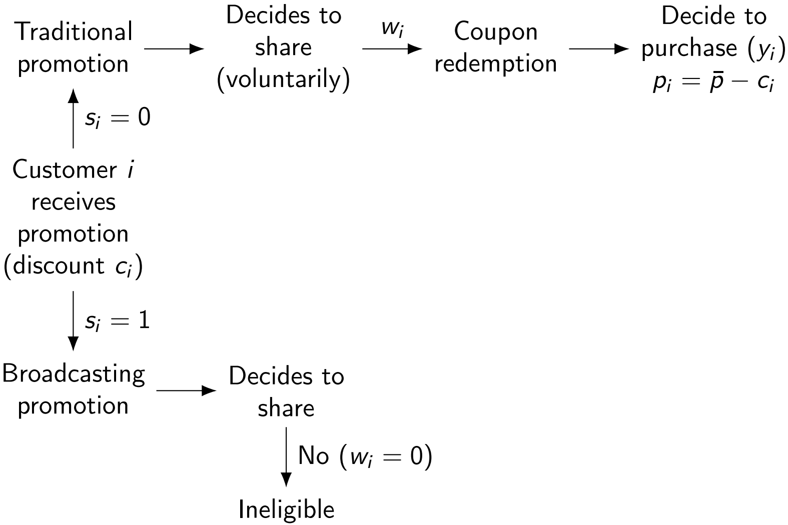

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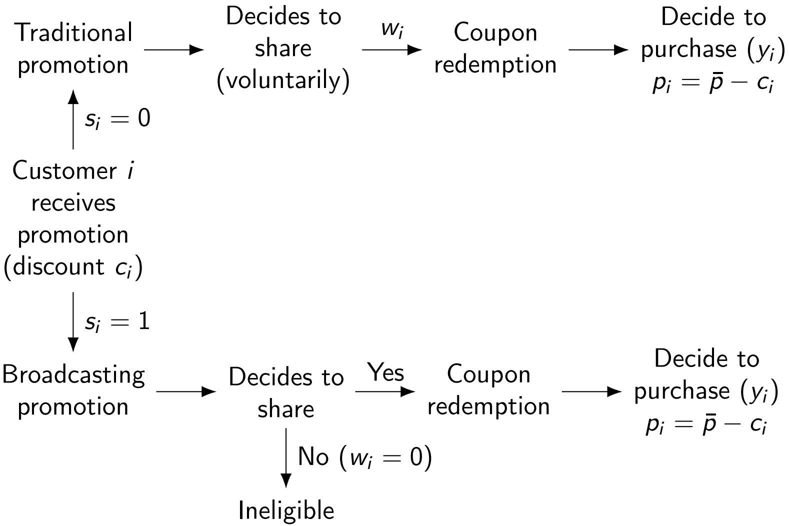

Purchasing Decision for Promoted Product

- Let y_i denote customer i's purchasing decision
- Utility from purchasing the promoted product

$$U_i^y = v_i - \alpha_i \cdot p_i + \epsilon_i^y,$$

  - v_i: baseline utility for promoted product
  - α_i: price sensitivity
  - p_i: post-discount price $(= \bar{p} - c_i)$
  - v_i and α_i are projected onto covariates Parameterization
  - ϵ_i^y: idiosyncratic error (Type I extreme value)
- Utility from not purchasing is normalized to 0
- Customer i will purchase $(y_i = 1)$ iff $U_i^y > 0$
- Continuation value

$$EU_i^y = \mathbb{E}_{\epsilon_i^y}[\max\{U_i^y, 0\}]$$

Sharing Stage: Flow Utilities

- Flow utility from sharing is

$$U_i^w = -SC_i + \epsilon_i^w,$$

  - SC_i: sharing cost Parameterization
  - ϵ_i^w: idiosyncratic error, independent of ϵ_i^y
  - ϵ_i^w is type I extreme value with scale σ^{-1}
  - σ captures unobserved variation in sharing error relative to purchase error (scale normalized to 1)
  - $\sigma > 1$ indicates greater predictability in sharing costs relative to WTP
- Flow utility from not sharing is normalized to 0

Sharing Decisions

- For those assigned to broadcasting promotions ($s_i = 1$):
  - Utility if decides to share: $U_i^w + EU_i^y$
  - Utility if decides not to share: 0

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- Customer i will share ($w_i = 1$) iff

$$\underbrace{U_i^w}_{=-SC_i+\epsilon_i^w} + \underbrace{EU_i^y \cdot s_i}_{\text{``option value'' of sharing}} > 0$$

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$$\underbrace{U_i^w}_{=-SC_i+\epsilon_i^w} + \underbrace{EU_i^y \cdot s_i}_{\text{“option value” of sharing}} > 0$$

- Identification of sharing costs:
  - EU_i^y may be endogenous (correlated with ϵ_i^w)
    - For example, customers do not fully know v_i
  - s_i introduces exogenous variation that helps with identification ($\mathbb{E}[\epsilon_i^w \cdot s_i] = 0$)

