Optimized Sticky Targeted Pricing*

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Abstract

Emerging tracking data allow precise predictions of individuals' reservation values. However, firms are reluctant to conspicuously implement personalized pricing because of concerns about consumer reprisals. This paper examines a concealed form of personalized pricing. Specifically, firms sometimes tailor the "posted price" for the arriving consumer but privately commit to change price infrequently, making it nearly indistinguishable from traditional dynamic pricing. I find this strategy raises profits for medium and low popularity products. I then document the same pricing patterns at Amazon, suggesting it is already deployed and thus is a feature to include when modeling firm behavior in online markets.

*Disclaimer: Researcher(s) own analyses calculated (or derived) are based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1 Introduction

> "The scandal of asking too much and haggling over every sale is so great, and the vice is so common, so usual, so expectable, that there is but one way to avoid suspicion of it. That is to make prices inviolable without any exception, or thought of exception." (Wanamaker, 1883)[1]

Firms have always searched for ways to extract more surplus from consumers. One such strategy, personalized pricing, is quite old but has gained renewed attention as consumer tracking technologies have yielded large datasets with detailed information about individual consumers' habits and tastes. Such data have made personalized pricing more profitable, yielding profit gains of around 10% to 50% (Dong et al., 2009; Dube and Misra, 2017; Kehoe et al., 2018; Shiller, 2020; Shiller and Waldfogel, 2011; Zhang et al., 2014).

However, implementing personalized pricing too overtly risks severe backlash from consumers. Not surprisingly, firms perceived to personalize prices have reacted strongly to preempt consumer reprisals. Amazon, for example, called their pricing strategy a mistake and promised never again to simultaneously charge consumers different prices (Salkowski, 2000). The literature validates concerns of reprisals: personalized pricing is viewed as unfair (Campbell, 1999; Kahneman et al., 1986) and it reduces consumers' purchase intentions (Leibbrandt, 2020). Moreover, personalized pricing has increasingly been scrutinized by policy makers (Executive Office of the President, 2015), and a literature has developed with the stated intent of searching for its use (Cavallo, 2017; Hannak et al., 2014; Hupperich et al., 2018; Mikians et al., 2012; Iordanou et al., 2017).

Although firms are concerned about a possible backlash, they have not abandoned personalized pricing altogether.[2] Instead, firms have found better ways to reframe or discretely implement personalized pricing on online platforms. For example, finely targeted prices have been reframed as (effortless) customized coupons or discounts (Reimers and Shiller, 2019; Rossi et al., 1996; Shiller, 2020), which appear better tolerated by consumers.[3] Other firms have personalized rank-sorting algorithms, promoting more expensive items to less price-sensitive consumers (Hannak et al., 2014; Mikians et al., 2012). However, these methods are not as effective as hoped.

An alternative, and thus far understudied, strategy is to sometimes finely target prices to newly-arriving consumers, but refrain from changing prices too frequently. Such a strategy would be nearly indistinguishable from traditional dynamic pricing, which is common and tolerated by consumers.[4]

[1] An excerpt from the original advertisement is shown in Figure A2.

[2] Uniform pricing is still common at brick-and-mortar stores (DellaVigna and Gentzkow, 2019) but sophisticated pricing is increasingly used online (Aparicio et al., 2021).

[3] Firms also disguise use of third-degree price discrimination. See, for example, the "pink tax" (de Blasio and Menin, 2015).

[4] Traditional dynamic pricing arises, for example, from responses to changes in market conditions, such as

The basic premise is that the firm can observe the consumer's type before the webpage loads on the consumer's web browser. The firm can decide to raise the "posted price(s)"—not only to that consumer but to other consumers as well—at that exact moment. The price is designed to extract profits from the consumer that has just arrived. However, if the firm privately commits to keeping the new price for some length of time, making them sticky, then it would be difficult for consumers to verify that prices are finely targeted. I call this strategy *optimized sticky targeted pricing.*

Would this strategy effectively avoid resentment? Consider how consumers might try to verify personalized prices. A consumer offered a high price might check whether an acquaintance is offered the same price. They would: Any two consumers checking the price at the same moment would observe the same price because the firm has privately committed to maintaining the new price for some interval. It would be difficult, if not impossible, for consumers to distinguish whether price changes arise from personalized pricing or traditional dynamic pricing, which is widely accepted. The same reasoning implies that researchers searching for personalized pricing would fail to detect sticky personalized pricing.

This paper examines the impacts of optimized sticky targeted pricing. First, it presents a dynamic pricing model, which characterizes optimal price(s) to offer an arriving consumer, under the constraint that price remains locked for some interval following a change. The model shows firms face a tradeoff between exploiting the arriving consumer and profiting from later arrivals who must be charged the same price.

The model is then applied to one empirical context: Netflix. Individual-level demand is estimated as a function of an individual's web-browsing habits, using a method closely following Shiller (2020). The estimated distribution of individual-level demand functions is then used to apply optimized sticky targeted pricing to a simulated path of consumer arrivals. To investigate the impact of product popularity on this pricing strategy, optimal prices are simulated for various assumed rates of consumer arrivals.

Counterfactual simulations show that optimized sticky targeted pricing meaningfully raises profits for products of low and medium popularity. The change in profits in percentage terms is largest for unpopular products, the long tail of products. However, the absolute change in profits is largest for medium popularity products: the larger customer base outweighs the smaller increase in profits per person. For very popular products, the firm forgoes targeted pricing and instead uses uniform pricing; the profit gain from raising price to a high-value arriving consumer is offset by reduced profits from offering that same price during the sticky period to many later arrivals who, in expectation, have lower willingness to pay.

The model is then used to explore pricing patterns, yielding evidence suggesting that

aggregate demand shocks, competitor actions, and changes in inventory or costs, as well as from intertemporal (second-degree) price discrimination.

optimized sticky targeted pricing may currently be in use. The same relationships are found between prices and popularity in model simulations and for products sold directly by Amazon. However, the same patterns are not found for products sold by third parties who have far less data at their disposal to personalize prices, nor are they found at brick-and-mortar grocers, who lack the means to personalize prices to arriving consumers. Given its seemingly apparent use, understanding sticky personalized pricing may be needed to comprehend how concentrated online markets function.

Increasing use of inconspicuous but sophisticated pricing methods has large implications spanning the economics literature. For example, ignoring its use yields biased estimates of consumer demand (D'Haultfœuille et al., 2019) and misleading inflation measurements (Chevalier and Kashyap, 2019). Moreover, increasingly intense price discrimination has meaningful implications for consumer welfare (Bergemann et al., 2015) and the effects of competition on price levels (Thisse and Vives, 1988). These impacts, which extend beyond the direct effect on firm performance, should expand as use of sophisticated pricing grows.

The remainder of the paper is organized as follows. Section 2 describes the feasibility of sticky targeted pricing in online contexts. Section 3 introduces a model of optimized sticky targeted pricing, and Section 4 presents a model for estimating individual-level demand. Section 5 simulates counterfactual outcomes under optimized sticky targeted pricing and confirms similar patterns in empirical pricing data. A brief conclusion follows.

2 Background

This section first reviews how consumer devices and websites interact, and how the stages of this interaction enables firms to personalize prices inconspicuously. Then, it examines how a firm's private commitment to sticky pricing complicates others' attempts to discover its use of personalized pricing.

2.1 Feasibility of Personalized Pricing Online

The process of visiting a website involves two broad steps, depicted in appendix Figure A1. First, the client (e.g., a consumer's computer or phone) sends a request to the server to send packets (code and files) that comprise the requested website. The client's request includes information about the requester, including cookies and IP address.[5] Consumers can also be required to provide login credentials to access the requested domain.

Thus, before the server sends the client (consumer) the packets constituting the website, it already knows a lot about the consumer. The server knows the consumer's IP address,

[5]See `https://developer.mozilla.org/en-US/docs/Learn/Getting_started_with_the_web/How_the_Web_works`, and `https://developer.mozilla.org/en-US/docs/Web/HTTP/Cookies`

which reveals the consumer's location, allowing the server to infer local demographics such as average income and to respond to local demand shocks. The server retrieves cookies, which can reveal prior interactions on the client device and login information that reveals prior interactions with the same consumer on other devices. Gleaned information from login credentials includes browsing histories on the site and linked data from third parties (e.g., from Acxiom). Additionally, the server might access third-party cookies, revealing information about the consumer's activities at other websites. All of this information can then be used to create finely targeted prices.

