Consumption Stimulus with Digital Coupons

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Motivation

- Traditional monetary and fiscal policies face limitations
  - Cash payments/tax rebates often saved rather than spent
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- U.S. government distributed billions in tax rebates and economic stimulus payments to households during each of the last three recessions
  - Effectiveness hinges on household marginal propensity to consume (MPC) out of stimulus payments
  - Most studies find MPCs out of stimulus payments ranging from 0.25 to 0.5 (Johnson et al. 2006; Parker et al. 2013; Broda and Parker 2014; Borusyak et al. 2024; Orchard et al. 2025)

Motivation

- Digital coupons: new policy tool for short-term demand stimulus
  - Mobile-distributed consumption voucher
  - Minimum spending thresholds (e.g., spend ¥50 to get ¥15 off)
  - Short expiration periods (typically one day to a week)
  - Can target specific sectors or spending categories (e.g., food services)
  - Scalable, rapid deployment via mobile platforms

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  - More than ¥1.9 billion in government subsidies nationwide (≈260 million USD)
- Unique features of digital coupons
  - "Consumer-financed stimulus"— businesses receive funding from both government and consumers
  - For every ¥1 of government subsidy, consumers spend additional out-of-pocket
  - Result: direct spending multiplier > ¥1

Our Context

	Value-added (1000 million)	Change (%)
Agriculture, forestry, fishing, and hunting	113.1	-1.8
Industrial	5036.4	-14.6
Construction	1614.2	-1
Wholesale and retail	3110.3	-1.1
Transportation and warehousing	879.2	-4.6
Accommodation and food services	372.6	-13.7
Information, professional and business services	7456.2	-1.8
Finance	8196.7	9.8
Real estate	2594.5	6.4
Rental, leasing and commercial services	2581.4	-1.2
Others	9656.1	-1.3
Total	**41610.9**	**0.7**

Source: Beijing Municipal Bureau of Statistics

In summer 2022, the Beijing government allocated ¥100 million in subsidies to support the restaurant industry

This Paper

- Evaluates the effectiveness of this large-scale digital coupon program in Beijing that targeted the restaurant and food delivery sector
- We begin by estimating the ATE on consumer spending

Main Finding #1

- On average, digital coupons increased daily consumption by 12 percent during the program period
- No long-lasting effect. No evidence of inter-temporal, inter-category, or intra-household substitution
- For every ¥1 of government subsidy, consumers spent an additional ¥2.38 of their own money—implying an MPC of 3.38 out of coupon subsidies
  - Consistent with Liu et al. (2021), Xing et al. (2023), Ding et al. (2025).
  - "Consumer-financed stimulus" (Ding et al. 2025)

This Paper

- The average effect masks significant heterogeneity in individual responses.
- Understanding this heterogeneity is crucial:
  1. identifying the micro-drivers of consumption decisions
  2. assessing the distributional impact of the program
  3. designing strategies to enhance effectiveness

This Paper

- Nonparametrically estimates heterogeneous treatment effects across a rich set of covariates
  - Effects of stimulus programs vary among individuals and across space
- Demand-side vs. supply-side drivers
  - Demand-side: income & wealth
  - Supply-side: local consumption amenities
  - Wealthy individuals sort into neighborhoods with high consumption amenities
  - Existing research that identifies income or wealth as important drivers of MPC heterogeneity could be attributing supply-side effects to the demand-side

Main Finding #2

- Substantial heterogeneity
  - 50% of total stimulus driven by just 9% of users
  - 19% of consumers reduced out-of-pocket spending (MPC $<$ 1). 23% of consumers had MPCs $>$ 5
    - Limited informativeness of average MPC
  - Half of total spending increase concentrated in 11% of neighborhoods (3km-by-3km grids)

Main Finding #3

- Both rational and behavioral responses
  - Bunching of expenditures at coupon thresholds
    - Some consumers adjusted their spending to qualify for redemption.
  - Largest consumption responses observed among *inframarginal* consumers—those whose baseline spending well exceeded coupon thresholds and for whom the coupon discounts were economically equivalent to cash
    - Cannot be explained by threshold-based rational incentives models (Xing et al. 2023; Ding et al. 2025)
    - Evidence of behavioral mechanisms: mental accounting (Thaler, 1999), loss aversion (Tversky and Kahneman, 1991), salience (Bordalo et al., 2012, 2013) of design features