Referral Generation and Firm Valuation

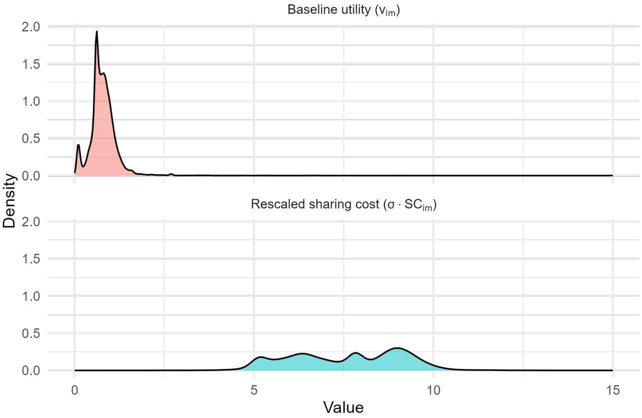
- If a customer decides to share, the number of referrals introduced is R_i, whose expectation (r_i, **referral generation capacity**) satisfies

$$\mathbb{E}[R_i | w_i = 1] = e^{r_0 + x_i^\mathsf{T} \beta^r}$$

- Firm's (implied) valuation of a referral is L
  - Identification: FOC from the firm's pricing decision
- We proceed with a standard GMM procedure

Moment Equation Details | Parameter Estimates

Greater Heterogeneity in Sharing Costs



- Unit of the horizontal axes: logit

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Personalized Schemes: How to Make Use of Heterogeneity in Sharing Primitives

We solve for the optimal personalized price (p_{im}) and the optimal personalized sharing assignment (s_{im}) for each customer, conditional on their observed covariates.

Under weak conditions, we show the following:

1. It is optimal to assign the broadcasting requirement to those who have lower sharing costs (SC) and higher referral generation capacities (r).
2. The optimal personalized price under broadcasting promotions should be decreasing in sharing costs (SC) and referral generation capacities (r).

Examples Propositions Procedure Details

Profit Comparison: Independent versus Joint Personalization

1. **No personalization**: Assign all customers to standard promotions; choose optimal market level price $\bar{p}_m^*$
2. **Personalizing pricing only**: Assign all customers to standard promotions; for each customer, choose the optimal personalized price, p_{im}^*
3. **Personalizing broadcasting requirements only**: Choose optimal s_{im}^* for each customer; choose prices to maximize market-level profits, $\bar{p}_{im}^*$
4. **Joint personalization**: Choose optimal p_{im}^* and s_{im}^* for each customer

We also compute 1 and 2 using broadcasting promotions as the benchmark, and find qualitatively similar results

Integrated Personalization Leads to Highest Profit

Personalization scheme	Average profit (focal + referral)	Profit increase relative to Scheme 1	Scheme 2	Scheme 3
1. No personalization	9.638	/		
2. Personalize prices only	9.871	0.234		
3. Personalize broadcasting requirements only	12.245	2.608	2.374	/
4. Integrated personalization	13.526	3.888	3.655	1.281

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Summary: Power of Integrated Personalization

We develop a multi-stage structural model to examine the profit lift of **integrated** personalization

We apply the model to a large-scale field experiment and found substantial **heterogeneity** in customers sharing costs and referral generation capacities

Takeaways: When price personalization alone does not work well, firms may obtain sizable gains from integrated personalization (e.g., with sharing)

- Sharing can yield additional dimensions of customer heterogeneity, with two uses:
  1. Personalizing sharing requirements
  2. Helps personalize prices (as they are interdependent)

Examples

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Toy Examples

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Optimal Integrated Personalization

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Additional Analyses

Heterogeneity in Sharing Cost Helps

SELLER: Would you like some coconuts? ¥109 for 9.
ALICE: Yes.
BOB: Yes.

- Insufficient information about heterogeneity in WTP

Heterogeneity in Sharing Cost Helps

SELLER: Would you like some coconuts? ¥109 for 9.
ALICE: Yes.
BOB: Yes.
. . .
SELLER: . . . if you share this deal with your friend.
ALICE: Sure.
BOB: No!

- Heterogeneity in **sharing cost**: higher for Bob

Heterogeneity in Sharing Cost Helps

SELLER: Would you like some coconuts? ¥109 for 9.
ALICE: Yes.
BOB: Yes.
...
SELLER: ... if you share this deal with your friend.
ALICE: Sure.
BOB: No!

- Heterogeneity in **sharing cost**: higher for Bob
- Implications for integrated personalization:
  - Lower the price for Bob, or
  - Waive the broadcasting requirement for Bob

Heterogeneity in Referral Generation Capacity Helps

SELLER: Would you like some coconuts? ¥109 for 9 if you share this deal with your friend.

CHARLIE: Yes.

DANA: Yes.

Heterogeneity in Referral Generation Capacity Helps

SELLER: Would you like some coconuts? ¥109 for 9 if you share this deal with your friend.
CHARLIE: Yes. [*Charlie brings in no referrals.*]
DANA: Yes. [*Dana brings in 10 referrals.*]

- Heterogeneity in **referral generation capacity**: higher for Dana

Heterogeneity in Referral Generation Capacity Helps

SELLER: Would you like some coconuts? ¥109 for 9 if you share this deal with your friend.