2.2 Concealment

Consumers, regulators, researchers, and competing firms have been interested in determining whether firms are personalizing prices, conspicuously or not. This section explains the difficulties of searching for optimized sticky targeted pricing in practice.

One can search for traditional (non-sticky) personalized pricing by examining whether two individuals are offered different prices for the same product at the same point in time. It is more challenging to verify use of optimized sticky targeted pricing: If two consumers check the price at the same time, the price is the same.

Regulators, researchers, or competitors using fingerprint methods to mimic different consumer types would also infer that consumers are offered the same price unless they leave long time lags between checking prices for different spoofed consumers. Instead, researchers have typically checked prices offered to different spoofed consumers in rapid succession to limit noise from price fluctuations and distinguish it from traditional dynamic pricing. Of the studies searching for personalized pricing online (Cavallo, 2017; Hannak et al., 2014; Hupperich et al., 2018; Iordanou et al., 2017; Mikians et al., 2012), none explicitly stated that they incorporated long lags between requests from different spoofed consumers. Thus, sticky personalized pricing would effectively avoid detection, at least from methods that have previously been used to search for personalized pricing.

If one instead searches for sticky personalized pricing by comparing prices offered to several consumers at different points in time, it is no longer sufficient to show that the prices differed. One must distinguish whether those price differences are attributed to optimized sticky targeted pricing, or the host of other factors that are known to cause prices to change over time. One might try relating price differences to consumer traits that are perceived to be useful for personalized pricing (e.g., income). However, this method suffices only if one can identify and has access to the variables the firm is using to personalize prices. Often, the variables most useful for personalizing prices are not immediately obvious. For example, Shiller (2020) found that income income and other demographics revealed relatively little about a consumer's valuation for Netflix's products. Instead, it was use of websites that deliver products by mail (e.g., Amazon) that most strongly indicated high valuations for Netflix's products. Furthermore, if firms intend to evade detection, they may intentionally exclude obvious and widely available variables from their pricing algorithm.

It thus appears that intentionally making personalized pricing sticky would at least substantially complicate (and perhaps completely block) others' efforts to verify use of personalized pricing. If simultaneously effective at extracting surplus, it may be very enticing to online retailers.

3 A Model of Optimized Sticky Targeted Pricing

This section presents a model of optimized sticky targeted pricing. The model is later applied to an empirical context.

Myopic consumers arrive at the marketplace randomly over time.[6] Interarrival times are assumed to be independent and identically distributed, implying that consumer interarrival times follow the exponential distribution. It follows that the number of consumer arrivals during a specified interval follows the Poisson distribution. A signal ψ of the arriving consumer's type is revealed before the firm decides which price (P') to offer. ψ encapsulates all information that the firm has at its disposal to determine the relationship between the offered price and the expected static profits ($\pi(P', \psi_i)$) from the arriving consumer.

Following a price change, it is assumed that the firm privately commits to maintaining the same price for an interval of length s in order to conceal finely targeted pricing. For simplicity, time is measured in units of s. Hence, $s = 1$.

The firm's overall value function is specified before the newly-arriving consumer's type (ψ) is revealed, and only at points in time when two conditions are met: the firm is able to change price (the price commitment period has elapsed), and a new consumer arrives. This leads to irregular time intervals between firm decisions, depending on interarrival times and whether the firm recently changed price. Specifically, the value function equals:

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

where the state variable P denotes the price last offered by the firm, P' is the price offered to the newly arriving consumer of then-known type ψ, and $g(\psi)$ denotes the distribution of consumer types. $W^{P'=P}(P, \psi)$ and $W^{P' \neq P}(P', \psi)$ are choice-specific value functions, conditional on the firm's chosen price. Note that two are specified because the formula depends

[6] One can extend the model to account for momentum in the types of consumers arriving or to account for patterns in the times certain types of consumers tend to arrive, utilizing individual-level arrival data.

on whether the chosen price is the same as the last offered price.

If the firm does not change price, then the choice-specific value function equals:

$$W^{P'=P}(P,\psi) = \pi(P,\psi) + V(P)\int_{\tau=0}^{\infty} \exp(-r\tau) f(\tau;\lambda) d\tau, \tag{2}$$

where $\pi(P,\psi)$ is the expected static profits from the arriving consumer of then-known type ψ at offered price P, $V(P)$ is the value function specified in Equation 1, and the integral represents the expected extent of time discounting, given uncertainty in the length of time until the next consumer arrival epoch. Note that $\exp(-r\tau)$ is the continuous-time analogue to the discount factor, r is the interest rate, and τ is the interarrival time: time until the next consumer arrives. $f(\tau|\lambda)$ is the probability mass function for interarrival times, which follows the exponential distribution with arrival rate parameter λ.

If the offered price changes, the choice-specific value function instead equals:

$$\begin{aligned} W^{P'\neq P}(P',\psi) = \Bigg[& \overbrace{\pi(P',\psi)}^{\text{A}} + \overbrace{\left(\int_{\psi'} \pi(P',\psi') g(\psi') d\psi'\right)}^{\text{B}} \times \overbrace{\sum_{n=0}^{\infty} n\delta(n) h(n|s\lambda) dn}^{\text{C}} \\ & + \underbrace{V(P')\int_{\tau=0}^{\infty} \exp\left(-r \times (s+\tau)\right) f(\tau;\lambda) d\tau}_{D} \Bigg]. \end{aligned} \tag{3}$$

Component A represents expected static profits from the arriving consumer. Components B and C represent expected profits at price P' during the price-commitment period. Component B is the expected profits at price P' for a subsequent consumer, whose yet-to-be-revealed type is denoted by ψ'. Component C is the expectation of the product of the count of consumer arrivals (n) and the average time discounting per consumer ($\delta(n)$), given arrival-count mass function $h(n|s\lambda)$.[7] Component D represents the expected discounted value function after the price-commitment period ends. Note that $\exp\left(-r \times (s+\tau)\right)$ represents the time discounting for the next consumer for which the firm can offer a different price, occurring $s+\tau$ time later: s is price-commitment interval and τ is the random time between when the price-commitment interval ends and the next consumer arrives.

The policy function is similar to the value function in Equation 1: the main difference is that the arriving consumer's type is known. Specifically, the policy function equals:

$$P'(P,\psi) = \arg\max_{P'} \left(1(P'=P) W^{P'=P}(P,\psi) + 1(P'\neq P) W^{P'\neq P}(P',\psi) \right). \tag{4}$$

[7]Component C can be simulated to an arbitrarily level of precision.

3.1 Observations

Equation 3 shows that firms face a trade-off when changing price. By tailoring the "posted price" to the arriving consumer, the firm can usually raise profits earned from that consumer. But there is an implied cost. The firm must offer the same price to consumers that arrive shortly thereafter (if it intends to use optimized sticky targeted pricing), which may lower expected profits from these later arrivals.

For example, suppose a high-value consumer arrives, and the firm raises the posted price at that moment to exploit this captive consumer. Then it must offer the same high price—much higher than the optimal uniform price—to subsequent consumers arriving soon thereafter. The price that maximizes expected profits from later arriving consumers—whose type is not yet known—is the optimal uniform price. Hence, raising price to the high-value consumer in expectation lowers profits from later arrivals.

The importance of this observation depends on the rate of customer arrivals. If arrivals are infrequent, then the gains from exploiting the high-value consumer may outweigh any expected losses from later arrivals, who are expected to be few in number. But for popular products—with many expected customer arrivals during the fixed price period—exploiting a captive consumer substantially lowers expected profits from later arrivals. For the most popular products, firms would likely forgo the opportunity to use sticky targeted pricing, even if the static gains from tailoring the "posted" price to the arriving consumer are large.

There is a second reason why firms may forgo changing the posted price when a new customer arrives, relevant when the static gains from personalizing price to that consumer are small. Keeping price the same maintains the flexibility to freely change price when the next consumer arrives, even if the next consumer arrives shortly thereafter.

