Optimized Sticky Targeted Pricing

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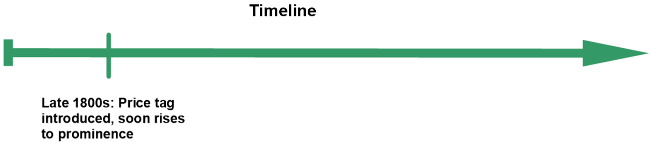
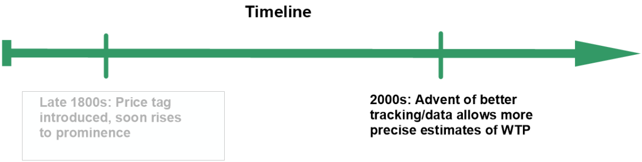
Motivation/Background
Haggling Abandoned



Motivation/Background
Better Data



[1] (Dong et al., 2009; Dube and Misra, 2017; Kehoe et al., 2018; Shiller, 2020; Shiller and Waldfogel, 2011; Zhang et al., 2014)

[2] "Big Data and Differential Pricing." Executive Office of the President (2015).

[3] "China Unveils New Rules Targeting Anticompetitive Practices by Internet Companies." Wall Street Journal. Aug 17, 2021.

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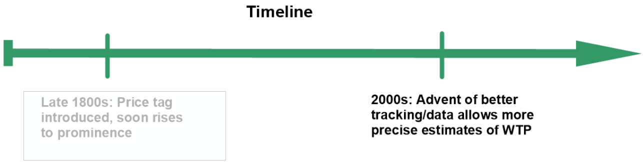

- Makes personalized pricing much more profitable
  - Profit gains in vicinity of 10% to 50%[1]

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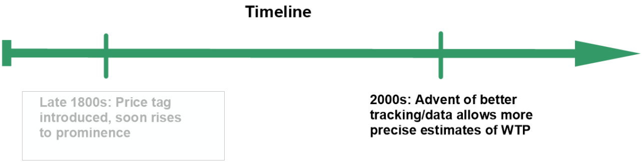

- Makes personalized pricing much more profitable
  - Profit gains in vicinity of 10% to 50%[1]
- But, consumer backlash remains an impediment
  - Notorious example: Amazon in 2000
- Also risks regulation
  - Concern spawned a White House Report[2]
  - China's new draft antitrust guidelines prohibit it[3]

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Inconspicuous Personalization

- Firms exploring ways to hide personalized pricing
  - Personalized search rankings[4]
  - Framing personalized pricing as coupons or discounts[5]
- However, these strategies are not that effective
- In this paper, I describe an alternative and document evidence suggesting it is already used

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

[5] Reimers and Shiller, 2019; Shiller, 2020

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

[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[6]
  - Changes relationship between competition and firm profits/consumer welfare[7]
  - etc.

[6] (Chevalier and Kashyap, 2019; D'Haultfœuille et al., 2019)
[7] (Thisse and Vives, 1988)

Outline

1. Present dynamic model of optimized sticky personalized pricing (OSTP)
2. Estimate static individual-level demand functions for Netflix, following Shiller (2020)
3. Combine (1) and (2) to simulate optimized sticky targeted pricing
   - Consider various consumer arrival rates (popularity)
4. Identify pricing patterns under sticky targeted pricing
5. Search for those patterns in practice

Dynamic Model of OSTP: 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

$$V(P) = \int_{\psi} \max_{P'} \begin{pmatrix} 1(P' = P) W^{P'=P}(P, \psi) \\ +1(P' \neq P) W^{P' \neq P}(P', \psi) \end{pmatrix} g(\psi) d\psi$$

- γ: arriving consumer's type
- $g(\gamma)$: consumer type density
- P: last offered price
- P': new "posted" price offered to the arriving consumer
- $W^{P'=P}(P, \psi)$: discounted profits $\mid P' = P$
- $W^{P' \neq P}(P', \psi)$: discounted profits $\mid P' \neq P$

$$V(P) = \int_{\psi} \max_{P'} \begin{pmatrix} 1(P' = P) W^{P'=P}(P, \psi) \\ +1(P' \neq P) W^{P' \neq P}(P', \psi) \end{pmatrix} g(\psi) d\psi$$

$$W^{P'=P}(P, \psi) = \pi(P, \psi) + V(P) \int_{\tau=0}^{\infty} \exp(-r\tau) f(\tau; \lambda) d\tau$$

