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. Empirically, I find this strategy raises profits for medium and low popularity products. I then document similar pricing patterns at Amazon, suggesting it may already be 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. As result, personalized pricing has become more profitable, with profit gains in the vicinity of 15% 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, firms that have implemented personalized pricing too overtly have faced severe backlash from consumers. For example, after Amazon was perceived to personalize prices, it called their pricing strategy a mistake and promised never to do so again (Salkowski, 2000). Such firms' concerns are well founded. The academic literature finds that consumers view targeted pricing as unfair (Campbell, 1999; Kahneman et al., 1986), and it reduces consumers' intention to purchase (Leibbrandt, 2020). Moreover, personalized pricing has increasingly been scrutinized by policy makers (Executive Office of the President, 2015), and concerns for consumers have seeded a literature 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). It is not surprising that firms are reluctant to use a pricing strategy that is easily recognized as personalized pricing.

Although firms are concerned about a possible backlash, they have not abandoned personalized pricing altogether.[2] The shift to online distribution has enabled better ways to discretely implement personalized pricing, or to reframe it.[3] 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. 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 indistinguishable from traditional dynamic pricing.

[1] Original ad 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).

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 a 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 the 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 pricing and outcomes 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; profit gains from raising price to a high-value arriving consumer are offset by losses arising from offering the same price 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 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 retailers, 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.

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 reviews how consumer devices and websites interact, and how the stages of this interaction enables firms to personalize prices inconspicuously. Specifically, pricing is presented as the traditional dynamic pricing that consumers are accustomed to.[4] Note that traditional dynamic pricing is not typically believed to elicit strong consumer resentment.

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. This request includes information about the requester, including cookies and IP address, the latter of which reveals the client's location.[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, which reveals the consumer's location, allowing the server to infer local demographics such as average income and 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 usage at other websites.

All of this information can then be used to create finely targeted prices. But to conceal the fact that prices are personalized, the website can change the "posted price" just before the client's computer is sent packets that constitute the website.

[4] Traditional dynamic pricing arises, for example, from intertemporal (second-degree) price discrimination and from responses to changes in market conditions, such as aggregate demand shocks, competitor actions, and changes in inventory or costs.

[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`

The distinction between sticky targeted pricing and static personalized pricing is the commitment. To mislead consumers, researchers, regulators, and competitors into believing prices are not personalized, the server locks in a new price for some period of time. If a consumer were to ask an acquaintance to check the price, the acquaintance would observe the same posted price, thus inferring that the firm is not personalizing prices.

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, three (Cavallo, 2017; Hannak et al., 2014; Mikians et al., 2012) explicitly stated that requests from different hypothetical users occurred in rapid succession, one (Iordanou et al., 2017) used a consumer-oriented price-checking browser extension that consumers presumably use soon after observing a price, and the other (Hupperich et al., 2018) does not state the time between price requests. None explicitly stated that they incorporated long lags between requests from different spoofed consumers.

Thus, if a website privately commits to changing prices infrequently, they can implement a form of personalized pricing without others realizing that they are doing so. Committing to prices for some time interval, however, comes at a cost. The website forgoes the opportunity to target prices to new arriving consumers during the interval when prices are locked.

3 A Model of Optimized Sticky Targeted Pricing

This section presents a model of optimized sticky targeted pricing. Myopic consumers are assumed to arrive at the marketplace randomly over time.[6] They are presented a price (or prices for multiple products) by the firm and decide whether and how much to purchase. 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.

It is assumed that the firm privately commits to maintaining a price level for an interval

[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.

of length s following a change in price in order to conceal finely targeted pricing.[7] Note that, even after interval s has passed, enabling the firm to change price when the next consumer arrives, it may not change price. By forgoing a price change, the firm maintains the option to change price at the subsequent consumer arrival epoch, even if the next consumer arrives shortly thereafter.

The value function is specified at points in time when two conditions are met: the firm is able to change price, 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. If price has changed less than s time ago, then the firm's price is determined: it has privately committed to keeping price the same and thus has no available action choices at that point in time. The next action choice for the firm occurs at the consumer arrival epoch following the expiration of the fixed-price commitment. For simplicity, time is measured in units of s. Hence, $s = 1$.