Finally, note that the policy function in Equation 4 implies that prices are path dependent: the price path depends on the order in which different types of consumers arrive. This path dependency can yield rich and seemingly random price paths like the ones often observed on online platforms.[8]

4 Individual-Level Demand Estimation

To apply the dynamic pricing model described in Section 3, one first needs estimates of both the distribution of consumer types $g(\psi)$ and of expected static (individual-level) profit functions $\pi(P, \psi)$. In this section, both are estimated in the context of Netflix, using data and methods closely following Shiller (2020).

[8] For examples of empirical price paths, see `https://camelcamelcamel.com/`.

4.1 Data

Data were obtained from the Wharton Research Data Service's (WRDS) 2006 ComScore dataset. The dataset contains demographics and browsing histories for a large representative sample ($\approx 60,000$) of computer users. I collapsed the data to a cross-section, yielding one observation per panelist.

The browsing data are used to form a set of variables that reveal consumers' habits and tastes: (1) the count of visits the user had to each of 4,600 websites during 2006, (2) total visits to all websites during 2006, and (3) the fraction of visits during select time periods and each day of the week.[9]

Additionally, Netflix subscription status is inferred. For a sample of panelists, the panelist's chosen subscription tier (1, 2, or 3 DVDs at a time) is observed directly.[10] For remaining panelists, browsing histories are used to impute whether the user subscribed to any tier of Netflix's services.[11] See Shiller (2020) for a detailed description of the dataset.

4.2 Individual-Level Demand Estimation

The estimation procedure includes demand-side and supply-side models. Typically, the supply-side model is used to estimate marginal costs. In this context, marginal costs are known a priori, based on information provided by a former employee in conjunction with financial reports.[12] The supply-side model is instead used to estimate consumers' mean price sensitivity, which is not identified by the demand-side model alone because Netflix did not change its prices during the observed period.

4.2.1 Demand

Consumers make a discrete choice, choosing the option providing the highest utility. The choices include the outside good and three tiered Netflix plans: a 1 DVD at-a-time plan for \$9.99, a 2 DVDs at-a-time plan for \$14.99, and a 3 DVDs at-a-time plan for \$17.99.[13] The conditional indirect utility consumer i receives from tier j of Netflix's services is:

$$u_{ij} = \alpha P_j + \nu_i + \delta_j + \epsilon_{ij} = \bar{u}_{ij} + \epsilon_{ij}, \tag{5}$$

[9] Visits to other movie rental chains were excluded, as were visits to pornographic sites and sites known to host malware.

[10] Netflix did not offer a streaming service during the observed period.

[11] It is assumed that a user subscribed if the user averaged more than 2 subpage visits per visit to the Netflix domain. A non-subscriber would be unlikely to do so, because a non-subscriber is unable to log in to view subpages available only to subscribers.

[12] See Shiller (2020) for details

[13] A fourth tier, a 4 DVDs at a time plan, was offered but rarely selected. Consumers of the 4 DVDs plan were assigned to the 3 DVDs plan in estimation.

where P_j denotes tier j's price, and α and $\nu_i + \delta_j$ denote the individual's price sensitivity and intrinsic valuation for product tier j, respectively. It is assumed that $\delta_1 = 0$ because it is not separately identified from ν_i. The error term ϵ_{ij} is assumed to follow the type 1 extreme value distribution.

The probability a given consumer i selects product j equals:

$$s_{ij}\left(\nu_i, \alpha, \delta, P\right) = \frac{\exp\left(\alpha P_j + \nu_i + \delta_j\right)}{1 + \sum_{k \in J} \exp\left(\alpha P_k + \nu_i + \delta_k\right)}. \tag{6}$$

The probability consumer i chooses any inside tier of service, as opposed to the outside good, equals:

$$s_{ij \neq 0}\left(\nu_i, \alpha, \delta, P\right) = 1 - s_{i0}\left(\nu_i, \alpha, \delta, P\right) = 1 - \frac{1}{1 + \sum_{k \in J} \exp\left(\alpha P_k + \nu_i + \delta_k\right)}. \tag{7}$$

The demand model is used to construct two sets of moment conditions: (1) ex-ante estimates of subscription probabilities less the multinomial logit model predictions: $\left(\hat{s}_{ij \neq 0}\left(X_i\right) - s_{ij \neq 0}\left(\nu_i, \alpha, \delta, P\right)\right)$, and (2) the aggregate share of consumers choosing each inside good less the multinomial logit model's prediction: $\left(\hat{s}_j - s_j, \forall j \text{ where } s_j = \int_\nu s_{ij}\left(\nu, \alpha, \delta, P\right) f\left(\nu\right) d\nu\right)$.

4.2.2 Supply

The formula for the firm's profit is:

$$\pi = \sum_{j \in J} \left(P_j(\theta) - c_j\right) M s_j - \Gamma = \sum_{j \in J} \theta c_j M s_j - \Gamma, \tag{8}$$

where c_j is the marginal cost of tier j, θ is a markup parameter, $P_j(\theta) = (1 + \theta) c_j$ is the price of tier j, s_j is the aggregate share of consumer observed selecting tier j, M is the market size, and Γ denotes fixed cost. Note the fraction markup over cost is the same for all tiers j. This assumption follows a conversation with a former Vice President of Marketing at Netflix, who indicated that this was approximately true.

The corresponding first-order condition is:

$$\frac{d\pi}{d\theta} = \sum_{j \in J} c_j \left(s_j + \theta \frac{ds_j}{d\theta}\right) = 0. \tag{9}$$

This first-order condition comprises the final moment condition.

4.2.3 Objective Function and Identification

Consumer preference parameters $(\nu_i, \alpha, \delta_j)$ are estimated by minimizing an objective function derived from the moments from the demand-side and supply-side models:

$$\min_{\alpha,\delta_1,..,\delta_J,\nu_1,...,\nu_N} \left(\begin{array}{l} \sum_{i=1}^{N} \left(\hat{s}_{ij\neq 0}(X_i) - s_{ij\neq 0}(\nu_i, \alpha, \delta, P)\right)^2 \\ + \sum_{j\in J} \left(\hat{s}_j - \int_\nu s_{ij}\left(\nu, \alpha, \delta, P(\theta)\right) f\left(\nu\right) d\nu\right)^2 \\ + \left(\sum_{j\in J} c_j \left(s_j + \theta \frac{ds_j}{d\theta}\right)\right)^2 \end{array} \right). \tag{10}$$

The first component is the squared difference between the ex-ante probability that each consumer subscribes to Netflix and the corresponding multinomial logit model's prediction, subsequently summed across consumers. This first set of moments identifies ν_i: it is apparent form Equation 7 that a consumer i's probability of selecting the inside good $(s_{ij\neq 0}(\nu_i, \alpha, \delta, P))$ monotonically rises with ν_i. The second set of moment conditions is the squared difference between the aggregate share known to choose each tier and the corresponding model prediction. It identifies δ_j: the implied share choosing tier j $\left(\int_\nu s_{ij}\left(\nu, \alpha, \delta, P(\theta)\right) f\left(\nu\right) d\nu\right)$ rises monotonically with δ_j. The last moment condition is the firm's first-order condition, from the supply-side model. As is explained next, it identifies the mean price sensitivity α.[14]

Note that there are four sets of terms in the last moment condition (from Equation 9 of the supply-side model): θ, c_j, s_j, and $\frac{ds_j}{d\theta}$. Three of these four are fixed: It is assumed that θ, c_j, and s_j are known ex-ante. The markup θ is estimated from annual financial reports: $\theta = 0.59$.[15] Given the prices of the three tiers [9.99, 14.99, 17.99], this markup implies marginal costs are \$6.28, \$9.43, and \$11.32, respectively. Finally, the aggregate share choosing each tier (s_j) is inferred from the data.[16]

The only remaining terms in last moment condition are $\frac{ds_j}{d\theta}, \forall j$. They depend on the parameters of the demand model in Section 4.2.1: in particular on price sensitivity α. Note that $\frac{ds_j}{d\theta}$ is monotonic in α, implying that α is identified.[17]

Finally, note that as the scale of α, ν_i, and δ_j jointly increase, the error draws ϵ become less likely to impact the consumer's choice. Hence, the scale of α, ν_i, and δ_j reflects the

[14] Note that the model is exactly identified.