- $\pi(P, \psi)$: expected static profits from arriving consumer
- $V(P)$: value function
- $\int_{\tau=0}^{\infty} \exp(-r\tau) f(\tau; \lambda) d\tau$: expected extent of time discounting until the next consumer arrives
  - r: interest rate
  - τ: random time until the next arrival
  - λ: consumer arrival rate
  - $\exp(-r\tau)$: time discounting

$$V(P) = \int_{\psi} \max_{P'} \begin{pmatrix} 1(P' = P) W^{P'=P}(P, \psi) \\ +1(P' \neq P) W^{P' \neq P}(P', \psi) \end{pmatrix} g(\psi) d\psi$$

$$W^{P' \neq P}(P', \psi) = \left(\overbrace{\pi(P', \psi)}^{A} + \overbrace{\left(\int_{\psi'} \pi(P', \psi') g(\psi') d\psi' \right)}^{B} \times \overbrace{\sum_{n=0}^{\infty} n\delta(n) h(n; \lambda) dn}^{C} \atop + \underbrace{V(P') \int_{\tau=0}^{\infty} \exp\left(-r \times (s + \tau)\right) f(\tau; \lambda) d\tau}_{D} \right)$$

- Component A: Expected static profits at price P'
- Component B: Expected profits from random consumer
- Component C: Expected product of:
  - # consumer arrivals during fixed-price period
  - Average discounting per arrival
- Component D: Expected discounted profits earned after fixed-price period

Tradeoff

$$W^{P' \neq P}(P', \psi) = \left(\overbrace{\pi(P', \psi)}^{\text{A}} + \overbrace{\left(\int_{\psi'} \pi(P', \psi') g(\psi') d\psi' \right)}^{\text{B}} \times \overbrace{\sum_{n=0}^{\infty} n\delta(n) h(n; \lambda) dn}^{\text{C}} \right.$$
$$\left. + \underbrace{V(P') \int_{\tau=0}^{\infty} \exp\left(-r \times (s + \tau)\right) f(\tau; \lambda) d\tau}_{D} \right)$$

- Tradeoff:
  - Targeting price to arriving consumer raises static profits (component A)
  - But deviating from optimal uniform price reduces profits later arrivals (components B & C)

Demand Estimation: Overview

Estimate individual-level demand parameters in context of Netflix

- Closely follows Shiller (2020)
  1. Estimate probability each consumer subscribes based on web-browsing data
  2. Infer individual preference parameters via GMM, by matching
     - Individual purchase probabilities (from step 1) w. model predictions
     - Observed and predicted aggregate share selecting each tier
     - Observed price w. model-implied optimal price
  3. Then infer profit functions from individual consumers $\pi\left(P(\theta), \psi = \frac{\nu_i}{|\alpha|}\right)$

Counterfactual Simulations: Setup

- Approximate value functions via value function iteration, given:
  - Estimated static individual-level profit functions: $\pi(P, \psi)$
  - Estimated distribution of types: $g(\psi)$
  - Assumed consumer arrival rate: λ
  - Interest rate (per period s) = $0.1/365$

- Calculate policy function:

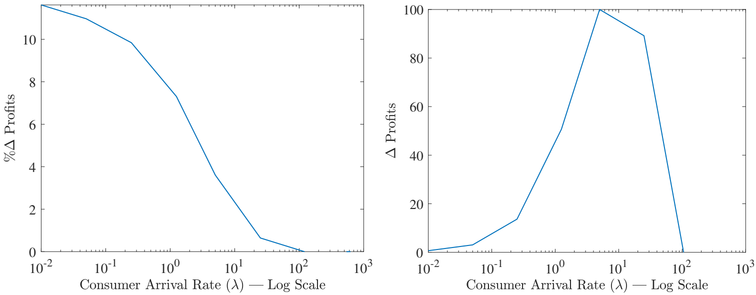
$$P'(P, \psi) = \arg\max_{P'} \begin{pmatrix} 1(P' = P) W^{P'=P}(P, \psi) \\ +1(P' \neq P) W^{P' \neq P}(P', \psi) \end{pmatrix}$$