The overall value function is specified at a time when a new consumer arrives and price is flexible but before the consumer's type ψ is revealed:

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

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. Each choice-specific value function assumes the arriving consumer's type is known and is conditional on the price P' offered to the newly arriving consumer. Two choice-specific value functions are specified, rather than one, because the formula for the choice-specific value function depends on whether the new offered price P' is the same as the last offered price P. Specifying two separate choice-specific value functions simplifies exposition.

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

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

where $\pi(P, \psi)$ is the expected static profits from the arriving consumer of type ψ at offered price P, $V(P)$ is the value function specified in Equation 1, and $\int_{\tau=0}^{\infty} \exp(-r\tau) f(\tau; \lambda) d\tau$ 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

[7]One might attribute this to initially high menu price costs arising from the risk of being discovered personalizing prices.

next consumer arrives. $f(\tau|\lambda) = \lambda \exp(-\lambda\tau)$ 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:

$$W^{P' \neq P}(P', \psi) = \Bigg[\pi(P', \psi) + \left(\int_{\psi'} \pi(P', \psi') g(\psi') d\psi' \right) \times \sum_{n=0}^{\infty} n\delta(n) h(n|s\lambda) dn \\ + V(P') \int_{\tau=0}^{\infty} \exp\left(-r \times (s + \tau)\right) f(\tau; \lambda) d\tau \Bigg]. \tag{3}$$

The first component, $\pi(P', \psi)$, represents expected static profits from the arriving consumer. The second component, $\left(\int_{\psi'} \pi(P', \psi') g(\psi') d\psi' \right) \times \sum_{n=0}^{\infty} n\delta(n) h(n|s\lambda) dn$, represents expected profits at price P' during the price-commitment period. It is composed of two sub-components. The first sub-component, $\int_{\psi'} \pi(P', \psi') g(\psi') d\psi$, is the expected profits at price P' for a subsequent consumer, whose yet-to-be-revealed type is denoted by ψ'. The second sub-component, $\sum_{n=0}^{\infty} n\delta(n) h(n|s\lambda) dn$, is the expectation of the product of consumer arrivals (n) and the time discounting per arriving consumer ($\delta(n)$), given arrival-count mass function $h(n|s\lambda)$.[8] The last component, $V(P') \int_{\tau=0}^{\infty} \exp\left(-r \times (s + \tau)\right) f(\tau; \lambda) d\tau$, 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. $s + \tau$ is composed of the price-commitment interval length s and the random time τ between when the price-commitment interval ends and the next consumer arrives.

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

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

Note that the policy function implies that prices are path dependent, for two reasons. First, the price offered to an arriving consumer depends on their type. Second, the value function also depends on state variable: previous price P, itself dependent on the previous path of consumer arrivals.

3.1 Observations

The Bellman equation in Equation 3 implies that firms face a tradeoff 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

[8] $\sum_{n=0}^{\infty} n\delta(n) h(n|s\lambda) dn$ can be simulated to an arbitrarily level of precision.

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 latest arriving consumer are large.

Additionally, note that firms may forgo changing the posted price when a new customer arrives if the static gains from personalizing price to that consumer are small. Doing so maintains the flexibility to freely change price when the next consumer arrives, and the gains from tailoring price to the next consumer may be larger.

The remainder of this paper explores the performance of this strategy and the implications for pricing patterns using a realistic example to determine the extent of observable variation in willingness to pay across consumers (individual-level demands). The next section explains the process for estimating individual-level demand.

4 Individual-Level Demand Estimation

To explore the empirical implications of the dynamic pricing model described in Section 3, one needs both an estimate of the static profit from the arriving consumer $\pi(P, \psi)$ as a function of price and consumer type ψ, as well as the distribution of consumer types $g(\psi)$. In this section, both are estimated in the context of Netflix, circa 2006. Specifically, individual-level demand is estimated as a function of an individual's web-browsing history, using data and methods closely following Shiller (2020). Because consumers face a discrete choice, predicted individual-level demand is represented as the probability the individual chooses a product at a given price.