This Paper

- Maps individual treatment effects into business revenue gains
  - Which businesses benefited most from the program?
  - Potential tradeoff: if larger establishments attract wealthier consumers, and if wealthier consumers have larger MPCs, then
    - Maximizing the total stimulus ⇒ concentrating benefits among large businesses
    - Prioritizing support for small businesses ⇒ relying on lower-income consumers for stimulus financing (welfare impact unclear)

Main Finding #4

- Regressive allocation of stimulus effects among businesses
  - Larger, higher-priced establishments received a disproportionate share of increased consumer spending
  - Driven by a key form of *consumer-business matching*: consumers with higher coupon MPCs tend to direct a greater share of their spending to large businesses
  - The incidence of the stimulus program among businesses may not align with policy objectives during economic downturns

This Paper

- Designs optimal targeting strategies to maximize the total stimulus effect or achieve a balance between consumption stimulus and support for small businesses

Main Finding #5

- Full targeting based on all observed individual covariates $\Rightarrow$ total stimulus can be more than doubled at no additional cost
  - The efficiency gain remains substantial when the government's targeting capacity is limited, due to correlations among individual features (e.g., spatial sorting)
- Targeting individuals more likely to patronize smaller establishments $\Rightarrow$ more revenue gains for small businesses, lower overall stimulus, greater reliance on lower-wealth consumers who reside in neighborhoods with more small-business for stimulus financing

Main Finding #5

- A hybrid design combining targeted distribution of digital coupons to the most responsive consumers with direct government support for small businesses improves both the efficiency and equity of the program

Links to the Literature
Consumption Subsidy

- **Digital Consumption Coupons:** Liu et al. (2020), Lin et al. (2020), Li (2022), Wang et al. (2022), Xing et al. (2023), Notowidigdo et al. (2022)
- **Subsidy and Fiscal Stimulus:** Hoynes & Schanzenbach (2009), Hsieh et al. (2010), Beatty & Tuttle (2015), Kan et al. (2017), Hastings & Shapiro (2018), Shapiro & Slemrod (2003, 2009), Johnson et al. (2006), Agarwal et al. (2007), Parker et al. (2013), Agarwal & Qian (2014), Broda & Parker (2014), Kaplan & Violante (2014), Misra & Surico (2014), Baker et al. (2020), Karger & Rajan (2021), Chetty et al. (2022)

Links to the Literature

Urban Amenities & HTE

- **Urban Consumption Amenities and Spatial Inequality:** Schiff (2015), Couture and Handbury (2021), Couture et al. (2023)
- **Forest-based HTE:** Athey & Imbens (2016), Davis & Heller (2017), Wager & Athey (2018, 2019), Athey et al. (2019), Knaus et al. (2021), Nie & Wager (2021); Davis and Heller (2020), Hitsch, Misra and Zhang (2023), Athey et al. (2023)

Background and Data

Digital Coupons in Beijing, 2022

- Overall:
  - 100 million government subsidy targeted to help the restaurant industry
  - Event window: 18th July to 28th August, 2022
  - Platforms: Ele.me (>20%), Meituan, and Construction Bank

Ele.me

Background

- Coupon design
  - Threshold based: 15 off 50, 30 off 100
  - Eligibility:
    - User IP located in Beijing
    - First come, first serve (starts at 10am)
    - At most one set of coupon per user
  - Redemption:
    - One coupon per order
    - Same-day expiration
    - All platform shops in Beijing
- Non-fungible, threshold, time sensitive, convenient and flexible

Sampling and Data from Ele.me

- User-level stratified sampling (2:2:1):
  1. 5980 users who participated and obtained coupons (treatment)
  2. 5785 Participated but did not obtain coupons (control)
  3. 2959 did not participate (non-participants)
- User-level panel of all Ele.me orders during the coupon event + 2 weeks before and after
- Additional data:
  - User time-invariant characteristics: demographic (age brackets, gender), phone price brackets, past consumption patterns (weekly ordering expenditure & frequency, delivery address, Ele.me membership status, etc.)