- Simulate prices and profits for long randomly-drawn path of consumer arrivals

- Repeat for array of different arrival rates (λ)

Profit Gain from OSTP (vs. Uniform Pricing)

Figure: Counterfactual Profit Gain v. Consumer Arrival Rate



(a) Percent Change

(b) Absolute Change

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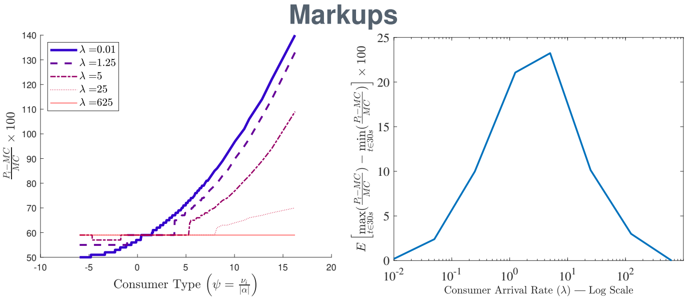
Markup Ranges

Figure: Simulated Pricing Patterns



(a) Across Consumers

(b) Range over Time

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Methods for Testing

- Recall: Direct methods used to find personalized pricing will fail to find OSTP
- A subtle but auspicious alternative approach:
  - Examine whether expected pricing patterns arise where OSTP feasible and absent elsewhere
    - Inverted U-shaped pattern between popularity and price ranges over period

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Two Contexts

- Amazon
  - Has detailed consumer browsing data (on their platform)
  - Can change prices in real time as consumers arrive
  - Accounts for 40% of <u>all</u> U.S. e-commerce
- Brick-and-mortar grocery stores
  - Do not observe consumer's type before price seen
  - Do not know which products a consumer will see
    - Cumbersome to change prices of all products for new arrival
  - Do extensively use other forms of dynamic price discrimination

Amazon

- For random set of products, use Keepa's API to collect:
  - Price histories (first-party, i.e. Amazon itself)
  - Lagged sales-rank histories
  - Static product features
- Construct monthly-level panel data with price ranges and average lagged sales-rank (proxy for inherent popularity)
- Then regress:

$$\max_{t \in m}(P_{jt}) - \min_{t \in m}(P_{jt}) = a + \sum_{\gamma} \kappa_{\gamma} 1(Sales\ Rank_{j,m-1} \in Range\ \gamma) + \epsilon_{jm},$$

Amazon Pricing Patterns

	The dependent variable is monthly price range: $\left(\max_{t\in m}(P_{jt}) - \min_{t\in m}(P_{jt})\right)$		
	Entire sample		
	(1)	(2)	(3)
Lagged sales rank:			
1(Btw. 100 & 500)	0.449	0.271	0.328
	(0.336)	(0.243)	(0.247)
1(Btw. 500 & 1000)	1.999***	1.151***	1.138***
	(0.358)	(0.256)	(0.259)
1(Btw. 1000 & 2000)	1.278***	0.683***	0.618**
	(0.357)	(0.256)	(0.260)
1(Btw. 2000 & 5000)	0.517	0.0675	0.184
	(0.349)	(0.250)	(0.255)
1(Btw. 5000 & 10,000)	0.387	-0.274	-0.112
	(0.348)	(0.249)	(0.255)
1(Exceeding 10,000)	-0.118	-1.229***	-0.382
	(0.343)	(0.243)	(0.260)
Fixed effects:			
Category	Y	Y	Y
List price decile		Y	Y
Date			Y
Observations	274,953	274,953	274,953
Adjusted R^2	0.041	0.131	0.143

Standards errors, clustered by product, are reported in parentheses.
*** p$<$0.01, ** p$<$0.05, * p$<$0.1.