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 panel ($\approx$ $60,000$) of computer users. The dataset was collapsed to a cross-section, with one observation per panelist.

The browsing data were used to form a set of variables that reflect consumers' tastes and habits: (1) the number 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 was determined. For a small 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] Aggregate shares choosing each tier s_j are estimated from the sample of consumers whose tier choice is observed directly in the ComScore browsing data. See Shiller (2020) for a more detailed description of the dataset.

4.2 Individual-Level Demand Estimation

The estimation model includes a demand-side model and a supply-side model. 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 employed static pricing over the observed period. Netflix offered three vertically differentiated tiers of unlimited DVDs services: 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]

4.2.1 Demand

The conditional indirect utility consumer i receives from tier j of Netflix's service equals:

[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.

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

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 last term, ϵ_{ij}, is an error term that is assumed to be independent and identically distributed and follow the type 1 extreme value distribution.

The consumer makes a discrete choice, choosing the tier of service with highest utility or the outside good. 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 precision of estimated demand.

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 probability less the multinomial logit model prediction: $\left(\hat{s}_{ij \neq 0}\left(X_i\right) - s_{ij \neq 0}\left(\nu_i, \alpha, \delta, P\right)\right)$, and (2) aggregate shares choosing each inside good less the multinomial logit model's prediction: $\left(\hat{s}_j - s_j, \forall j \text{ where } s_j = \int_\nu s_{ij}\left(\nu, \alpha, \delta, P\right) f\left(\nu\right) d\nu\right)$. The former moment condition identifies ν_i, and the latter identifies δ_j. The remaining preference parameter, α, is identified by the supply-side model.

4.2.2 Supply

The formula for the firm's variable 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, $P_j(\theta) = (1 + \theta)\, c_j$ is the price of tier j, θ is a markup parameter, 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 followed a conversation with a former Vice President of Marketing at Netflix, who indicated that this was approximately true.

The corresponding first-order condition is:

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

It is assumed that c_j, s_j, and θ are known ex ante. The markup θ is estimated from annual financial reports, assuming variable costs equal the listed costs of subscription and fulfillment in Netflix's annual financial report: $\theta = 0.59$.[14] At the observed prices for the three tiers [9.99, 14.99, 17.99], this implies marginal costs are \$6.28, \$9.43, and \$11.32, respectively.

The only term in Equation 9 that is not known ex ante is $\frac{ds_j}{d\theta}$, which depends on the parameters of the demand model in Section 4.2.1. Thus, the third moment condition, shown in Equation 9, can be used to identify mean price sensitivity in the demand model, because all cost-side parameters are known ex ante.

4.2.3 Moment Conditions

In summary, there are three sets of moments conditions from the demand- and supply-side models used to estimate consumer preference parameters $(\nu_i, \alpha, \delta_j)$. The objective function created from theme moments is:

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

The first component is the squared difference between the model's prediction of individual subscription probabilities and ex-ante estimates of subscription probabilities. It identifies ν_i. The second component is the squared difference between the aggregate share choosing each tier and the corresponding model prediction. It identifies δ_j. The last component is the firm's first-order condition. It identifies the mean price sensitivity α. Note that the model is exactly identified.

4.2.4 Ex-ante Estimates of Individual Subscription Probabilities

The first component of the moment conditions in Equation 10 is the difference between model predictions and ex-ante estimates of individual subscription probabilities $(\hat{s}_{ij \neq 0}(X_i))$. Hence, to estimate the model, one must first estimate the probability each consumer subscribes from the web-browsing data.