[15] It is assumed that marginal cost is constant and thus equal to average variable cost. According to Netflix's 2016 financial statement, the costs of subscription and fulfillment were 62.9% of revenues, implying a markup θ of $\frac{1}{0.629} - 1 = 0.59$. See Netflix (2006) for further details.

[16] Tier choice is observed for a sample of panelists.

[17] $s_{ij}(\nu_i, \alpha, \delta, P(\theta)) = \frac{exp(\alpha(1+\theta)c_j+\nu_i+\delta_j)}{1+\sum_{k\in J} exp(\alpha(1+\theta)c_k+\nu_i+\delta_k)}$

Hence,

$\frac{ds_{ij}(\nu_i,\alpha,\delta,P(\theta))}{d\theta} = \frac{\alpha c_j exp(\alpha(1+\theta)c_j+\nu_i+\delta_j)}{1+\sum_{k\in J} exp(\alpha(1+\theta)c_k+\nu_i+\delta_k)} - \frac{exp(\alpha(1+\theta)c_j+\nu_i+\delta_j)}{\left(1+\sum_{k\in J} exp(\alpha(1+\theta)c_k+\nu_i+\delta_k)\right)^2} \left(\sum_{k\in J} \alpha c_k exp\left(\alpha(1+\theta)c_k + \nu_i + \delta_k\right)\right)$.

$\longrightarrow \frac{ds_{ij}(\nu_i,\alpha,\delta,P(\theta))}{d\theta} = \alpha c_j s_{ij}(\nu_i, \alpha, \delta, P(\theta)) - s_{ij}(\nu_i, \alpha, \delta, P(\theta)) \left(\sum_{k\in J} \alpha c_k s_{ik}(\nu_i, \alpha, \delta, P(\theta))\right)$.

$\longrightarrow \frac{ds_{ij}(\nu_i,\alpha,\delta,P(\theta))}{d\theta} = \alpha s_{ij}(\nu_i, \alpha, \delta, P(\theta)) \left(c_j - \sum_{k\in J} c_k s_{ik}(\nu_i, \alpha, \delta, P(\theta))\right)$.

Because $s_{ij}(\nu_i, \alpha, \delta, P(\theta))$ is pinned down by the first two components of the objective function, this then implies that $\frac{ds_{ij}(\nu_i,\alpha,\delta,P(\theta))}{d\theta}$ is a monotonic function of α.

precision of estimated demand. Thus, when ex-ante estimates of individual prescription probabilities ($\hat{s}_{ij\neq 0}(X_i)$) are more precise (i.e., individual subscription probabilities are close to either 0 or to 1) then this will be reflected in the model by larger estimates of α, ν_i, and δ_j.

4.2.4 Ex-ante Estimates of Individual Subscription Probabilities

The first component of objective function is the difference between ex-ante estimates ($\hat{s}_{ij\neq 0}(X_i)$) and model predictions ($s_{ij\neq 0}(\nu_i, \alpha, \delta, P)$) of individual subscription probabilities. Hence, before estimating the model, one must first estimate the probability each consumer subscribes from the web-browsing data ($\hat{s}_{ij\neq 0}(X_i)$).

The probability that an individual subscribes to any one of Netflix's tiers is estimated using a LASSO-penalized logit model. Specifically, the penalized likelihood function equals:

$$L = \sum_i \ln \left(s_{ij\neq 0}(X_i) \times I\left(buy\right) + \left(1 - s_{ij\neq 0}(X_i)\right) \times \left(1 - I(buy)\right)\right) - \omega \sum_{k=1}^{K} |\beta_k|, \tag{11}$$

where $I(buy)$ is an indicator for subscription, and $s_{ij\neq 0}(X_i)$ denotes the predicted probability of subscribing:

$$s_{ij\neq 0}(X_i) = \frac{\exp(\phi + X_i\beta)}{1 + \exp(\phi + X_i\beta)}. \tag{12}$$

Parameters to estimate include ϕ, β, and the Lasso penalty parameter ω.

The model of individual subscription probabilities is estimated on a set of 4,633 variables, including the browsing data variables and available demographics, each of which was normalized beforehand. Note that variables that had the largest impact on predicted subscription probabilities (largest β) were variables indicating the number of visits to individual websites. Hence, browsing data seem to reveal far more about tastes than basic demographics reveal. See Shiller (2020) for a detailed analysis of the importance of different variables.

4.3 Estimation Results

The next step is to calculate expected profits from each individual type $\psi = \nu_i/|\alpha|$ as a function of individualized prices (markup θ):

$$\pi\left(P(\theta), \psi = \frac{\nu_i}{|\alpha|}\right) = \sum_j s_{ij}(\nu_i, \alpha, \delta, P_j(\theta)) \times (P_j(\theta) - c_j) = \sum_j s_{ij}(\nu_i, \alpha, \delta, (1+\theta)c_j) \times \theta c_j. \tag{13}$$

These static individual-level profit functions, as a function of individualized prices (markup θ), are key inputs needed for simulating the dynamic pricing model described in Section 3.

Before shifting focus to the dynamic pricing model, some results from static personalized pricing are presented as a benchmark. Figure 1 shows the expected profits from each consumer type, both when the firm personalizes the markup for each consumer, and when the firm offers the same prices to all consumers. Note that in this context, the gains from price personalization are large for captive consumers (with large $\psi = \nu_i / \ |\alpha|$), but for low valuation types the gains are small enough that they are not visually apparent in Figure 1a. The density of different consumer types, $g(\psi)$, is shown in Figure 1b. Overall, personalizing the markup raises profits by 12.99% relative to status-quo uniform pricing, if ignoring impacts of personalized pricing on consumer backlash.[18]

5 Counterfactuals

This section simulates counterfactual outcomes under optimized sticky targeted pricing based on estimates of demand functions for individual consumer types $\pi(P, \psi)$ and the distribution of types $g(\psi)$ from Section 4. To explore the importance of product popularity, an array of different consumer arrival rates (λ) are considered: [0.01, 0.05, 0.25, 1.25, 5, 25, 125, 625].

Counterfactual simulations proceed in several steps. For each assumed consumer arrival rate (λ), the firm's value functions presented in Section 3 are approximated using value function iteration, by iterating back and forth between updating the Bellman equations in Equations 2 and 3 and the Bellman equation in Equation 1. The value function is then used to determine the corresponding policy function. Outcomes under optimized sticky targeted pricing are then simulated from the policy function and a long randomly drawn path of consumer arrivals.

In these simulations, it is assumed that the per-period (length $= s$) interest rate (r) equals 0.00027397.[19] If s equals one day, then this would approximately correspond to a

[18] The percent profit increase, 12.99%, incorporates Netflix's fixed cost. Assume variable costs equal the "cost of revenues" from Netflix's 2006 Annual Report, about \$627 million. "Operating expenses" are assumed to be fixed costs, about \$305 million. Revenues were \$997 million. Thus, variable profits were \$370 million and total profits were \$65 million. Multiplying the percent change in variable profits by 370/65 yields the percent change in total profits.

[19] The value function converges slowly at such low assumed interest rates, which may pose problems in models with many state variables.

10% yearly interest rate.

5.1 Comparative Statics

The profit firms gain from optimized sticky targeted pricing is perhaps of greatest interest. The discounted variable profits from optimized sticky targeted pricing, assuming the prior price equaled the optimal uniform price $\hat{P}$, equals the value function: $V(\hat{P})$. Discounted variable profit from uniform pricing equals $\frac{\lambda}{r}\int_{\psi}\pi(\hat{P},\psi)g(\psi)d\psi$.

Figure 2 compares discounted profits from optimized sticky targeted pricing, relative to uniform pricing, for an array of different consumer arrival rates. Note that profit gains expressed in percentage terms are largest when the consumer arrival rate is small (i.e., for relatively unpopular products). However, the total change in profits has a more nuanced relationship with the consumer arrival rate. Initially, as the consumer arrival rate increases, the gains from having more consumers outweighs the impact of earning less per consumer, gains from optimized sticky targeted pricing initially rise with the arrival rate. However, eventually the latter effect dominates. In the extreme, for very large consumer arrival rates, the firm forgoes the opportunity to personalize prices altogether: personalizing prices for one consumer locks in a suboptimal price for the many consumers arriving soon thereafter (during which price is locked). Hence, one should expect firms to use and gain from optimized sticky targeted pricing for products with lower and medium popularity.