CHARLIE: Yes. [*Charlie brings in no referrals.*]

DANA: Yes. [*Dana brings in 10 referrals.*]

- Heterogeneity in **referral generation capacity**: higher for Dana
- Implications for integrated personalization:
  - Lower the price for Dana, or
  - Waive the broadcasting requirement for Charlie

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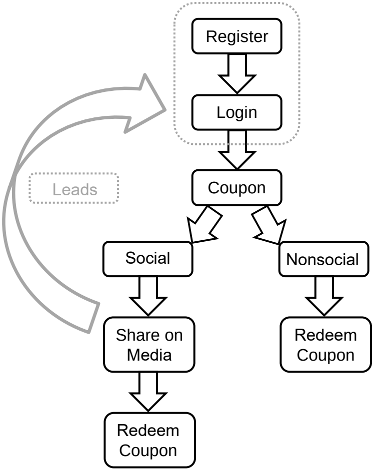
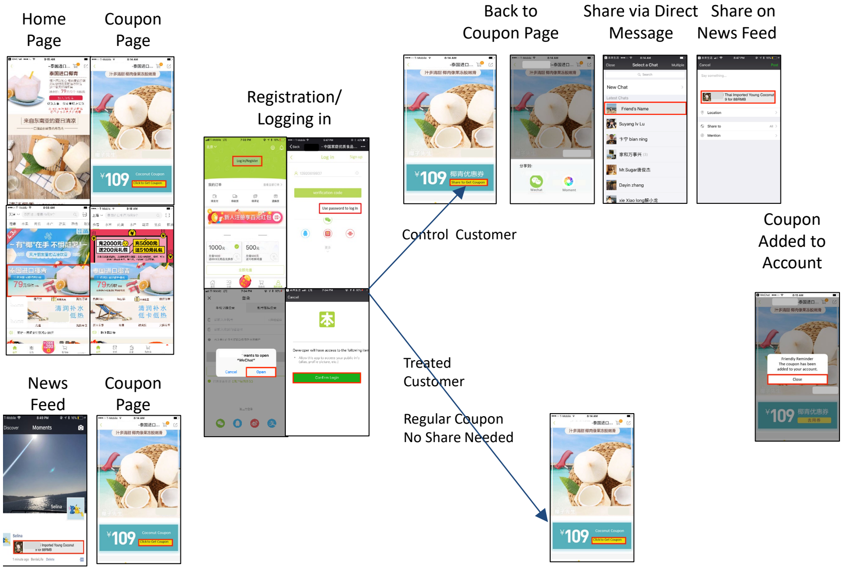
Flow Chart: Randomization



Treatment Control Back

Flow Chart: Treatment Condition



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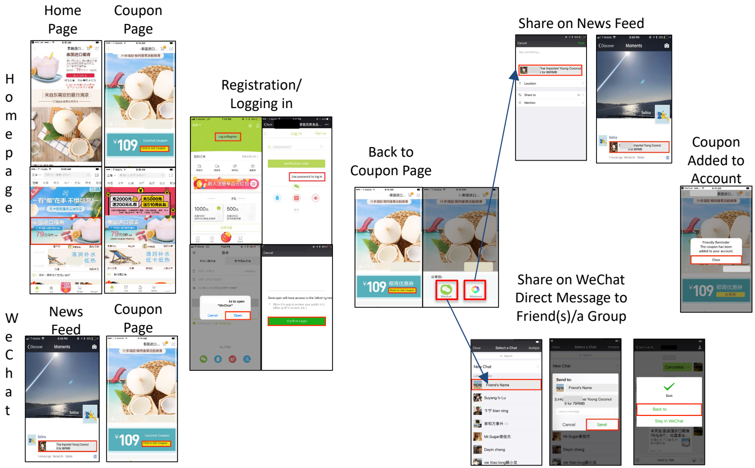
Flow Chart: Control Condition



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Summary Statistics of Promotion Cycles

Focal Products Post-Discount Price	Time Period	Focal Products Post-Discount Price	Time Period	Focal Products Post-Discount Price	Time Period
Pilot Experiment		**Randomization 2**		**Randomization 3**	
79	8/10/17 – 8/10/17	88	3/21/18 – 4/4/18	98/118	5/28/18 – 6/18/18
Randomization 1		98	4/5/18 – 4/16/18	118	6/19/18 – 7/9/18
79	11/7/17 – 11/10/17	98/118	4/17/18 – 4/23/18	88	7/10/18 – 7/10/18
59	11/10/17 – 11/20/17	79/98	4/24/18 – 5/2/18	118	7/11/18 – 7/15/18
79	11/21/17 – 11/29/17	98	5/3/18 – 5/14/18	88	7/16/18 – 7/18/18
59	11/30/17 – 11/30/17	98/118	5/15/18 – 5/27/18	118	7/19/18 – 7/25/18
				88	7/26/18 – 7/27/18
				118	7/28/18 – 8/8/18

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Summary Statistics: Propensity to Share/Purchase

Post-Discount Price (in CNY)	Number of Markets	Number of Focal Customers	Average Duration (Days)	Average Wholesale Cost (in CNY)	Outcomes		
					Propensity to Share	Propensity to Purchase	Average Number of Referred Customers per Focal Customer
59	6	9,760	5.5	48.1	0.332	0.342	0.054
79	4	6,793	3.5	71.0	0.257	0.260	0.023
88	5	4,127	7.2	78.7	0.191	0.147	0.007
98	2	1,193	10.5	80.0	0.165	0.125	0.009
118	4	1,393	13.5	89.1	0.128	0.054	0.004
Total	21	23,266	7.5	64.3	0.264	0.255	0.031