Spatial Characteristics

- Source:
  - Measures of consumption amenities from *DaZhongDianPing*
  - Housing transaction records from *Lianjia*
- Mapping users with spatial data geographically:
  - PCA of housing price and phone price (wealth)
  - Number of restaurants in a 3km radius buffer (amenities)

Summary Statistics

Methodology

Average Treatment Effect

$$y_{it} = \alpha \cdot \text{Treat}_i \times \text{Post}_t + \gamma_i + \lambda_t + \epsilon_{it}, \tag{1}$$

- User-day regression to estimate ATT of *coupon assignment*
- y_{it} : (out-of-pocket) spending
- Treat_i indicates treatment group status
- Post_t indicates treatment period (coupon event)

Heterogeneous Treatment Effect

$$\Delta y_i = \alpha\left(\mathbf{X}_i\right) \cdot \text{Treat}_i + f(\mathbf{X}_i) + \varepsilon_i, \tag{2}$$

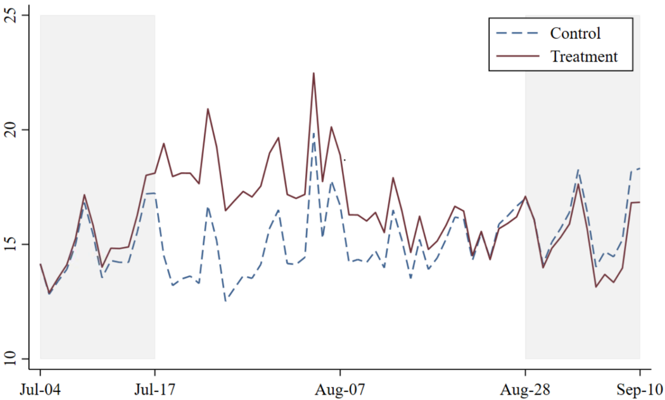
- Estimates CATT $\alpha\left(\mathbf{X}_i\right) = \mathbb{E}\left[\alpha_i \middle| \mathbf{X}_i\right]$
- Δy_{it} : change in (out-of-pocket) spending before and during the coupon event
- $\mathbf{X}_i$: set of observed and constructed demographic, wealth, and locational attributes
- Technical details:
  - $f(\mathbf{X}_i)$ orthogonalized away using Double Machine Learning (Chernozhukov et al., 2018)
  - $\alpha\left(\mathbf{X}_i\right)$ estimated using causal forest (Wager and Athey, 2018; Athey et al., 2019)

Average Treatment Effects on the Treated

Average Effects of Obtaining Coupons on Different Types of Expenditure

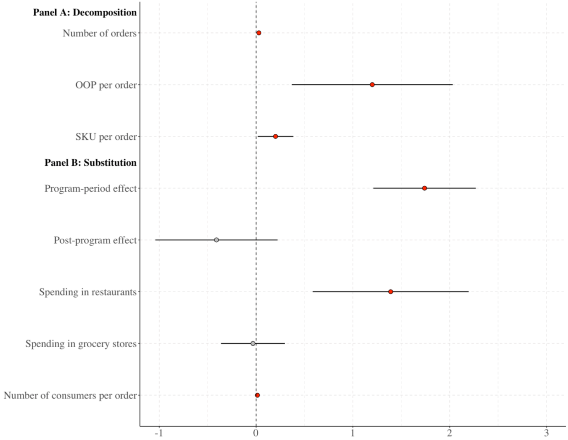
	Out-of-pocket expenditure (1)	Total expenditure (2)	Unsubsidized expenditure (3)
Treat×Post	1.801***	2.558***	-0.008
	(0.636)	(0.639)	(0.635)
Observations	416,570	416,570	416,570

Parallel Trends



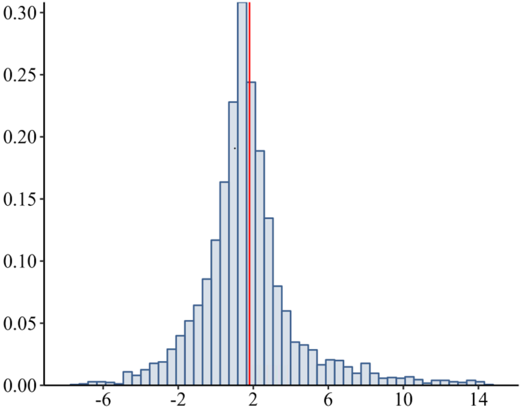
Notes: The F-stat is 0.31.