A similarly nuanced relationship is apparent for the range of prices offered. The range of prices offered across different consumer types is largest when consumers arrive infrequently (see Figure 3a). However, the simulated range of prices over time—rather than across different consumer types—is more nuanced because of two competing forces. As just shown, the range of prices offered across consumers is smaller when consumers arrive frequently. However, frequent arrivals imply more consumers to set separate prices to during a specified length of time: more price draws. Initially, the latter effect dominates, and range of prices offered over a given time interval increases in the rate of consumer arrivals. However, for very high consumer arrival rates, the firm forgoes changing prices altogether. Therefore, the relationship between the price range over an interval and the consumer arrival rate has an inverted U-shape (see Figure 3b). Note, this inverted U-shaped relationship will be particularly useful when searching for use of optimized sticky targeted pricing.

Finally, the relationship between consumer arrival rates and the frequency of price changes is depicted in Figures 3c and 3d. Figure 3c shows the firm is less likely to change the price for a newly arriving consumer when consumers arrive frequently; the relationship is monotonic. However, for reasons similar to those stated above, the simulated frequency of price changes over time—rather than conditional on a consumer arrival—changes non-monotonically with the consumer arrival rate (see Figure 3d). .

5.2 Evidence of Optimized Sticky Targeted Pricing

Section 2.2 explained why direct (and existing) methods are likely to fail to discover use of sticky personalized pricing. This section uses an alternate method, searching for use of sticky personalized pricing by comparing pricing patterns implied by the model to empirically observed pricing patterns. With optimized sticky targeted pricing, the relationship between the range of prices offered over an interval and the consumer arrival rate has an inverted U-shape, as shown in Figure 3b. One can thus examine whether this pattern is apparent in contexts where sticky personalized pricing is feasible, and absent in other contexts.

5.2.1 Amazon's Pricing Patterns

Amazon provides a convenient context for searching for the inverted U-shaped pattern between price ranges and consumer arrivals rates, which is expected when optimized sticky targeted pricing is used. Amazon has both the tracking capabilities and the ability to update prices in real time, suggesting that it is fully capable of implementing this pricing strategy. Furthermore, price histories for products on Amazon's platform are easily acquired.

To investigate, Amazon price and sales-rank histories for a random set of products were collected from Keepa's API. Data were collapsed to the monthly level, yielding average sales ranks and ranges of prices offered over the month, defined as the maximum minus the minimum price.[20] Price ranges are then regressed on indicators for various lagged-sales rank intervals. Specifically:

$$\max(P_{it}) - \min(P_{it}) = a + \sum_{\ell} \kappa_\ell 1(\textit{Sales Rank}_{i,t-1} \in \textit{Range } \ell) + \epsilon_{it}, \tag{14}$$

where $\max(P_{it}) - \min(P_{it})$ is the range of prices offered in month t, and $1(\textit{Sales Rank}_{i,t-1} \in \textit{Range } \ell)$ indicates the lagged sales rank falls within the range denoted by ℓ. The results are reported in Table 1.

Patterns for Amazon prices in Columns (1-3) match the simulated price patterns for optimized sticky targeted pricing. Relative to the omitted category—lagged ranks better than 100—slightly less popular products have significantly larger price ranges over a month. Much less popular products, however, have smaller price ranges. This inverted U-shaped pattern matches the pattern from simulations of optimized sticky targeted pricing, depicted in Figure 3b. Moreover, it persists after controlling for product category, list price, and date. Note, in Columns (4-6), that prices for third-party sellers on Amazon—who presumably lack Amazon's expertise and proprietary consumer data to personalize prices—do not exhibit this

[20]The range of prices, rather than the standard deviation, is used because the latter may be influenced by frequent small price adjustments. Small price changes may be frequent for popular products, because there is more information about changing market conditions and greater gains to adjusting prices to such changes, reasons unrelated to sticky targeted pricing.

inverted U-shaped pattern.[21]

The next section provides further evidence that the inverted U-shaped pricing pattern is particular to contexts where retailers have the means to implement optimized sticky personalized pricing. Specifically, it shows the pattern is absent in another context (brick-and-mortar grocers) where optimized sticky personalized pricing would be challenging to implement but other forms of dynamic pricing are common.

5.2.2 Brick-and-Mortar Grocers' Pricing Patterns

This section explore whether the inverted U-shaped pattern between popularity and product price ranges occurs in a context where dynamic price changes arise for traditional reasons. Data on weekly prices and unit sales at brick-and-mortar grocery stores were acquired from Kilt's Nielsen scanner dataset. For computational simplicity, data are restricted to "dry food" (a broad category) in 2019 at stores located in Rhode Island.[22] The restricted data include 792,162 product/store pairs. As with the Amazon price data, the grocery scanner data are collapsed to the monthly level. The collapsed data contain price ranges, average prices, and unit sales separately for each combination of product, store, and month.

The panel dataset is divided into two time periods: (i) January and February 2019, and (ii) the remainder of 2019. The latter set, months March through December, are used for analyses. Data from the first two months are used to construct pre-period popularity, measured by store-level unit sales of the product, and typical price, measured by the average price. The distribution of Jan-Feb unit sales across product/store pairs is highly skewed. The 10th percentile of Jan-Feb unit sales is 2, the median is 16, the 75th percentile is 41, and the 99th percentile is 371.

Price ranges in months March through December are then regressed on indicators for pre-period unit-sale ranges. The specification is analogous to Equation 14, except that lagged-sales ranks are replaced with pre-period unit-sale ranges. The results are shown in Table 2. Note that price fluctuation ranges are typically lower for less popular products, compared to the omitted category with pre-period sales exceeding 500 ($<1\%$ of product/store pairs). Clearly, there is a monotonic relationship—not an inverted U-shaped relationship—between price range and popularity.

Thus, out of the three contexts considered (Amazon first party, Amazon third-party sellers, and grocery stores), the inverted U-shaped relationship between popularity and price ranges arises only in the case where the seller could plausibly implement optimized sticky targeted pricing. These pricing patterns are strong suggestive evidence that optimized sticky

[21]In Appendix Section A.2, we show that another pattern, between price change frequencies and popularity, is not found at Amazon. However, quite plausible explanations suggest such patterns for price change frequencies, even in the presence of sticky targeted pricing.

[22]The dry food includes many common grocery items, (e.g., baby food, baking mixes, beverages, candy, cereal, coffee, condiments, crackers, pet food, prepared foods, snacks, soup, and canned vegetables).

personalized pricing is currently used in practice. However, optimized sticky targeted pricing is difficult to conclusively verify: Evading detection is the primary motive for optimized sticky targeted pricing.

6 Conclusion

This paper describes optimized sticky targeted pricing, a method firms may use, and appear to be using already, to implement fine-grained pricing without generating consumer resentment. The findings show that it raises profits for lower and medium popularity products, and pricing patterns at Amazon are consistent with its use.

These findings are novel, to my knowledge, but perhaps should not be surprising. Recent anecdotes suggest a trend towards more sophisticated pricing strategies that simultaneously allow finer targeting while assuaging consumer concerns about unfairness. If firms can raise profits via more sophisticated pricing methods, without their methods being discovered, why would they not?

There is ample room for future work. Currently, most economic models assume that firms are not targeting prices at a fine level. However, as digitization has provided firms with the means to implement more sophisticated and better concealed pricing strategies, the impacts of omitting such pricing from economic models has grown. For example, sophisticated pricing strategies have large implications for the consumer price index (Chevalier and Kashyap, 2019), consumer welfare (Bergemann et al., 2015), the effects of competition (Kehoe et al., 2018; Thisse and Vives, 1988), and bias in empirical models of consumer demand (D'Haultfœuille et al., 2019). Continuing to overlook use of sophisticated pricing techniques may soon become (or may already be) untenable.

References

Aparicio, D., Z. Metzman, and R. Rigobon (2021). The pricing strategies of online grocery retailers. *Working Paper*.

Bergemann, D., B. Brooks, and S. Morris (2015). The limits of price discrimination. *The American Economic Review 105*(3), 921–957.