Median time-lapse between arrival and sharing: 8 seconds

Median time-lapse between arrival and purchasing: 6 minutes

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Balance Test

	(1) Both	(2) NS	(3) S	(4) *t*-test *p*-value	(5) *U* test *p*-value	(6) KS test *p*-value
Past Purchase Behavior						
Number of Days Since Most Recent Purchase	1	1.002	0.998	0.861	0.838	0.889
Number of Orders in the Past Year	1	1.019	0.980	0.249	0.329	0.056
Purchased Promoted Product Before	1	1.003	0.997	0.671	0.671	1.000
Average Monetary Value Per Order in the Past Year	1	1.002	0.998	0.733	0.687	0.217
Response to Marketing Activities in the Past Year						
Number of Orders Using Coupons	1	1.029	0.970	0.185	0.383	0.332
Number of Orders Using Gift Cards	1	1.105	0.892	0.103	0.560	0.979
Number of Orders Using Direct Discounts	1	1.042	0.956	0.040	0.397	0.160
Average Monetary Value of Coupons Per Order	1	1.001	0.999	0.872	0.925	0.978
Average Monetary Value of Gift Cards Per Order	1	1.032	0.967	0.284	0.632	0.998
Average Monetary Value of Direct Discounts Per Order	1	0.998	1.002	0.887	0.602	0.954
Experiment Specific						
New Customer	1	0.995	1.005	0.803	0.803	1.000
Customer Tenure	1	0.994	1.006	0.286	0.280	0.433
City Characteristics First Principal Component	1	0.991	1.009	0.093	0.105	0.440
Number of Times Clicking Share Button in the Past Month	1	0.975	1.026	0.227	0.005	0.019
Number of Observations	23,266	11,834	11,432			

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Parameterization: Purchasing Decisions

- For the primitives underlying the purchasing decision, we assume a linear specification for the baseline utility

$$v_{im} = \bar{v} + x_{im}^{\mathsf{T}} \beta^{v} + \xi_{m}^{y}$$

  - ξ_m^y: unobserved demand shock
- We assume a linear specification for price sensitivity

$$\alpha_{im} = \bar{\alpha} + x_{im}^{\mathsf{T}} \beta^{\alpha}$$

- ϵ_{im}^{y} admit independent standard logistic distribution
- We standardize the customer characteristics, so
  - $\bar{v}$ can be interpreted as the average baseline utility for the promoted product
  - $\bar{\alpha}$ can be interpreted as the average price sensitivity

Parameterization: Sharing Decision

- For the primitives underlying the sharing decision, we also assume that the sharing cost is linear in the observed characteristics

$$SC_{im} = \overline{SC} + x_{im}^{\intercal}\beta^{SC} + \xi_m^w$$

  - $\overline{SC}$: average sharing cost
  - ξ_m^w: unobserved shock on sharing costs
- The error terms ϵ_{im}^w admit independent standard logistic distribution with scale parameter σ^{-1} for $\sigma > 0$
  - This captures that the uncertainty at the sharing stage, compared to that at the purchasing stage, may be of different scales

Sharing Stage

Parameterization: Overview

- The first set of (purchasing) parameters is

$$\theta^y = (\bar{v}, \beta^{v\mathsf{T}}, \bar{\alpha}, \beta^{\alpha\mathsf{T}})^\mathsf{T}$$

  The second set of (sharing) parameters is

$$\theta^w = (\overline{SC}, \beta^{SC\mathsf{T}}, \sigma)^\mathsf{T}$$

- The third set of (leads generation) parameters is

$$\theta^r = (r_0, \beta^{r\mathsf{T}})^\mathsf{T}$$

- We also would like to estimate the life-time value for a lead L, so the set of parameters is

$$\theta = (\theta^{y\mathsf{T}}, \theta^{w\mathsf{T}}, \theta^{r\mathsf{T}}, L)^\mathsf{T}$$

Moment Equations: Purchasing Decision

- The appropriate 'market' here is the set of customer who enter the purchasing stage, that is, those who are required to share and decide to share, or not required to share $(s_{im}w_{im} + (1 - s_{im}) = 1)$
- Define market level constant δ_m^y

$$\delta_m^y = \bar{v} - \bar{\alpha} \cdot p_m + \xi_m^y$$

- First solve δ_m^y from

$$\sum_{i \in \mathcal{I}_m} (D_{im}(\delta_m^y, \theta) - y_{im})(s_{im}w_{im} + (1 - s_{im})) = 0,$$

  where D_{im} is the predicted demand
- By abuse of notation, we plug δ_m^y back and write D_{im} as a function of θ only

Moment Equations: Purchasing Decision

- Our first set of moment equations, which identifies θ^y, is then

$$\mathbb{E}[\xi_m^y(\theta)(1 \ \ MC_m)^\intercal] = 0,$$

$$\mathbb{E}[(D_{im}(\theta) - y_{im})(s_{im}w_{im} + (1 - s_{im}))x_{im}] = 0,$$

$$\mathbb{E}[(D_{im}(\theta) - y_{im})(s_{im}w_{im} + (1 - s_{im}))e^{x_{im}^\intercal \beta^\alpha} MC_m (1 \ \ x_{im}^\intercal)^\intercal] = 0$$