Potential Decomposition and Substitution



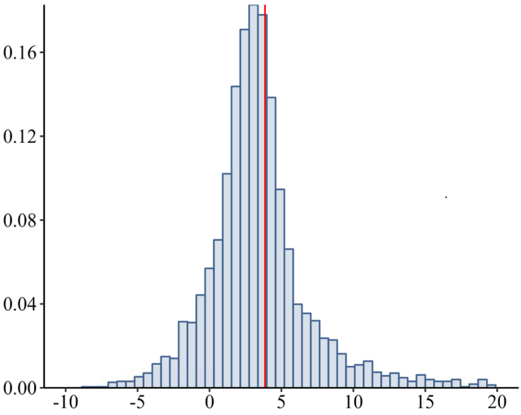
Heterogeneous Treatment Effects

Distribution of Conditional Average Treatment Effects



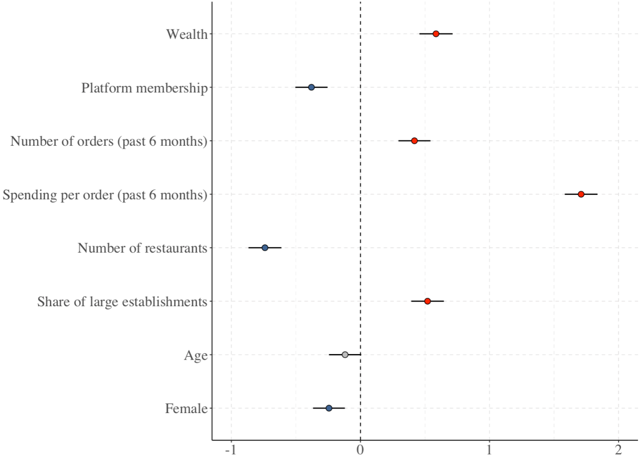
Notes: The vertical red line indicates the average treatment effect on the treated of 1.8 RMB.

Distribution of Individual MPC



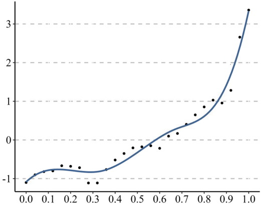
Notes: Individual marginal propensity to consume (MPC), calculated as the ratio of CATT to expected government subsidy, with the vertical red line marking the average MPC of 3.38.

Drivers of Heterogeneous Treatment Effects

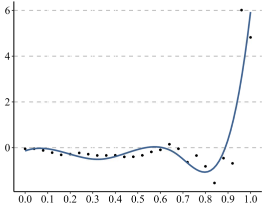


Notes: Best linear projection of estimated CATT on standardized covariates. All variables are standardized to have mean zero and standard deviation one, allowing direct comparison of coefficient magnitudes.

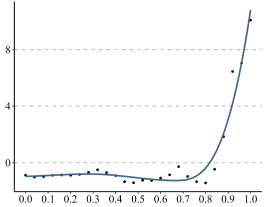
Nonlinear Effects: Demand-Side Characteristics



(a) Wealth



(b) Order Frequency

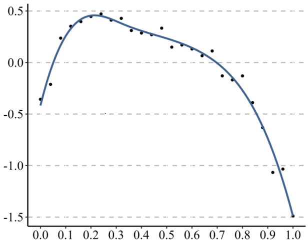


(c) Spending per Order

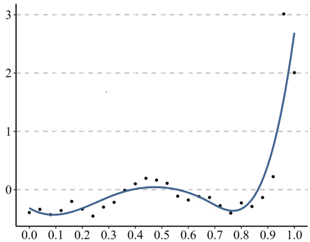
Notes: Accumulated local effects curves showing how demand-side factors influence treatment effects while controlling for other variables.

Visible bunching

Nonlinear Effects: Supply-Side Characteristics



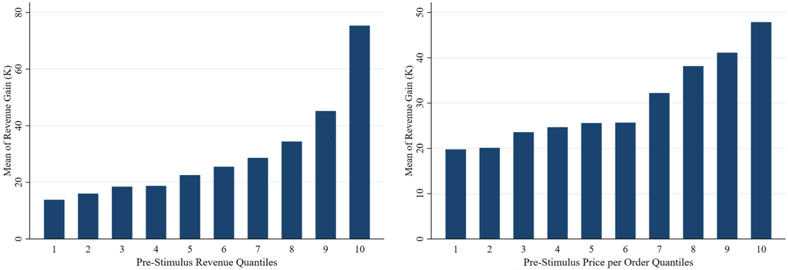
(a) Number of Establishments



(b) Share of Non-SME Establishments

Notes: Accumulated local effects curves showing how supply-side factors influence treatment effects while controlling for other variables.