Detailed Timing (Amazon)

	The dependent variable is monthly price range: $\left(\max_{t\in m}(P_{jt}) - \min_{t\in m}(P_{jt})\right)$		
	2015-2016	2017-2018	2019-2020
	(4)	(5)	(6)
Lagged sales rank:			
1(Btw. 100 & 500)	-3.201	0.716**	0.484***
	(2.430)	(0.332)	(0.185)
1(Btw. 500 & 1000)	-3.499	0.0938	1.363***
	(2.434)	(0.363)	(0.206)
1(Btw. 1000 & 2000)	-3.892	0.541	1.010***
	(2.403)	(0.389)	(0.224)
1(Btw. 2000 & 5000)	-4.601*	0.191	0.494**
	(2.414)	(0.374)	(0.207)
1(Btw. 5000 & 10,000)	-4.854**	0.123	-0.116
	(2.408)	(0.380)	(0.193)
1(Exceeding 10,000)	-5.111**	-0.569*	0.118
	(2.469)	(0.322)	(0.211)
Fixed effects:			
Category	Y	Y	Y
List price decile	Y	Y	Y
Date	Y	Y	Y
Observations	40,266	74,126	123,113
Adjusted R^2	0.163	0.180	0.131

Standards errors, clustered by product, are reported in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Grocery Stores

- Kilt's Nielsen Retail Scanner Dataset
  - Restrict to "dry food" at Rhode Island grocery stores in 2019
  - Collapse data to monthly level yielding, for each product-store-month combination:
    - Price range (monthly)
    - Unit sales
- Use first two months to calculate popularity measure (unit sales)
- Use remaining months regress price range on popularity measure

Grocery Store Results

	The dependent variable is monthly price range: $\max_{t\in m}(P_{jt}) - \min_{t\in m}(P_{jt})$			
	(1)	(2)	(3)	(4)
Jan-Feb unit sales (at single store):				
Sales $<$ 10	-0.527***	-0.496***	-0.497***	-0.524***
	(0.0377)	(0.0352)	(0.0352)	(0.0352)
10 $\leq$ sales $<$ 25	-0.361***	-0.348***	-0.348***	-0.370***
	(0.0375)	(0.0352)	(0.0352)	(0.0350)
25 $\leq$ sales $<$ 50	-0.253***	-0.249***	-0.249***	-0.266***
	(0.0375)	(0.0352)	(0.0352)	(0.0349)
50 $\leq$ sales $<$ 75	-0.203***	-0.200***	-0.200***	-0.213***
	(0.0376)	(0.0352)	(0.0352)	(0.0349)
75 $\leq$ sales $<$ 100	-0.180***	-0.178***	-0.178***	-0.189***
	(0.0376)	(0.0353)	(0.0353)	(0.0349)
100 $\leq$ sales $<$ 150	-0.158***	-0.158***	-0.158***	-0.167***
	(0.0376)	(0.0353)	(0.0353)	(0.0348)
150 $\leq$ sales $<$ 200	-0.136***	-0.140***	-0.140***	-0.144***
	(0.0374)	(0.0352)	(0.0352)	(0.0347)
200 $\leq$ sales $<$ 250	-0.117***	-0.121***	-0.121***	-0.122***
	(0.0375)	(0.0353)	(0.0353)	(0.0347)
250 $\leq$ sales $<$ 500	-0.105***	-0.108***	-0.108***	-0.106***
	(0.0347)	(0.0325)	(0.0325)	(0.0320)
Fixed effects:				
Jan-Feb price decile	Y	Y	Y	Y
Category		Y	Y	Y
Month			Y	Y
Store				Y
Observations	5,830,148	5,830,148	5,830,148	5,830,148
Adjusted R^2	0.079	0.116	0.118	0.122

Standards errors, clustered by product, are reported in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Taking Stock

- Pricing patterns expected with OSTP appear at Amazon
- But only recently
- Same patterns not present at grocery stores unable to implement OSTP

Conclusions

- Big data enables profitable personalized pricing
- But, firms concerned about backlash
- New sophisticated pricing hides true intentions
- Evidence used in practice
- Not surprising!
  - If firms can raise profits through targeted pricing while keeping consumers, regulators, and competitors unaware, why would they not?

Thank you!

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