- In the second and the third equations, x_{im} and MC_m are exogenous variables, so functions of them are uncorrelated with the demand
- Moreover, in the third equation, $e^{x_{im}^\intercal \beta^\alpha}$ captures the non-linearity of price sensitivity in parameters

Moment Equations: Sharing Decision

- Define market level constant

$$\delta_m^w = -\overline{SC} - \xi_m^w$$

- After solving for the δ^y's, we calculate the continuation value EU_{im}^y, and then solve for the δ^w's by matching the propensity to share
- That is, δ_m^w is solved from

$$\sum_{i \in \mathcal{I}_m} \left(S_{im}(\delta_m^w, \theta) - w_{im} \right) = 0,$$

where S_{im} is the predicted propensity to share

Moment Equations: Sharing Decision

- Our second set of moment equations, which identifies θ^w given θ^y, is then
$$\mathbb{E}[\xi_m^w(\theta)] = 0,$$
$$\mathbb{E}[(S_{im}(\theta) - w_{im})(s_{im} \quad x_{im}^\intercal)^\intercal] = 0.$$
- In the second equation, s_{im} and x_{im} are exogenous variables. Here s_{im} is an instrument variable for the endogenous term $EU_{im}^y \cdot s_{im}$ in the indirect utility

Moment Equations: Leads Generation

- The third set of moments are leads generation moments
- It identifies θ^r in the Poisson regression model, which has the following moment equation:

$$\mathbb{E}\left[\left(\frac{R_{im}}{r_{im}(\theta)} - 1\right) w_{im}(1 \quad x_{im}^{\mathsf{T}})^{\mathsf{T}}\right] = 0$$

Moment Equations: Leads Valuation

- We directly observe the marginal cost of the firm, and this further allows us to identify the firm's valuation for leads
- The question we ask: What level of lead value L justifies the firm's current pricing decisions?
- We assume the firm observed a noisy marginal cost $\widetilde{MC}_m = MC_m + \eta_m$, for $\mathbb{E}[\eta_m] = 0$
- Let S_{im}^{S} and S_{im}^{NS} be the propensity to share when required to share and not, respectively
- The market profit

$$\Pi_m(p, \frac{1}{2}, \theta) = \sum_{i \in \mathcal{I}_m} \frac{1 + S_{im}^{\mathrm{S}}(p,\theta)}{2} D_{im}(p,\theta)(p - \widetilde{MC}_m) + \frac{S_{im}^{\mathrm{NS}} + S_{im}^{\mathrm{S}}(p,\theta)}{2} r_{im} L.$$

Moment Equations: Leads Valuation

- The market price solves

$$p_m = \arg\max_p \Pi_m(p, \frac{1}{2}, \theta)$$

- FOC yields

$$\widetilde{MC}_m(\theta) = p_m + \frac{\sum_{i \in \mathcal{I}_m} (1 + S^{\mathsf{S}}_{im}(\theta)) D_{im}(\theta) + r_{im} L \cdot \partial_p S^{\mathsf{S}}_{im}(\theta)}{\sum_{i \in \mathcal{I}_m} (1 + S^{\mathsf{S}}_{im}(\theta)) \cdot \partial_p D_{im}(\theta) + D_{im}(\theta) \cdot \partial_p S^{\mathsf{S}}_{im}(\theta)}$$

where ∂_p denotes the partial derivative with respect to p

- The fourth set of moment equations, which identifies L given $\theta^y, \theta^w, \theta^r$, is then

$$\mathbb{E}[\widetilde{MC}_m(\theta) - MC_m] = 0$$

Identification of L

- Our identification of L essentially answer: What level of lead value justifies the firm's current pricing decisions?
- L appears only in the fourth set of moment equations
  - Then if in some applications, the assumption that the firm is maximizing its profit is violated, one can simply replace this equation with alternative moment equations (or moment inequalities for the purpose of partial identification), and the rest of the estimation procedure would remain the same
- We also carry out sensitivity analysis with respect to L

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Parameter Estimates: Market Constants

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Parameter	Estimate
Average Baseline Utility ($\bar{v}$)	0.790^{***}
	(0.062)
Average Price Sensitivity ($\bar{\alpha}$)	0.023^{***}
	(0.001)
Average Sharing Cost ($\overline{SC}$)	0.401^{***}
	(0.001)
Ratio of Standard Deviation (σ)	18.858^{**}
	(7.773)
Average Log Number of Referrals (r_0)	-2.284^{***}
	(0.078)
Implied Referral Value (L)	125.742^{***}
	(47.043)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Parameter Estimates: Interaction Terms Back