The probability that an individual subscribes to any one of Netflix's tiers is estimated

[14] 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.

using a LASSO-penalized logit model. Specifically, the penalized likelihood function equals:

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

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_k, 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 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 seems 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

After estimating the demand model, the next step is to calculate expected profits from each individual type $\psi = \nu_i/|\alpha|$ as a function of prices (markup θ) offered to each individual:

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

These static profit functions, as a function of prices (markup θ), are a key input 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. Overall, personalizing the markup raises profits by 12.99% relative to status-quo uniform pricing, if ignoring impacts of personalized pricing on consumer sentiment.[15]

[15] The percent profit increase, 12.99%, incorporates Netflix's fixed cost. Assume variable costs equal the

5 Counteractuals

This section simulates counterfactual outcomes under optimized sticky targeted pricing based on estimates of $\pi(P, \psi)$ from Section 4.3. 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]. Recall that the consumer arrival rate is the expected number of consumers arriving during a period of length s, during which the firm has privately committed to maintaining a new posted price.

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.

The per-period (length $= s$) interest rate (r) is assumed to equal 0.00027397.[16] If s equals one day, then this would approximately correspond to a 10% yearly interest rate.

5.1 Comparative Statics

This subsection investigates the impacts of optimzied sticky targeted pricing on profits, pricing patterns, and consumers. The findings are relevant both for optimal firm strategy and consumers and regulators attempting to verify its use in practice.

Perhaps of greatest interest is the profit firms gain from optimized sticky targeted pricing. The discounted variable profits from optimized sticky targeted pricing, assuming the prior price equaled the optimal uniform price $\hat{P}$, equals $V(\hat{P})$. 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,

"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.

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

firms forgo the opportunity to personalize prices altogether: personalizing prices for one consumer locks in a suboptimal price for the many consumers arriving soon thereafter. Hence, one should expect firms to use and gain from optimized sticky targeted pricing for products with lower and medium popularity.

The relationship between consumer arrival rates and percentage profit gains, depicted in Figure 2a, follows from the frequency and intensity of price discrimination. First, see Figure 3a, which depicts the firm's pricing policy function assuming the last price offered was the optimal uniform price. Note that the range of prices offered to different consumer types is inversely related to the consumer arrival rate. Second, Figure 4a shows that the simulated frequency in which the firm changes the posted price for the arriving consumer, conditional on the fixed-price interval having elapsed, is monotonically declining in the consumer arrival rate.

These patterns reflect the dynamic tradeoff between earning higher static profits from targeting price to newly arriving consumers and lowering expected profits from consumers arriving later during the fixed-price interval. For high consumer arrival rates, the firm offers most consumers the optimal uniform price instead of a personalized price. For example, for a consumer arrival rate of $\lambda = 25$, the firm offers the uniform price to all but the highest-value consumers (See Figure 3a). The decision to personalize appears to follow an optimal stopping rule (or set of rules): the posted price is changed for consumers for which the profit gains from personalization are large (i.e., whose reservations prices are predicted to substantially differ from the average). For other consumers, the firm forgoes personalization to maintain price flexibility. Also note that, for $\lambda = 25$, price increases to high-value customers are relatively meager to avoid the substantial reduction in expected profits from the many later arrivals when the offered price substantially differs from the optimal uniform price.

Finally, note that the simulated frequency of price changes over time—rather than conditional on a consumer arrival—is more nuanced because of two competing forces. An arriving consumer is less likely to receive a different price when consumer arrivals are frequent, as shown in figure 4a. However, more consumer arrivals implies more chances to draw a consumer type for which the firm would change its price. Initially, the latter effect dominates, and price change frequency during a given time interval increases in the consumer arrival rate. However, eventually, for high consumer arrival rates, the firm forgoes changing prices altogether. Therefore, the relationship between price change frequency and the consumer arrival rate has an inverse U-shape (see Figure 4b).

5.2 Evidence of Optimized Sticky Targeted Pricing

Consumers, regulators, researchers, and competing firms have been interested in determining whether firms are personalizing prices, conspicuously or not. However, well-known anecdotes suggest such discoveries may harm firms using personalized pricing. Hence, they prefer to keep its use secret. This section examines how one might search for personalized pricing, and optimized sticky targeted pricing, in practice.

One can search for traditional personalized pricing by examining whether two individuals are offered different prices for the same product at the same time, a strategy previously employed by consumers and in academic articles (Cavallo, 2017; Hannak et al., 2014; Hupperich et al., 2018; Mikians et al., 2012; Iordanou et al., 2017). 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. The same is true for spoofed consumers used by researchers, regulators, or competing firms to search for personalized pricing.