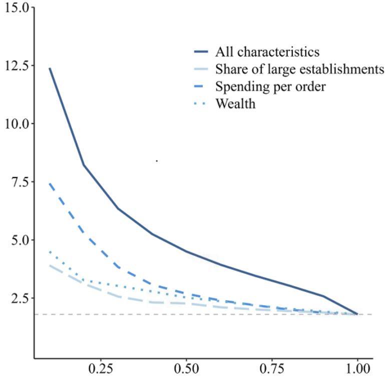
Distribution of Revenue Gains Across Establishments



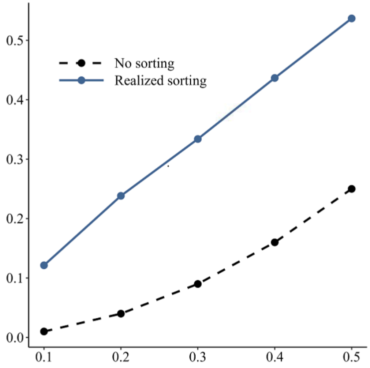
(a) By Establishment Size (b) By Price Level

Notes: The uneven distribution of revenue gains generated by the digital coupon program.

Efficiency Gains from Targeted Coupon Distribution

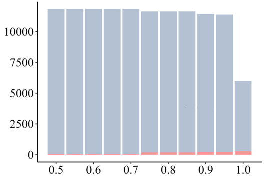


(a) Rank-Weighted Average Treatment Effects

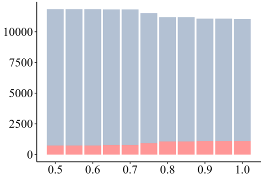


(b) Correlation Between Wealth and Restaurant Composition

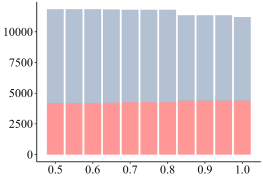
Tradeoff Between Overall Stimulus and SME Support



(a) SME at 20th percentile



(b) SME at 50th percentile



(c) SME at 80th percentile

Hybrid Approach

- Strategy: Target high-response consumers + direct subsidies to SMEs
  - Target consumers only until their total spending matches actual scenario
  - Transfer remaining budget directly to small businesses
- Budget efficiency:
  - Saves 85% of government budget compared to untargeted distribution
  - Redirects saved funds as direct support to vulnerable SMEs
- Balances efficiency and equity considerations without additional costs

Hybrid Approach

Policy Design	**Consumers Treated**	**Government Budget**	**Consumer Spending**	**Funds for SMEs**	**Total Stimulus**
Reality	50%	2,856.284	7,701.772	0.000	7,701.772
Full targeting	50%	2,856.284	17,706.346	0.000	17,706.346
Hybrid approach	6%	408.690	7,701.729	2,447.594	10,149.320

Conclusion

Summary

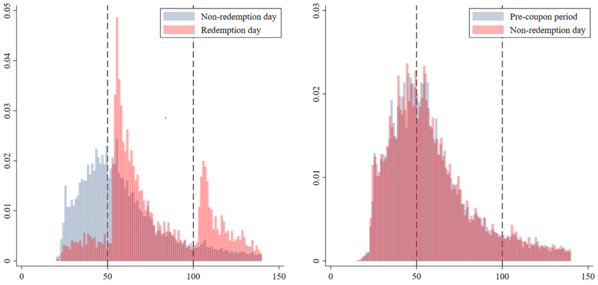
- Digital coupons are effective:
  - High effectiveness in consumption stimulus
  - Purchasing more items to meet the threshold
  - Effects are short-lived with limited substitutions
- The effects are heterogeneous and working through:
  - Past consumption habits, wealth, and local amenities
  - Both rational and behavioral mechanisms
- Policy alternatives
  - Targeting the most responsive individuals
  - Targeting SME's
  - Hybrid approach

Ele.me

- One of the two major online food delivery platforms in China
- Hosting 450 million users, 6 million restaurants, and over 1 million riders

Back to Background

Bunching Pattern



Back to ALE Demand