Parameter	Interaction with (1) Baseline Utility	(2) Price Sensitivity	(3) Sharing Cost	(4) Log Number of Referrals
Number of Days Since Most Recent Purchase	0.130	−0.000	0.024***	−0.055
	(0.101)	(0.001)	(0.008)	(0.072)
Number of Orders in the Past Year	0.111	0.001	−0.011	−0.048
	(0.408)	(0.006)	(0.013)	(0.540)
Purchased Promoted Product Before	0.130	−0.002	0.075***	0.150**
	(0.105)	(0.001)	(0.009)	(0.069)
Average Monetary Value Per Order in the Past Year	0.119	−0.001	0.049***	−0.173*
	(0.139)	(0.002)	(0.009)	(0.104)
Number of Orders Using Coupons	0.131	0.003	0.001	0.054
	(0.352)	(0.005)	(0.011)	(0.451)
Number of Orders Using Gift Cards	0.158	0.003	−0.001	−0.932
	(0.324)	(0.005)	(0.003)	(1.370)
Number of Orders Using Direct Discounts	0.082	0.001	0.007	−0.635**
	(0.307)	(0.004)	(0.006)	(0.288)
Average Monetary Value of Coupons Per Order	0.018	−0.000	0.001	0.150**
	(0.109)	(0.002)	(0.007)	(0.073)
Average Monetary Value of Gift Cards Per Order	0.041	0.001	−0.011	0.170
	(0.144)	(0.002)	(0.007)	(0.378)
Average Monetary Value of Direct Discounts Per Order	0.007	0.001	−0.020***	0.106*
	(0.215)	(0.003)	(0.006)	(0.056)
New Customer	0.151	−0.001	0.042***	0.074
	(0.120)	(0.002)	(0.008)	(0.067)
Customer Tenure	0.150	0.002	0.001	0.194**
	(0.109)	(0.002)	(0.006)	(0.090)
City Characteristics First Principal Component	−0.020	−0.000	0.006	−0.009
	(0.122)	(0.002)	(0.007)	(0.057)
Number of Times Clicking Share Button in the Past Month	−0.014	0.001	−0.009**	0.164
	(0.374)	(0.006)	(0.004)	(0.103)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

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Personalization Schemes

- The firm observes a large set of customer characteristics, so we assume the firm fully observes $v_{im}, \alpha_{im}, SC_{im}, r_{im}$
- Two main policy decision vectors: pricing $\mathbf{p}_m = (p_{im})_{i \in \mathcal{I}_m}$ and sharing requirements $\mathbf{s}_m = (s_{im})_{i \in \mathcal{I}_m}$, where $\mathcal{I}_m$ be the set of customers in market m
- The policy schemes differ in
  - The firm can charge a uniform post-discount price, or personalize the price;
  - It can require everyone to share, or not requiring, or personalize the requirement
- Six combinations of personalization schemes

Personalized Price: Profit Functions

- Let $\Pi_{im}(p, s)$ be the expected profit from customer i in market m when charging post-discount price p and having social requirement s
- Ignore the profit from the lead generated by a customer who is assigned a non-social coupon
- NS profit

$$\Pi_{im}(p, 0) = D_{im}(p)(p - MC_m),$$

  where MC_m denotes the marginal cost of the promoted product in market m.
- S profit function

$$\Pi_{im}(p, 1) = \underbrace{S_{im}(p)D_{im}(p)(p - MC_m)}_{\text{self}} + \underbrace{S_{im}(p)r_{im}L}_{\text{leads}},$$

  where L is the lifetime value of a lead

Personalized Price: Optimal Price

- Optimal personalized non-social price

$$p_{im}^{*\,\mathrm{NS}} = \arg\max_{p \in \mathcal{P}} \Pi_{im}(p, 0)$$

- Optimal personalized social price

$$p_{im}^{*\,\mathrm{S}} = \arg\max_{p \in \mathcal{P}} \Pi_{im}(p, 1)$$

- Personalizing both price and social requirements

$$(p_{im}^{*}, s_{im}^{*}) = \arg\max_{p \in \mathcal{P}, s \in \mathcal{S}} \Pi_{im}(p, s)$$

- Assume the solution to each problem is unique throughout

Personalized Price: Optimal Price Comparison

- Decision of ${p_{im}^{*}}^{\mathrm{NS}}$ involves the standard trade-off: increasing the price leads to higher markup from infra-marginal customers, but lower demand
- Decision of ${p_{im}^{*}}^{\mathrm{S}}$ has two more ingredients: increasing the price leads to a even weaker effective demand; it also decreases the profit from leads

Proposition (1)

The optimal personalized social price is no higher than the optimal personalized non-social price for a given customer i, that is, ${p_{im}^{*}}^{\mathrm{S}} \leq {p_{im}^{*}}^{\mathrm{NS}}$.

Optimal Personalized Social Price

Proposition (2)

The optimal personalized social price p^{*S} for a social promotion is decreasing in both SC and r. That is, suppose customer i and i' are in market m, such that $v_{im} = v_{i'm}$, $\alpha_{im} = \alpha_{i'm}$, and $SC_{im} \geq SC_{i'm}$, $r_{im} \geq r_{i'm}$, then $p^{*S}_{im} \leq p^{*S}_{i'm}$.

Intuition:

- With an increase in the sharing cost, the propensity to share function shifts downwards, and hence the effective demand function also shifts downwards
- With an increase in the expected number of leads, the marginal profit from increasing the price is less

Personalized Social Requirement

Proposition (3)

The optimal personalized social requirement s^* is decreasing in SC and increasing in r. That is, suppose customer i and i' are in market m, and $v_{im} = v_{i'm}$, $\alpha_{im} = \alpha_{i'm}$, and $SC_{im} \geq SC_{i'm}$, $r_{im} \leq r_{i'm}$, then $s^*_{im} \leq s^*_{i'm}$.