If searching for sticky personalized pricing by comparing prices offered to 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 method to verify personalized pricing is to relate price differences to consumer traits that are perceived to be useful for personalized pricing (e.g., income). However, this method suffices only if researchers can identify and have access to the variables the firm is using to personalize prices. Often, the variables most useful for personalizing pricing are not immediately obvious. For example, Shiller (2020) found that, rather than income or other demographics, it was instead use of sites that deliver products by mail (e.g., Amazon) that mostly strongly indicated high valuations for Netflix's products.

Another method of searching for optimized sticky targeted pricing is to examine whether dynamic pricing patterns are consistent with its use. With optimized sticky targeted pricing, the relationship between the range of prices offered over an interval and the consumer arrival rate has an inverse U-shape, arising from two competing forces. First, the range of prices offered to different consumers is larger for lower consumer arrival rates, as shown in Figure 3a. However, a large number of consumers arriving implies more consumers to set separate prices: more price draws. The combination of these forces yields the inverse U-shape depicted in Figure 3b.

To investigate using this method, 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.[17] Price ranges are then regressed on indicators for various lagged-sales rank intervals. Specifically:

[17] 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.

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

where $\max(P_{it}) - \min(P_{it})$ is the range of prices offered in month t, and $1(Sales\ Rank_{i,t-1} \in Range\ \ell)$ 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 inverse 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 inverse U-shaped pattern.[18] Appendix Section A.3 provides further evidence suggesting that this inverse U-shape at Amazon is attributed to optimal sticky targeted pricing rather than to other common causes of price fluctuations. Specifically, it shows that the inverse U-shape is absent in another context (brick-and-mortar grocers) where such pricing would be challenging to implement but other forms of dynamic pricing are common.

Pricing patterns suggest that Amazon may be using optimized sticky targeted pricing.[19] However, they are not conclusive evidence. 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 opimized sticky targeted pricing, a method firms may use, and appear to be using already, to implement fine-grained pricing that is not viewed as unfair. 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 not surprising. Recent examples 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

[18] 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.

[19] Section A.2 explores whether price change frequency patterns also match patterns caused by optimized sticky targeted pricing.

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 size of potential biases from omitting them 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), and the effects of competition (Kehoe et al., 2018; Thisse and Vives, 1988). Thus, continuing to assume away the effects of sophisticated pricing strategies may soon become problematic.

