Discreet Personalized Pricing

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Motivation/Overview

- New vast consumer tracking datasets:
  - Reveal much more than demographics
  - May enable profitable personalized pricing (Dubé and Misra, 2022; Shiller, 2020)
- Yet, common wisdom suggests goods still sold via posted prices
- **Question:** Are firms using but hiding personalized pricing
- This paper investigates a method for doing so

Why Disguised?

- Consumer backlash concerns
  - Notorious example: Amazon in 2000
  - Firms discussing how to implement without incurring backlash (Lina Kahn, 2014)

- Regulatory concerns
  - Consumer protection concerns spawned a White House Report[1]
  - Europe's GDPR [article 22] may forbid it (Wong, 2021)
  - China's new (2021) draft antitrust guidelines explicitly prohibit it

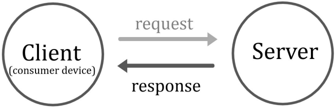
How Disguised?

- Firms exploring ways to hide personalized pricing
  - Personalized search rankings[2]
  - Framing personalized pricing as coupons or discounts[3]
- However, these strategies are not that effective
- I describe an alternative and provide evidence may already be used

Optimized Sticky Targeted Pricing

Pricing Strategy

- Tailor “posted price” to the arriving consumer



- To avoid detection, privately commit to maintaining price for some time after a change

Successfully Disguised?

- Test: are consumers offered different prices at same time?
  - Easy for consumers
  - Existing research used similar method[a]
- Optimized sticky targeted pricing disguised
  - Private commitments to infrequently change price implies consumers see the same price at the same point in time
- Long lags between spoofed consumers creates challenges
  - Unclear whether price changes due to personalization or traditional dynamic pricing:
    - Response to demand shocks
    - Exploiting predictable demand changes (e.g., early-bird special)
    - Dynamic price discrimination (periodic sales)

[a](Cavallo, 2017; Hannak et al., 2014; Hupperich et al., 2018; Iordanou et al., 2017; Mikians et al., 2012)

Implications

- Pricing determines how markets function
- Overlooking personalized pricing:
  - Biases demand and inflation estimates[4]
  - Changes relationship between competition and firm profits/consumer welfare[5]
  - etc.

Outline

1. Characterize optimal sticky personalized pricing
2. Apply to several contexts
   - One empirical
   - Various theoretical distributions of valuations

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Model Setup

- Myopic consumers arrive randomly over time (i.i.d.)
- The firm observes type before setting the “posted price”
- Following a price change, price locked for length s
- Time measured in units of s

Value Function

Value function:

$$V(P,\psi,t) = \max_{P'} \begin{cases} W^{P'=P}(P,\psi,t) & \text{if } P' = P \\ W^{P'\neq P}(P',\psi,t) & \text{if } P' \neq P \end{cases},$$

- γ: arriving consumer's type
- P: last offered price
- P': new "posted" price offered to the arriving consumer
- $W^{P'=P}(P,\psi,t)$: discounted profits $\mid P' = P$
- $W^{P'\neq P}(P',\psi,t)$: discounted profits $\mid P' \neq P$

$$V(P,\psi,t) = \max_{P'} \begin{cases} W^{P'=P}(P,\psi,t) & \text{if } P' = P \\ W^{P'\neq P}(P',\psi,t) & \text{if } P' \neq P \end{cases},$$

$$W^{P'=P}(P,\psi,t) =$$

$$\pi(P,\psi,t) + \int_{\tau=0}^{\infty}\int_{\psi'} \exp(-r\tau)V(P,\psi',t+\tau)g(\psi';t+\tau)f(\tau;\lambda,t)d\psi' d\tau,$$

- $\pi(P,\psi)$: expected static profits from arriving consumer
- $\exp(-r\tau)$: continuous analogue of discount factor
- $V(P,\psi',t+\tau)$: value function
- $g(\gamma;t+\tau)$: consumer type density
- τ: (random) time until next consumer arrival
- r: interest rate
- λ: consumer arrival rate
- $\exp(-r\tau)$: time discounting

$$V(P,\psi,t) = \max_{P'} \begin{cases} W^{P'=P}(P,\psi,t) & \text{if } P' = P \\ W^{P'\neq P}(P',\psi,t) & \text{if } P' \neq P \end{cases},$$

$$W^{P'\neq P}(P',\psi,t) =$$

$$\overbrace{\pi(P',\psi,t)}^{A}$$

$$\overbrace{+\left(\int_{\tau=0}^{s} h(\lambda,t+\tau)\exp(-r\tau)\int_{\psi'}\pi(P',\psi',t+\tau)g(\psi';t+\tau)d\psi' d\tau\right)}^{B}$$

$$\underbrace{+\int_{\tau=s}^{\infty}\int_{\psi''}\exp(-r\tau))\, V(P',\psi'',t+\tau)g(\psi'';t+\tau)f(\tau;\lambda,t+s)d\psi'' d\tau}_{C}\,.$$