Campbell, M. C. (1999). Perceptions of price unfairness: antecedents and consequences. *Journal of marketing research 36*(2), 187–199.

Cavallo, A. (2017). Are online and offline prices similar? evidence from large multi-channel retailers. *American Economic Review 107*(1), 283–303.

Chevalier, J. A. and A. K. Kashyap (2019). Best prices: Price discrimination and consumer substitution. *American Economic Journal: Economic Policy 11*(1), 126–59.

de Blasio, B. and J. Menin (2015). From cradle to cane: The cost of being a female customer. *New York City Department of Consumer Affairs*.

DellaVigna, S. and M. Gentzkow (2019). Uniform pricing in us retail chains. *The Quarterly Journal of Economics 134*(4), 2011–2084.

Dong, X., P. Manchanda, and P. K. Chintagunta (2009). Quantifying the benefits of individual-level targeting in the presence of firm strategic behavior. *Journal of Marketing Research 46*(2), 207–221.

Dube, J.-P. and S. Misra (2017). Scalable price targeting. *Working Paper*.

D'Haultfœuille, X., I. Durrmeyer, and P. Février (2019). Automobile prices in market equilibrium with unobserved price discrimination. *The Review of Economic Studies 86*(5), 1973–1998.

Executive Office of the President (2015). Big data and differential pricing. *Washington DC*.

Hannak, A., G. Soeller, D. Lazer, A. Mislove, and C. Wilson (2014). Measuring price discrimination and steering on e-commerce web sites. In *Proceedings of the 2014 Conference on Internet Measurement Conference*, pp. 305–318. ACM.

Hupperich, T., D. Tatang, N. Wilkop, and T. Holz (2018). An empirical study on online price differentiation. In *Proceedings of the Eighth ACM Conference on Data and Application Security and Privacy*, pp. 76–83.

Iordanou, C., C. Soriente, M. Sirivianos, and N. Laoutaris (2017). Who is fiddling with prices? building and deploying a watchdog service for e-commerce. In *Proceedings of the Conference of the ACM Special Interest Group on Data Communication*, pp. 376–389.

Kahneman, D., J. L. Knetsch, and R. Thaler (1986). Fairness as a constraint on profit seeking: Entitlements in the market. *The American Economic Review 76*(4), 728–741.

Kehoe, P. J., B. J. Larsen, and E. Pastorino (2018). Dynamic competition in the era of big data. Technical report, Working paper, Stanford University and Federal Reserve Bank of Minneapolis.

Leibbrandt, A. (2020). Behavioral constraints on price discrimination: Experimental evidence on pricing and customer antagonism. *European Economic Review 121*, 103303.

Mikians, J., L. Gyarmati, V. Erramilli, and N. Laoutaris (2012). Detecting price and search discrimination on the internet. *Proceedings of the 11th ACM Workshop on Hot Topics in Networks*, 79–84.

Netflix (2006). Netflix annual report. *http://ir.netflix.com/annuals.cfm*.

Reimers, I. and B. R. Shiller (2019). The impacts of telematics on competition and consumer behavior in insurance. *The Journal of Law and Economics 62*(4), 613–632.

Rossi, P. E., R. E. McCulloch, and G. M. Allenby (1996). The value of purchase history data in target marketing. *Marketing Science 15*(4), 321–340.

Salkowski, J. (2000). Amazon.com's variable pricing draws ire. *Chicago Tribune*.

Shiller, B. and J. Waldfogel (2011). Music for a song: an empirical look at uniform pricing and its alternatives. *The Journal of Industrial Economics 59*(4), 630–660.

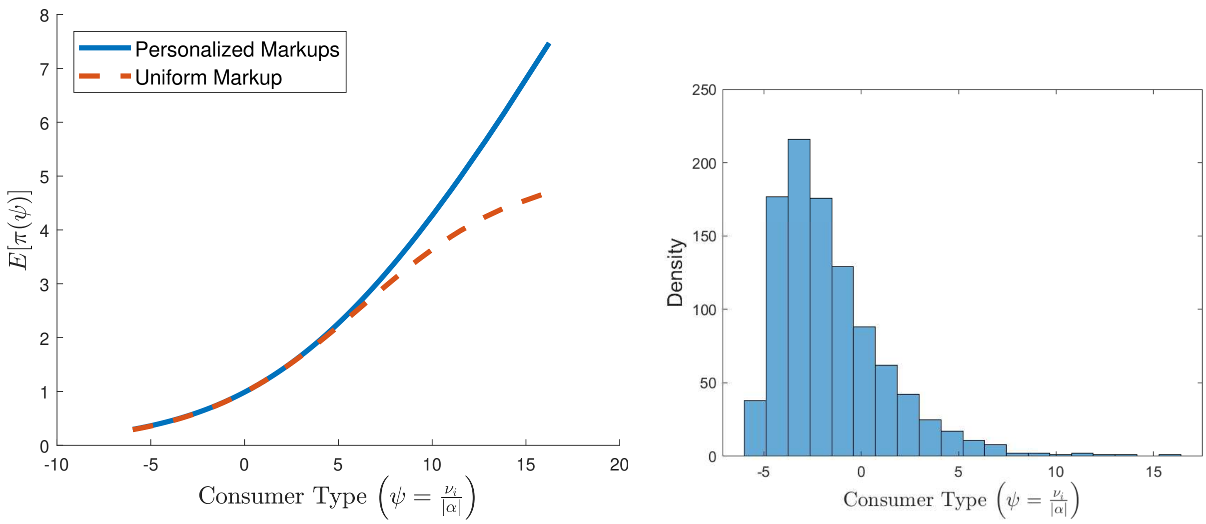
Shiller, B. R. (2020). Approximating purchase propensities and reservation prices from broad consumer tracking. *International Economic Review 61*(2), 847–870.

Thisse, J.-F. and X. Vives (1988). On the strategic choice of spatial price policy. *The American Economic Review 78*(1), 122–137.

Wanamaker, J. (1883, Mar). John wanamaker's department store advertisement. *The Philadelphia Inquirer*.

Zhang, J. Z., O. Netzer, and A. Ansari (2014). Dynamic targeted pricing in b2b relationships. *Marketing Science 33*(3), 317–337.

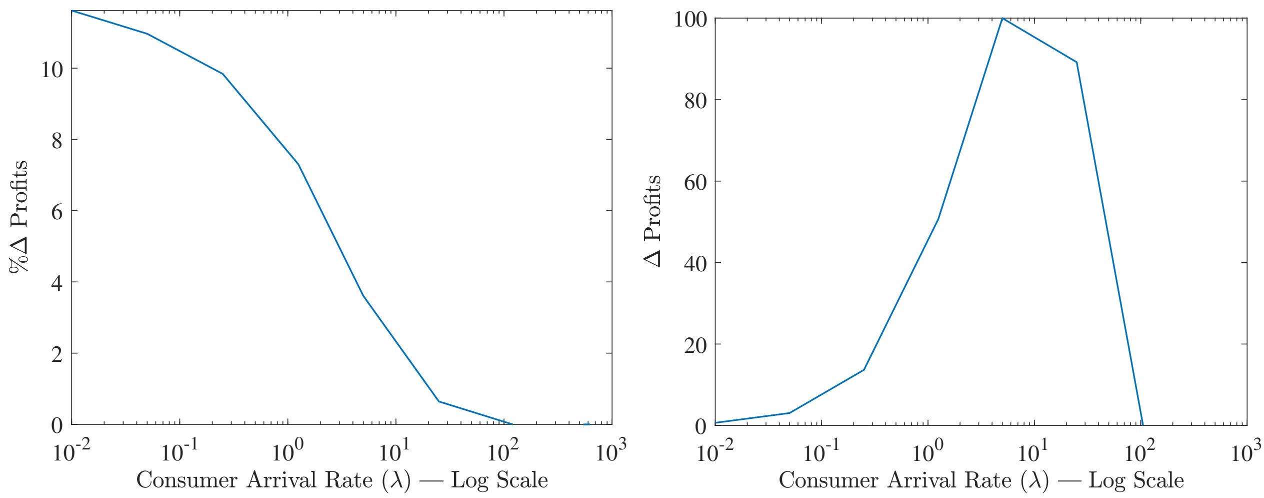
Figure 1: Profits by Type: Static Personalized Pricing



(a) Profits by Type **(b)** Consumer Type Density

Notes: Figure 1a shows the markup (price) offered to each consumer type. The red dashed line shows expected profit from each consumer type when all consumers are offered the same prices. The blue solid line shows expected profit from each consumer type when the markup is personalized. Figure 1b shows a histogram of consumer types.