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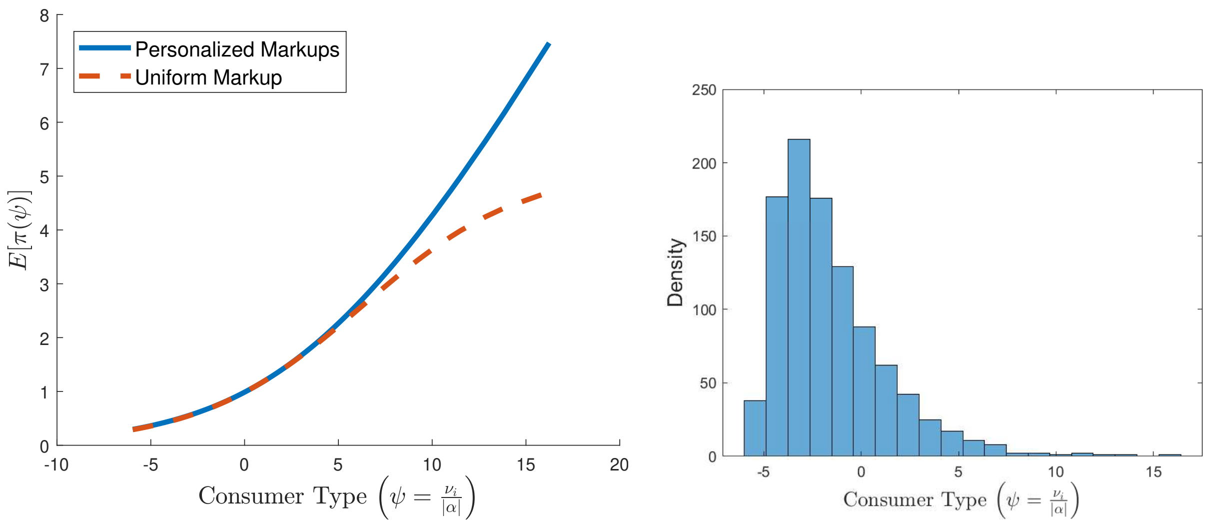
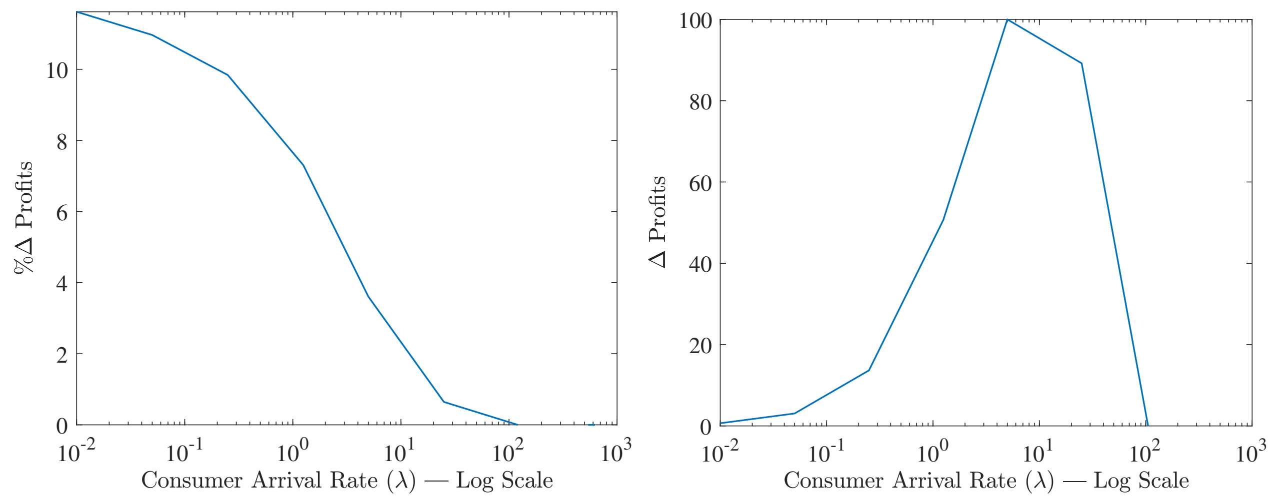
Figure 1: Profits by Type: Static Personalized Pricing



(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.

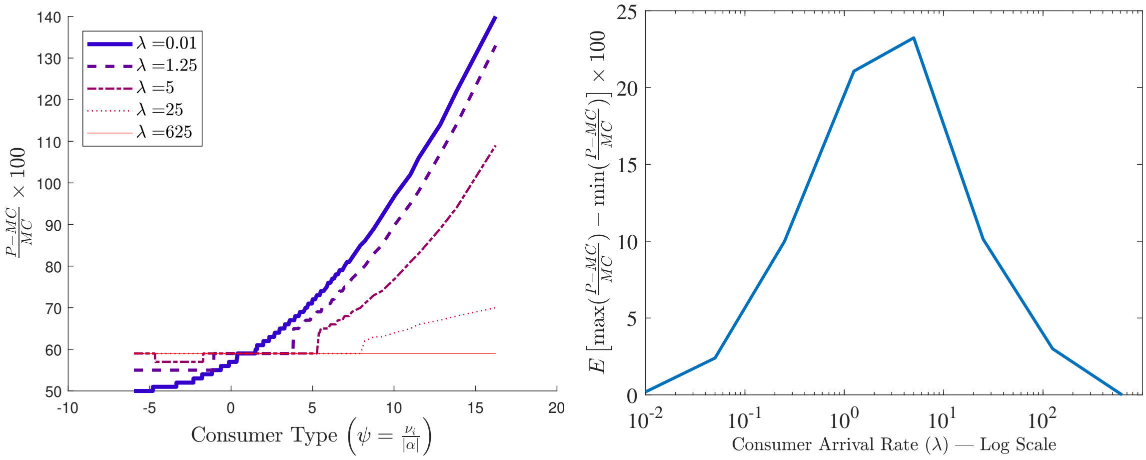
Figure 2: Profit Gain from Dynamic Personalized Pricing v. Consumer Arrival Rate



(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.