- Component A: Expected static profits at price P'
- Component B: Discounted expected profits from consumers arriving while price fixed
- Component C: Expected discounted profits earned after fixed-price period

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Tradeoff

$$W^{P'\neq P}(P',\psi,t) =$$

$$\overbrace{\pi(P',\psi,t)}^{A}$$

$$\overbrace{+\left(\int_{\tau=0}^{s} h(\lambda,t+\tau)\exp(-r\tau)\int_{\psi'}\pi(P',\psi',t+\tau)g(\psi';t+\tau)d\psi' d\tau\right)}^{B}$$

$$\underbrace{+\int_{\tau=s}^{\infty}\int_{\psi''}\exp\left(-r\tau\right)) V(P',\psi'',t+\tau)g(\psi'';t+\tau)f(\tau;\lambda,t+s)d\psi'' d\tau}_{C}\ .$$

- Tradeoff:
  - Targeting price raises static profits (component A)
  - Deviating from optimal uniform price reduces profits later arrivals (component B)
- Relevant factors:
  - Count of arrivals while price fixed
  - Precision of estimated willingness to pay

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Counterfactual Simulations: Setup

Array of different distributional assumptions

- One empirical distribution of valuations (Shiller, 2020)
  - Individual-level demand for Netflix estimated from web-browsing data
- Three theoretical (with and without uncertainty)
  - Uniform
  - Normal
  - Exponential

Various consumer arrival rates λ (product popularity)

For each:

- Approximate value functions/policy function, given:
  - Interest rate (per period s) = $0.1/365$
- Simulate prices and profits

Model of Individual Demand (Shiller, 2020)

Standard utility function for 2^{nd} degree PD demand:

$$u_{ij} = \alpha P_j + \nu_i + \delta_j + \epsilon_{ij} = \bar{u}_{ij} + \epsilon_{ij},$$

- α - "mean" price sensitivity
- P_j - Price of product j
- ν_i - consumer i's specific valuation for Netflix generally
- δ_j - "mean" utility for product j
- ϵ_{ij} - iid logit error term

$$s_{ij}(\nu_i, \alpha, \delta, P) = \frac{exp(\alpha P_j + \nu_i + \delta_j)}{1 + \sum_{k \in J} exp(\alpha P_k + \nu_i + \delta_k)},$$

$$s_{ij \neq 0}(\nu_i, \alpha, \delta, P) = 1 - s_{i0}(\nu_i, \alpha, \delta, P) = 1 - \frac{1}{1 + \sum_{k \in J} exp(\alpha P_k + \nu_i + \delta_k)}.$$

Key Parameters

$$u_{ij} = \alpha P_j + \nu_i + \delta_j + \epsilon_{ij} = \bar{u}_{ij} + \epsilon_{ij},$$

- α - "mean" price sensitivity
- ν_i - consumer *i*'s specific valuation for Netflix generally
- δ_j - "mean" utility for product *j*
- If knew these parameters, can calculate probability any consumer *i* buys at any price
- Can predict profits under personalized pricing

Identification (1)

Suppose we knew values of α and δ_j

$$u_{ij} = \alpha P_j + \nu_i + \delta_j + \epsilon_{ij} = \bar{u}_{ij} + \epsilon_{ij},$$

Also suppose have estimate individual *i* subscribes

Can then find value of ν_i that implies this probability (only one specific value does)

$$s_{ij\neq 0}\left(\nu_i, \alpha, \delta, P\right) = 1 - s_{i0}\left(\nu_i, \alpha, \delta, P\right) = 1 - \frac{1}{1 + \sum_{k\in J} exp\left(\alpha P_k + \nu_i + \delta_k\right)}.$$

Identification (2)

Suppose only didn't know value of α

- Larger values of α imply consumers more price sensitive
  - Hence price change alters completed sales by more

- Only one value of α implies that observed markup (price) is the markup that maximizes profits (assuming marginal costs are known)
  - Larger α imply firm should reduce price
  - Smaller α imply firm should increase price

Identification (3)

Suspose only didn't know value of δ_j

- Can find values which imply predicted aggregate share of consumers buying each tier of service matches empirical observations
- Note that not all three values of δ_j separately identified from ν_i
  - So *normalize* δ_1 to equal 0.