Figure 2: Profit Gain from Dynamic Personalized Pricing v. Consumer Arrival Rate

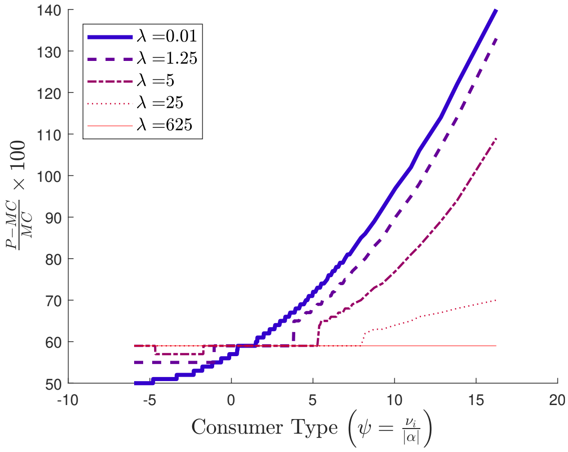


(a) Percent Change **(b)** Absolute Change

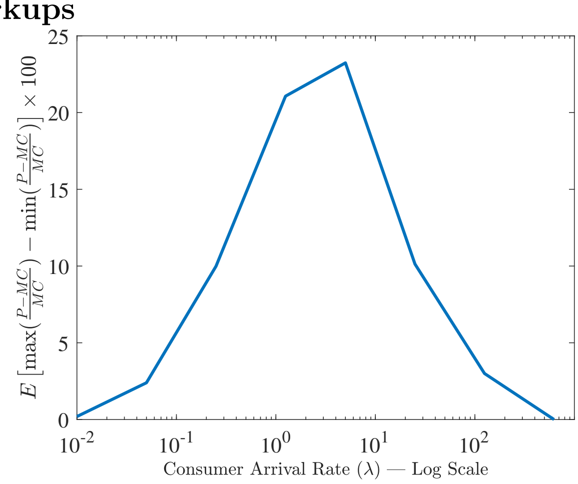
Notes: Figure 2a shows the percent increase in profits from implementing optimized sticky targeted pricing. The consumer arrival rate parameter λ denotes the expected number of consumer arrivals during the period s when price is locked (following a price change). Figure 2b shows the absolute increase in profits against the consumer arrival rate (λ). Absolute profits are normalized so that the highest value across the various λ equals 100.

Figure 3: Price Patterns

Markups

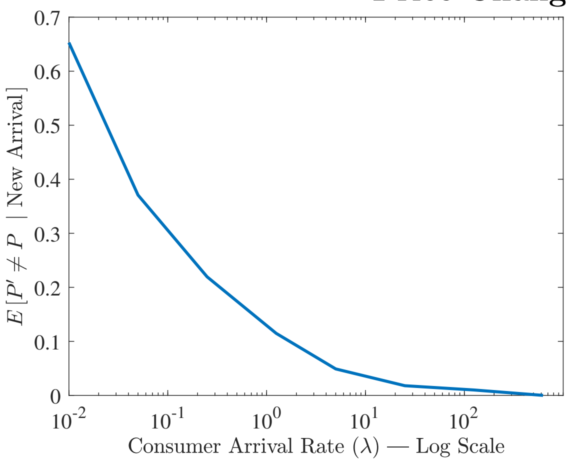


(a) Range of Markups Across Consumers

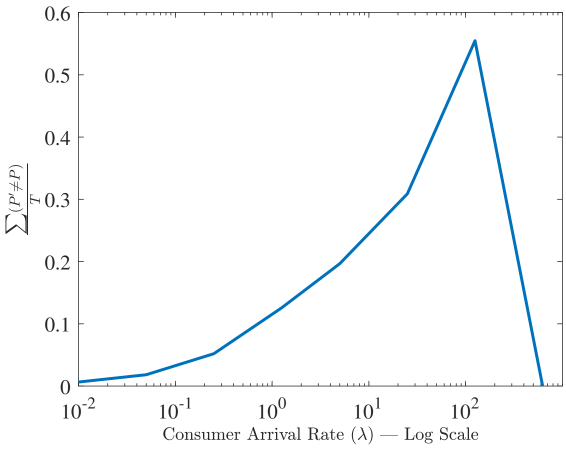


(b) Expected Range of Markups, $t = 30s$

Price Change Frequencies



(c) Conditional on Consumer Arrival



(d) Time-Normalized

Notes: Figure 3a shows the range of percent markups across consumers, assuming the previous markup was the optimal static uniform markup. Each line on the graph shows the range of markups for a specific arrival rate parameter λ. The consumer arrival rate parameter λ denotes the expected number of consumer arrivals during the period of length s when price is locked (following a price change). Figure 3b shows the expected range of percent markups offered to arriving consumers during an interval of length $30 \times s$, against the consumer arrival rate λ. 3c shows the fraction of the time the firm changes the markup for the newly arriving consumer, conditional on the price-commitment period having ended (allowing price changes) and a new consumer arriving. Figure 3d shows the expected number of price changes occurring during a particular length of time (time elapsed = s).

Table 1: Price Patterns on Amazon.com

	The dependent variable is monthly price range: $\max(P_{it}) - \min(P_{it})$					
	Sold directly by Amazon			Third-party seller		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Sales Rank':						
1(Btw. 100 & 500)	0.449	0.271	0.328	-0.927*	-1.693*	-1.390*
	(0.336)	(0.243)	(0.247)	(0.535)	(0.884)	(0.838)
1(Btw. 500 & 1000)	1.999***	1.151***	1.138***	-0.532	-0.455	-0.0446
	(0.358)	(0.256)	(0.259)	(0.608)	(0.684)	(0.686)
1(Btw. 1000 & 2000)	1.278***	0.683***	0.618**	-0.453	-0.839	-0.748
	(0.357)	(0.256)	(0.260)	(0.523)	(0.714)	(0.715)
1(Btw. 2000 & 5000)	0.517	0.0675	0.184	-1.127**	-2.858***	-2.764**
	(0.349)	(0.250)	(0.255)	(0.532)	(1.062)	(1.076)
1(Btw. 5000 & 10,000)	0.387	-0.274	-0.112	-1.661***	-1.912***	-1.836**
	(0.348)	(0.249)	(0.255)	(0.551)	(0.726)	(0.740)
1(Exceeding 10,000)	-0.118	-1.229***	-0.382	1.784	0.993	-0.144
	(0.343)	(0.243)	(0.260)	(1.673)	(1.857)	(1.209)
Fixed Effects:						
Category	Y	Y	Y	Y	Y	Y
List price decile		Y	Y		Y	Y
Date			Y			Y
Observations	274,953	274,953	274,953	282,963	282,963	282,963
Adjusted R^2	0.041	0.131	0.143	-0.000	0.000	0.001

Notes: The dependent variable is the range of first-party Amazon prices offered over a month in Columns (1-3). In Columns (4-6), the dependent variable is the range of third-party prices over time. If there are multiple third-party sellers, the reported price is from the third-party shown first by Amazon. Standards errors, clustered by product ID, are reported in parentheses.

Table 2: Grocery Store Price Patterns

	The dependent variable is monthly price range: $\max(P_{it}) - \min(P_{it})$			
	(1)	(2)	(3)	(4)
Jan-Feb Unit Sales:				
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

Notes: Standard errors, clustered by product, are shown in parentheses. The data used in these regressions includes seasonal products. Similar (unreported) results were found when restricting the data to a balanced panel.