Intuition:

- With an increase in the sharing cost, requiring a customer to share is more costly
- With an increase in the expected number of leads, requiring a customer to share is more beneficial

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Policy Schemes Summary

- We discuss six policy schemes, which are combinations of the pricing policy schemes and social requirement policy schemes
- Let ${\Pi_m^*}^{PS}, {\Pi_m^*}^{PNS}, {\Pi_m^*}^{PP}, {\Pi_m^*}^{US}, {\Pi_m^*}^{UNS}, {\Pi_m^*}^{UP}$ be the resulting market profits, where the first letter in the superscript means whether the prices are personalized (P) or uniform (U), and the second letter(s) mean whether the social requirements are all social (S), all non-social (NS), or personalized (P)
- To quantify the performance differences of the six policy schemes, we calibrate the model and compare the policies

Procedure: Feasible Prices

- We set the set of prices $\mathcal{P}$ to be a predetermined discrete set in this section
- Due to the left-digit bias and that customers favor prices ending with 8 in China, many prices end with 8 and 9
- Also, many prices end with 5 since 5 is the midpoint of 0 and 10
- Thus, we set $\mathcal{P}$ as nonnegative integers that are no greater than the regular retail price and end with $5, 8, 9$

Procedure: Estimands

- We discuss six policy schemes, denoted as $\mathcal{K} = \{\text{US}, \text{UNS}, \text{UP}, \text{PS}, \text{PNS}, \text{PP}\}$
- Our quantities of interest for each policy scheme $k \in \mathcal{K}$:
    1. The vectors of corresponding pricing and sharing requirement schemes $\mathbf{p}^{*k}(\theta) = (p^{*k}_{im}(\theta))_{im}$ and $\mathbf{s}^{*k}(\theta) = (s^{*k}_{im}(\theta))_{im}$
    2. The average profit per customer $\bar{\Pi}^{*k}(\theta)$
- Our estimators of the quantities of interests are the plug-in estimators
    - That is, we assume that the estimates $\hat{\theta}$ are the true values of θ, and then calculate $\mathbf{p}^{*k}(\hat{\theta})$, $\mathbf{s}^{*k}(\hat{\theta})$, and $\bar{\Pi}^{*k}(\hat{\theta})$ for each policy scheme $k \in \mathcal{K}$
- We calculate the standard errors of $\bar{\Pi}^{*k}(\hat{\theta})$ using delta method

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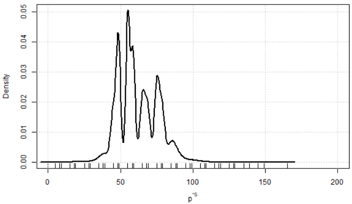
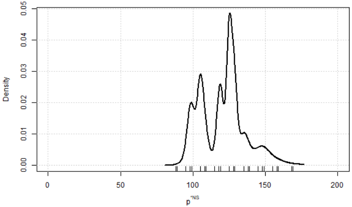
Optimal Personalized Policy

- Under the optimal personalized policy, 77.8% of customers are assigned to the social condition
- This means that for most customers, assigning them to social is more profitable than non-social

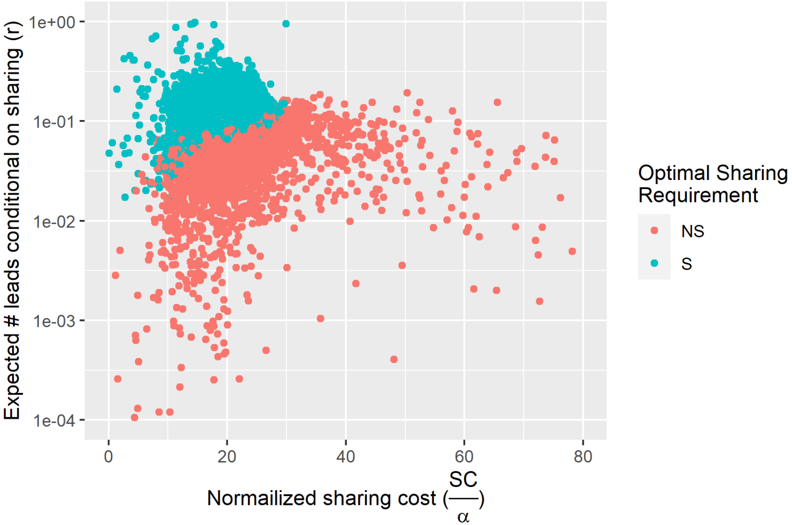


(a) Social Prices



(b) Non-social Prices

Who Are Assigned to S: Low SC, High r



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- There has been surprisingly little understanding when the price discrimination decision needs to be jointly considered with another related personalization decision
- In our case, this is whether or not to impose a social incentive on the discount
- We develop a model to address this question and use a large-scale field experiment in the online grocery setting to estimate the model
- Building on this model, we explore a firm's optimal strategy
- We expect the multi-stage structural model we develop to drive future research on targeted marketing, where firms may wish to jointly personalize several marketing variables that interact among themselves

Related Literature

- Broadcasting promotions and social interactions in marketing
  - Chen et al. (2024): Carry out a market-level cost-benefit analysis of broadcasting promotions
  - Iyengar and Park (2017): Study the effectiveness of shareable coupon v. regular coupon.
  - Sun et al. (2021): Examine the incentive designs to engage consumers to share promotional, varying in the shareability and scarcity of promotion codes.
- Personalized pricing
  - Dubé and Misra (2017): Develops a scalable Bayesian Decision-Theoretic framework that compute targeted price, and verifies the pricing scheme using a second experiment
  - Kehoe et al. (2020): Finds that consumers are better off and firms are slightly worse off under price discrimination relative to uniform pricing