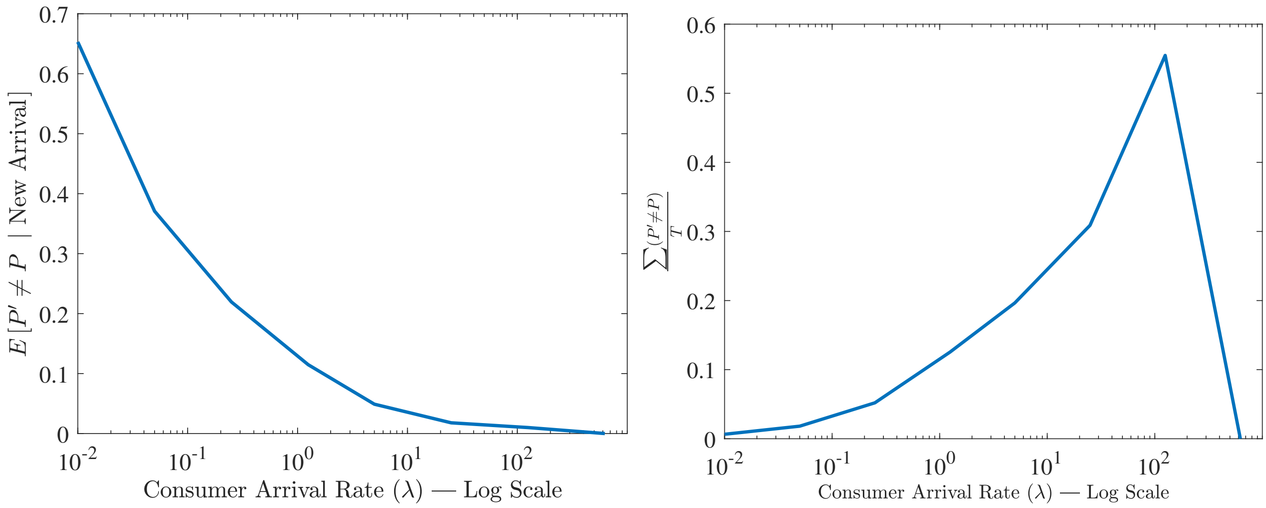
Figure 3: Range of Offered Prices



(a) Range of Markups Across Consumers **(b)** Expected Range of Markups, $t = 30s$

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. It depends on the range of prices across consumers and the expected number of consumer arrivals over the interval.

Figure 4: Price Change Frequency



(a) Conditional on Consumer Arrival **(b)** Time-Normalized

Notes: Figure 4a 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 4b 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.