A Online Appendix

A.1 Additional Images: Background

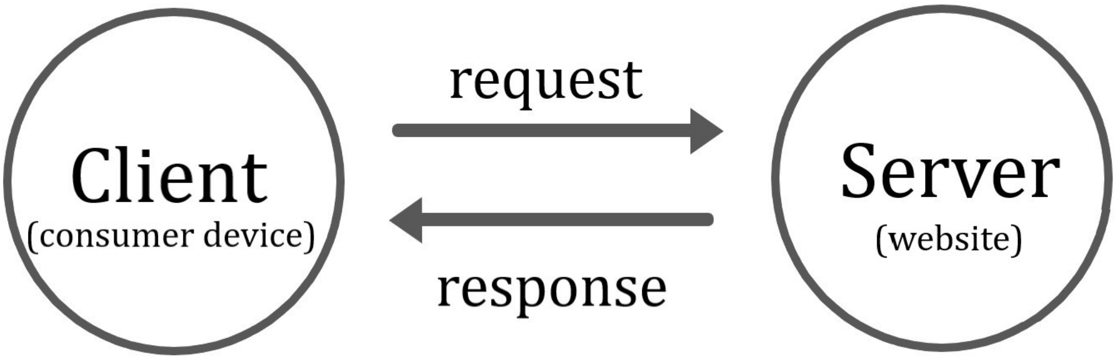
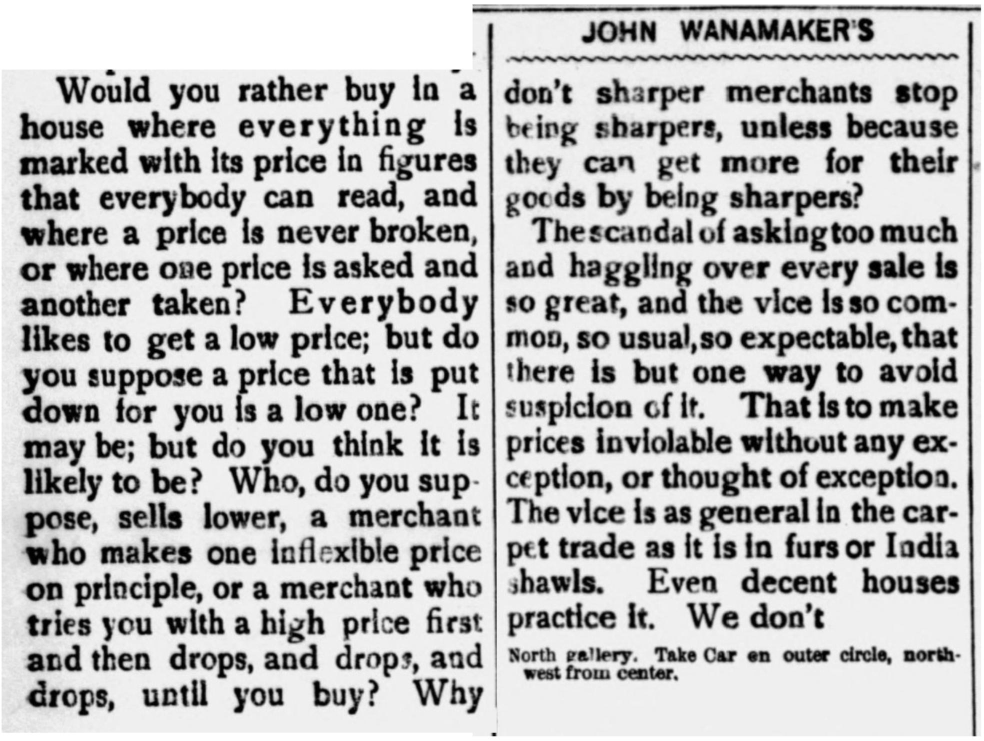


Figure A1: Consumers' Interactions with a Website



JOHN WANAMAKER'S

Would you rather buy in a house where everything is marked with its price in figures that everybody can read, and where a price is never broken, or where one price is asked and another taken? Everybody likes to get a low price; but do you suppose a price that is put down for you is a low one? It may be; but do you think it is likely to be? Who, do you suppose, sells lower, a merchant who makes one inflexible price on principle, or a merchant who tries you with a high price first and then drops, and drops, and drops, until you buy? Why don't sharper merchants stop being sharpers, unless because they can get more for their goods by being sharpers?

The scandal of asking too much and haggling over every sale is so great, and the vice is so common, so usual, so expectable, that there is but one way to avoid suspicion of it. That is to make prices inviolable without any exception, or thought of exception. The vice is as general in the carpet trade as it is in furs or India shawls. Even decent houses practice it. We don't

North gallery. Take Car on outer circle, northwest from center.

Figure A2: Advertisement for John Wanamaker's

The excerpt of the advertisement shown originally appeared on the 5th page of *The Philadelphia Inquirer* on March 29, 1883.

A.2 Price Change Frequency Patterns at Amazon

Figure 3d suggests that optimized sticky targeted pricing causes an inverted U-shape pattern between product popularity and price change frequencies. This subsection explores whether goods sold directly from Amazon exhibit this pattern. It shows that the inverted U-shape pattern does not hold but that an obvious explanation for price change frequencies can explain the observed pattern, even in the presence of optimized sticky targeted pricing.

To determine the relationship between price change frequencies and popularity, the monthly price change frequency is regressed on sales rank range indicators and various controls. To account for the impracticality of changing prices of out of stock items, price change frequencies are normalized by the fraction of the month a given product was out of stock. Specifically:

$$\frac{\sum(P' \neq P)_{it}}{\rho_{it}} = a + \sum_{\ell} \kappa_\ell 1(Sales\ Rank_{i,t-1} \in Range\ \ell) + \epsilon_{it}, \tag{15}$$

where ρ_{it} denotes the fraction of the time the product was in stock in month t. The results are shown in Table A1. Note that the inverted U-shape pattern is not readily apparent. Rather, it appears that the most popular set of products changes price most frequently.

The observed pattern may arise because it is possible for firms to quickly identify small demand shocks when the underlying volume of sales is higher, or because the profit gains from adjusting prices to small demand shocks are greater for products with high sales volume. Due to these other reasons, firms may make very small changes to prices of popular products at every opportunity (i.e., the end of every fixed-price interval s). By contrast, the price change frequency in Figure 3d peaks at about 0.5, suggesting optimized sticky targeted pricing would cause price changes half as often as feasible, less often than popular products change price for other reasons. The lack of an inverted U-shaped pattern may thus reflect simultaneous motivations for changing prices and does not rule out sticky targeted pricing.

Table A1: Price Change Frequency Patterns on Amazon.com

	The dependent variable is monthly price change frequency					
	Sold directly by Amazon			Third-party seller		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Sales Rank:						
1(Btw. 100 & 500)	-1.286*	-1.227*	-1.209*	-2.784*	-2.789*	-2.877*
	(0.697)	(0.707)	(0.711)	(1.598)	(1.574)	(1.571)
1(Btw. 500 & 1000)	-1.936***	-1.961***	-1.931***	-3.435**	-3.693**	-3.631**
	(0.711)	(0.733)	(0.730)	(1.621)	(1.612)	(1.604)
1(Btw. 1000 & 2000)	-0.858	-1.025	-0.928	-2.420	-2.877*	-2.826*
	(0.723)	(0.741)	(0.740)	(1.645)	(1.641)	(1.634)
1(Btw. 2000 & 5000)	-1.959***	-2.139***	-2.186***	-3.212*	-3.624**	-3.809**
	(0.735)	(0.756)	(0.754)	(1.671)	(1.661)	(1.661)
1(Btw. 5000 & 10,000)	-1.272	-1.526*	-1.654**	-3.669**	-4.044**	-4.353***
	(0.798)	(0.814)	(0.816)	(1.660)	(1.650)	(1.656)
1(Exceeding 10,000)	-5.161***	-5.475***	-4.875***	-7.274***	-7.874***	-7.465***
	(0.679)	(0.697)	(0.720)	(1.616)	(1.600)	(1.638)
Fixed Effects:						
Category	Y	Y	Y	Y	Y	Y
List price decile		Y	Y		Y	Y
Date			Y			Y
Observations	204,284	204,284	204,284	207,404	207,404	207,404
Adjusted R^2	0.019	0.025	0.032	0.033	0.040	0.047

Notes: In Columns (1-3), the dependent variable is the number of price changes of first-party Amazon prices offered over a month. In Columns (4-6), the dependent variable is the corresponding price change frequency for third-party prices. If there are multiple third-party sellers, the reported price is the price of the third-party seller shown first by Amazon. Standards errors, clustered by product ID, are reported in parentheses.