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Social v. Non-social: Acquisition Cost

The acquisition cost of a lead introduced by customer i is

$$
\begin{aligned}
AC_{im} &= \frac{\Delta\text{Profit from self under NS v. S}}{\text{Expected number of leads}} \\
&= \frac{D_{im}(p^{*\,\mathrm{NS}}_{im}, 0)(p^{*\,\mathrm{NS}}_{im} - MC_m) - S_{im}(p^{*\,\mathrm{S}}_{im}) D_{im}(p^{*\,\mathrm{S}}_{im}, 1)(p^{*\,\mathrm{S}}_{im} - MC_m)}{S_{im}(p^{*\,\mathrm{S}}_{im}) \cdot r_{im}}
\end{aligned}
$$

Optimal to assign a customer to S

$$
\begin{aligned}
&\iff \Pi_{im}(p^{*\,\mathrm{NS}}_{im}, 0) \leq \Pi_{im}(p^{*\,\mathrm{S}}_{im}, 1) \\
&\iff AC_{im} \leq L
\end{aligned}
$$

Customer Acquisition Costs

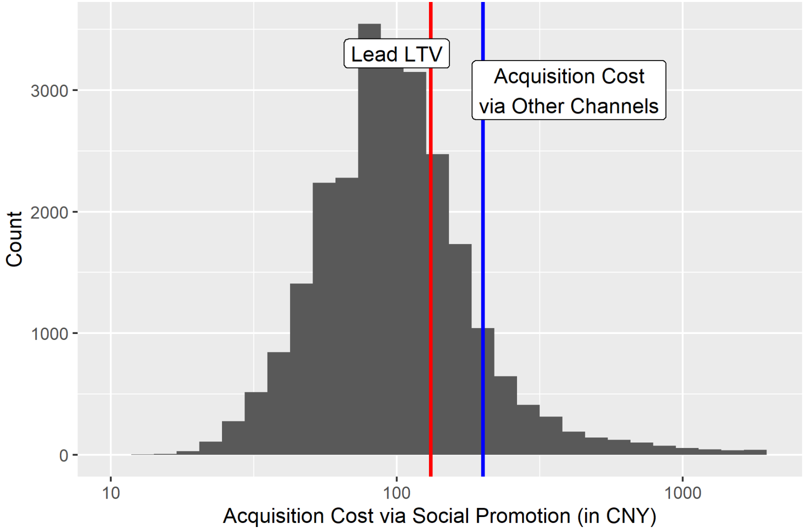

Figure 2: Customer Acquisition Cost Comparison

Sensitivity Analysis

- We assume that the actual $L = \gamma \hat{L}$, where $\gamma \geq 0$ is the ratio of the actual lead value to the firm's estimate
- When γ is sufficiently low, the optimal uniform policy would be not required everyone to share, so an appropriate measure of the profit increment would be comparing $\bar{\Pi}^{*\,\mathsf{PP}}(\theta, \gamma)$ with $\max\{\bar{\Pi}^{*\,\mathsf{US}}(\theta, \gamma), \bar{\Pi}^{*\,\mathsf{UNS}}(\theta, \gamma)\}$
- Estimand

$$\frac{\bar{\Pi}^{*\,\mathsf{PP}}(\theta, \gamma)}{\max\{\bar{\Pi}^{*\,\mathsf{US}}(\theta, \gamma), \bar{\Pi}^{*\,\mathsf{UNS}}(\theta, \gamma)\}} - 1$$

for a range of γ's

Sensitivity Analysis

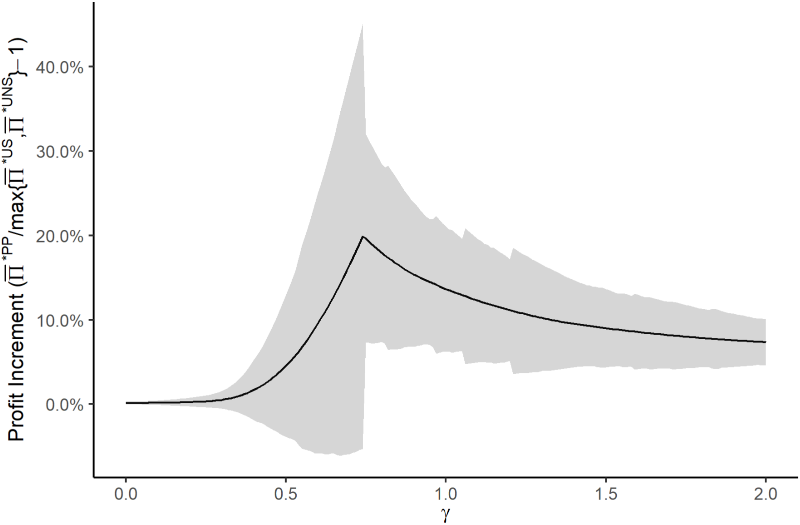

Figure 3: Profit Increment (with 90% Confidence Band)