A Online Appendix

A.1 Additional Images: Background

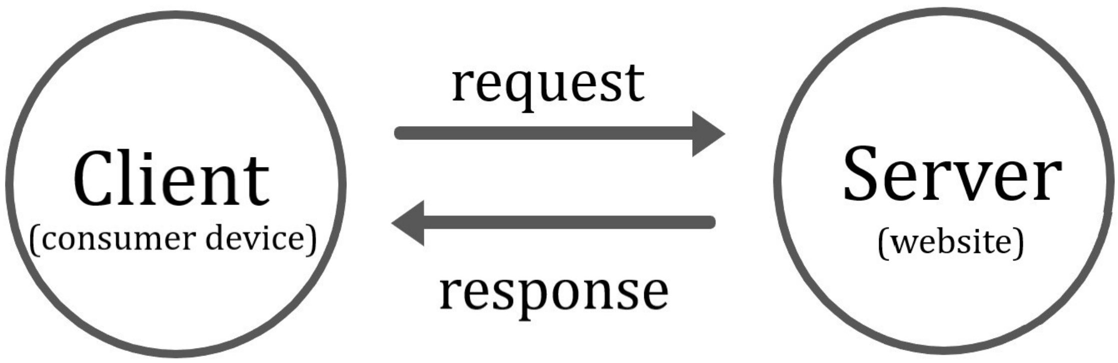
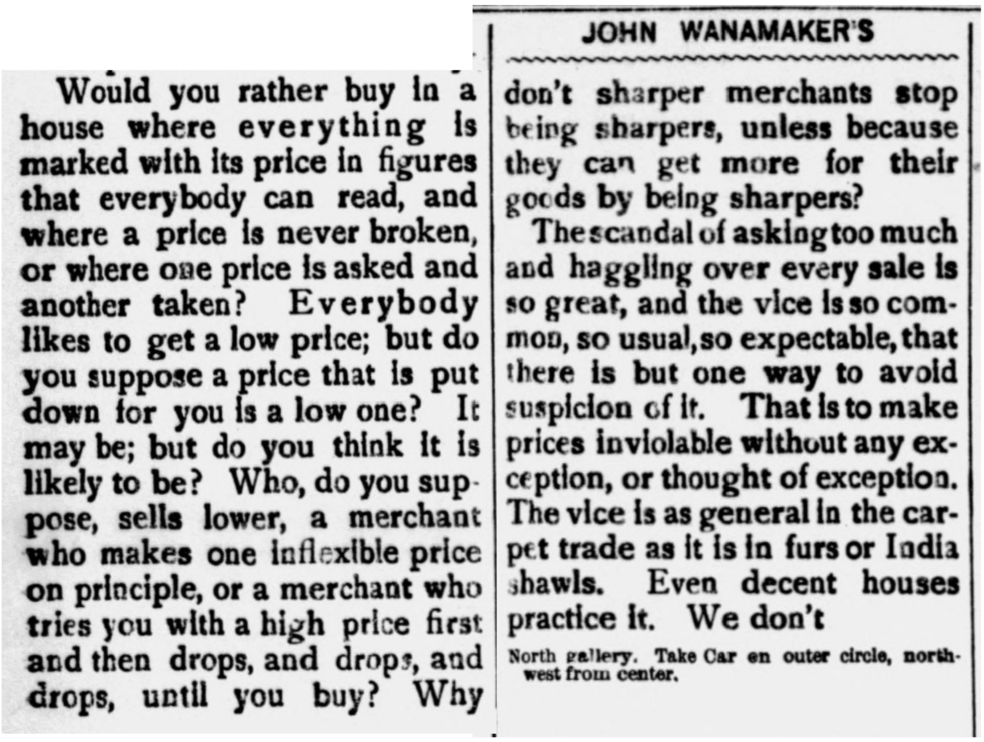


Figure A1: Consumers' Interactions with a Website



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: Advertisment 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 4b suggests that optimized sticky targeted pricing causes an inverse 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 inverse 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 inverse 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 change 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 4b 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 inverse 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.

A.3 Price Range Patterns at Brick-and-Mortar Grocers

This section further explores whether the inverse U-shape pattern between popularity and product price ranges occurs in a context where optimized sticky targeted pricing would be challenging to implement, and therefore price changes arise for traditional reasons. Data on weekly prices and unit sales at brick-and-mortar grocery stores are 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.[20] The data includes 43 stores, and 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 store location.

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 A2. Note that typical price fluctuation ranges are lower for less popular products, compared to the omitted category with pre-period sales exceeding 500, which accounts for less than one percent of product/store pairs. Moreover there is a clear monotonic relationship—not an inverse U-shape relationship—between price range and popularity. Thus, out of the three contexts considered (Amazon first party, Amazon third-party sellers, and grocery stores), the inverse U-shape relationship between popularity and price ranges that is expected under optimized sticky targeted pricing arises only in the case where the seller could plausibly implement optimized sticky targeted pricing.

[20] 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).

Table A2: 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.