Estimation Routine

Find values of ν_i, α, and δ_j which satisfy *moment conditions* implied above.

$$\min_{\alpha,\delta_1,..,\delta_J,\nu_1,\dots,\nu_N} \left(\begin{array}{l} \sum_{i=1}^{N} \left(\hat{s}_{ij\neq 0}(X_i) - s_{ij\neq 0}(\nu_i,\alpha,\delta,P)\right)^2 \\ + \sum_{j\in J} \left(\hat{s}_j - \int s_{ij}\left(\nu_i,\alpha,\delta,P(\theta)\right) f\left(\nu_i\right) d\nu_i\right)^2 \\ + \left(\sum_{j\in J} c_j \left(s_j + \theta \frac{ds_j}{d\theta}\right)\right)^2 \end{array} \right)$$

Note, to do this, need estimates of probability each consumer subscribes

Predicting Subscription Probabilities

- Use penalized logistic regression to relate consumer characteristics to probability of subscribing (after normalizing all variables)

$$L = \sum_i \ln\left(s_{ij\neq 0}(X_i) \times I(buy) + (1 - s_{ij\neq 0}(X_i)) \times (1 - I(buy))\right) - \lambda \sum_{k=1}^{K} |\beta_k|,$$

$$s_{ij\neq 0}(X_i) = \frac{exp(\phi + X_i\beta)}{1 + exp(\phi + X_i\beta)}.$$

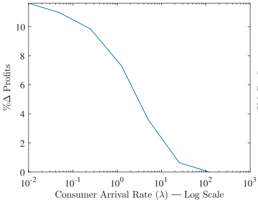
Table: Estimation Results: Prediction Whether Individual Subscribes

Order	Visits to:	Coef. Value	Δ Pr(Subscribe) (w. One Standard Deviation Increase in Visits)
1	gamefly.com	0.78	11.78
2	ameblo.jp	-0.48	-5.03
3	slysoft.com	0.36	4.80
4	audible.com	0.33	4.40
5	dvdfab.com	0.30	4.01
6	sutterhealth.org	0.30	3.96
7	4chan.org	0.29	3.84
8	jambase.com	0.29	3.83
9	imdb.com	0.28	3.72
10	houstonpress.com	0.27	3.49
11	kw.com	-0.26	-2.90
12	somethingawful.com	-0.25	-2.83
13	jacksonville.com	-0.24	-2.72
14	lacity.org	-0.24	-2.65
15	jalopyjournal.com	0.23	3.03
16	uhaul.com	0.23	2.99
17	smackjeeves.com	0.23	2.98
18	dailypress.com	-0.23	-2.58
19	sonlight-email.com	-0.22	-2.54
20	fairfaxcounty.gov	0.22	2.89
21	ganeshaspeaks.com	0.22	2.89
22	onstation.com	-0.22	-2.49
23	whig.com	0.21	2.74
24	techdirt.com	0.21	2.68
25	zylom.com	-0.21	-2.36
26	npr.org	0.20	2.64
27	baseballamerica.com	0.20	2.63
28	apunkachoice.com	0.20	2.63
29	elpais.com	0.20	2.61
30	amazon.com	0.20	2.56

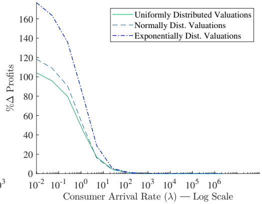
Profit Gain from OSTP (vs. Uniform Pricing)

Figure: Counterfactual Profit Gain v. Consumer Arrival Rate

$\%\Delta\pi$

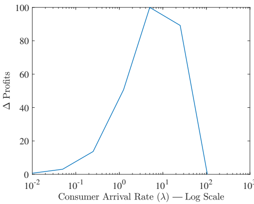


(a) Empirical: Netflix

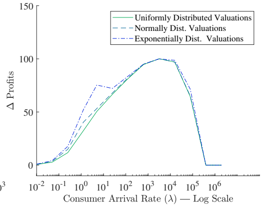


(b) Theoretical Distributions

$\Delta\pi$



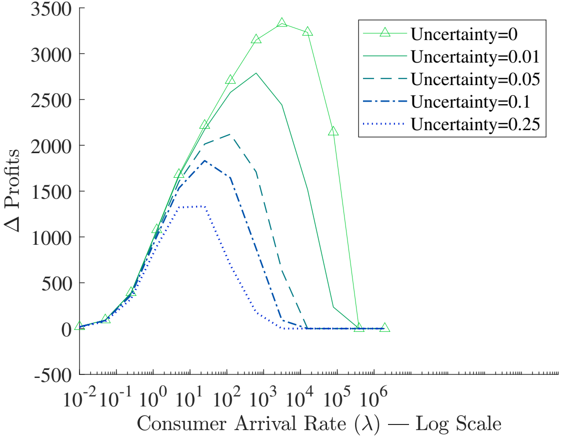
(c) Empirical: Netflix



(d) Theoretical Distributions

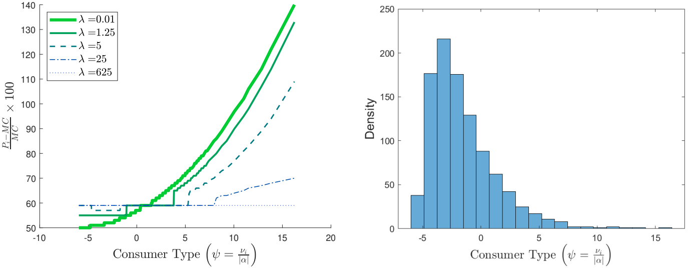
Impact of Uncertainty

Figure: Counterfactual Profits and the Impact of Uncertainty



Prices Across Consumer Types: Empirical

Figure: Simulated Price Range: Across Consumers



(a) Empirical: Netflix (b) Type Density

Notes: *The left panel shows the range of percent markups across consumer types for the empirical application, assuming the previous markup was the optimal uniform markup. Each line on the graph shows the range of markups across consumers for a specific arrival rate (λ). The right panel shows the density of consumer types.*

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Prices Across Consumer Types: Theoretical

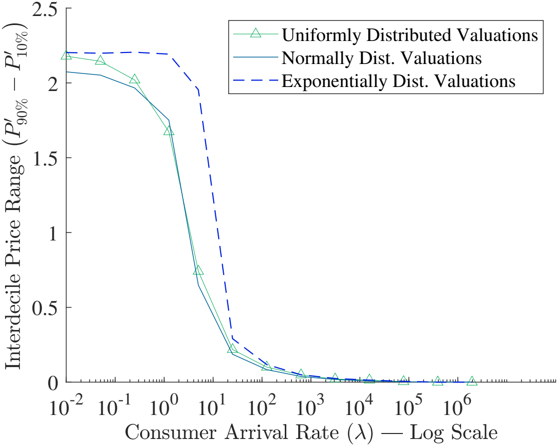
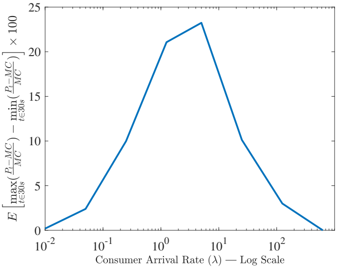


Figure: Price Range Across Consumers: Theoretical Distributions

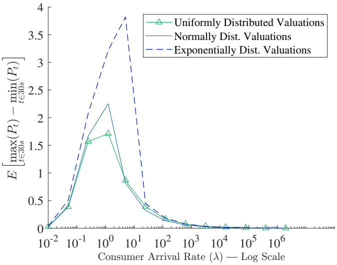
Notes: *This figure shows the interdecile range of simulated prices offered across different consumer types—when the firm can freely change price—against the consumer arrival rate, for the three theoretical distributions.*

Prices Over Time

Figure: Simulated Price Range: Time-Normalized



(a) Empirical: Netflix



(b) Theoretical Distributions

Notes: *This figure shows the expected range of markups and prices offered over a time interval of length* 30 × *s against the consumer arrival rate, for the empirical distribution (on the left) and the theoretical distributions (on the right).*

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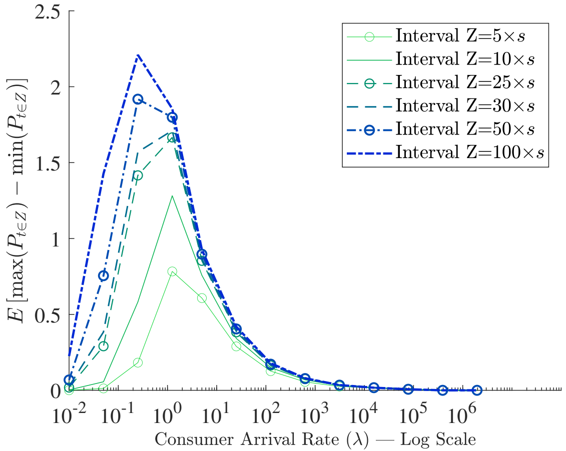
Prices Over Time: Robustness

Figure: Simulated Price Range: Time-Normalized—Various Period Lengths



Notes: *This figure shows the expected range of prices offered over a a variety of different time interval lengths when the distribution of*

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Conclusions (1)

- Big data enables profitable personalized pricing
- But, firms concerned about backlash/policy

If firms can raise profits through targeted pricing while keeping consumers, regulators, and competitors unaware, why would they not?

Conclusions (2)

Absent regulations, <u>why assume</u> firms are not using personalized pricing?

Thank you!

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