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 similar pricing patterns at Amazon, suggesting it is already deployed. Thus, continuing to omit covert but intensifying price discrimination from economic models risks biased conclusions.

*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 (nearly effortless) customized coupons or discounts (Reimers and Shiller, 2019; Rossi et al., 1996; Shiller, 2020), which appear better tolerated by consumers.[3] Other

[1] An excerpt from the original advertisement is shown in Figure A1.

[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] See, for example, American Express's program: `tinyurl.com/usvt2t7m`.

firms have personalized rank-sorting algorithms, promoting more expensive items to price-insensitive 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 change price to extract surplus from 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]

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 prices 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 looking 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.

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

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; profit gains from raising price to a high-value arriving consumer are offset by reduced profits from setting the same high price to many subsequent 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. Similar relationships are found between prices and popularity in model simulations and for products sold directly by Amazon. However, these 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, become more problematic as use of sophisticated pricing intensifies.

The remainder of the paper is organized as follows. Section 2 discusses how effectively sticky personalized pricing conceals use of price discrimination. Section 3 introduces a model of optimized sticky targeted pricing, and Section 4 presents a model for estimating a key input: individual-level demands. Section 5 simulates counterfactual outcomes under optimized sticky targeted pricing and confirms similar patterns in empirical pricing data. A brief conclusion follows.

2 Background

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.[5]

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 distinguish personalized pricing 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

[5]Appendix Section A.1.2 details how online prices can be personalized in practice.

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 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 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

A few assumptions are used to simplify exposition while retaining the features of optimized sticky personalized pricing. Myopic consumers arrive at the marketplace randomly over time.[6] Interarrival times are assumed to be independent and identically distributed.[7] The arriving consumer's type (ψ) is revealed before the firm chooses which price (P') to offer them. Following a price change, the firm privately commits to maintaining the same price for an interval of length s. For simplicity, time is measured in units of s. Hence, $s = 1$.

The firm's overall value function is specified 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 is arriving. More specifically, it is defined at a time when the consumer

[6] One can extend the model to account for forward-looking consumers or to allow time-varying expectations of the arrival rate and time-varying distributions of arriving consumer types.

[7] This implies that consumer interarrival times follow the exponential distribution and the count of consumer arrivals during a specified interval follows the Poisson distribution.

is about to arrive and thus before their type is revealed. This is done for expositional purposes and does not reflect firm's information when setting prices: the firm does observe the consumer's type before choosing the offer price. The overall value function is:

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

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. They depend on the firm's chosen action, i.e., the offer price. Note that two are specified because the formula depends on whether the new offer price is the same as the last.

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, and $V(P)$ is the value function at the next consumer arrival epoch. 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, where r is the interest rate and τ is the random time until the next consumer arrives. $f(\tau|\lambda)$ is the probability mass function for interarrival times, given arrival rate parameter λ.

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

$$W^{P'\neq P}(P',\psi) = \Bigg[\overbrace{\pi(P',\psi)}^{\text{A}} + \overbrace{\left(\int_{\psi'} \pi(P',\psi')g(\psi')d\psi'\right)}^{\text{B}} \times \overbrace{\sum_{n=0}^{\infty} n\delta(n)h(n|s\lambda)dn}^{\text{C}}$$

$$+ \underbrace{V(P')\int_{\tau=0}^{\infty} \exp\left(-r \times (s+\tau)\right) f(\tau;\lambda)d\tau}_{D} \Bigg]. \tag{3}$$

Component A represents expected static profits from the arriving consumer at targeted price P'. Components B and C represent expected profits at that same price during the price-commitment period. Component B is the expected profits earned from 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 $h(n|s\lambda)$. Component D equals expected discounted profits earned after the price commitment period ends. Note that $\exp\left(-r \times (s+\tau)\right)$ represents the time discounting until the firm has another opportunity to change the offer price for a newly-arriving consumer, which occurs $s+\tau$ time later.

Finally, the firm's policy function equals:

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

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. However, 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 extract more surplus from the arriving 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 for a 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 a high-value consumer likely outweigh forgone profits 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—forgone profits from later arrivals are large. For the most popular products, firms forgo sticky targeted pricing altogether, even if the static gains from tailoring the "posted" price to the arriving consumer are large.

Finally, note that the model implies rich and seemingly random price paths like those frequently observed online, for two reasons.[8] First, prices are path dependent: the price path depends on the order in which different types of consumers arrive. Second, intervals between price changes are irregular: their length depends on consumer interarrival lengths, whether the firm has recently committed to a new price, and whether the firm chooses to change price for a new arrival. In regards to the last point, note that firms may forgo changing the posted price when a low-value customer arrives: keeping price the same maintains the flexibility to change price when the next consumer arrives.

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. 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

Each consumer makes a discrete choice, selecting from 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

[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.

a 3 DVDs at-a-time plan for \$17.99.[12] The conditional indirect utility consumer i receives from tier j of Netflix's services is:

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

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 (described in Section 4.2.4) 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:

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

[12]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 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

The demand- and supply-side model moment conditions yield an objective function:

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

Estimated consumer preference parameters minimize the objective function. The first component of G is the squared differences between the ex-ante probability that each consumer subscribes to Netflix and the corresponding multinomial logit model's prediction, summed across consumers. This first set of moments identifies ν_i: it is apparent from Equation 7 that a consumer i's probability of selecting the inside good 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 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.[13]

[13]Note that the model is exactly identified.

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: θ, c_j, and s_j are known ex-ante. The markup θ is estimated from annual financial reports: $\theta = 0.59$.[14] 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.[15]

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 $\frac{ds_j}{d\theta}$ monotonically increases with α, implying that α is identified.[16]

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 precision of estimated demand. Thus, when one has access to a useful data that allows precise predictions of individuals' choices (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.

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:

[14] According to Netflix's 2016 financial statement, the costs of subscription and fulfillment were 62.9% of revenues, implying a (constant marginal cost) markup θ of $\frac{1}{0.629} - 1 = 0.59$.

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

[16] The derivation relies on the point that $s_{ij}(\nu_i, \alpha, \delta, P(\theta))$ determined by the first two components of the objective function. Hence as α changes, other parameters in the model adjust to keep $s_{ij}(\nu_i, \alpha, \delta, P(\theta))$ unchanged. Then, $\frac{ds_j}{d\theta}$ is monotonic in α when there is a flat markup over costs. See Shiller (2020) for details.

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

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

After estimating the model in Section 4.2, the next step is to calculate expected static profits from each individual type $\psi = \nu_i/|\alpha|$ as a function of individualized prices (markup θ):

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

Figure 1 shows expected static profits from each consumer type, both when the firm personalizes the markup for each consumer, and under classic uniform pricing. 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.[17]

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 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 until convergence. The value function is then used to determine the corresponding policy function. Some outcomes directly follow, e.g., expected discounted variable profits equal $V(P)$. Other outcomes can be 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.[18] If s equals one day, then this would approximately correspond to a 10% yearly interest rate.

5.1 Comparative Statics

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

[17]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.

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

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 (while price is locked). Hence, one should expect firms to use and gain from optimized sticky targeted pricing for products with low 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 a longer 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 explains 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.[19]

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, Amazon represents a large share of all U.S. e-commerce; typical estimates suggest about 40%.[20]

To investigate, Keepa's API was used to collect Amazon price and (category-specific) sales-rank histories for a random set of (31,188) products sold directly by Amazon in February 2021.[21] Separate price histories were collected for Amazon's own price and the lowest price offered by third-party sellers on Amazon Marketplace, the latter of which presumably lacked sufficient data to target prices.[22] Some static product characteristics were available as well, including product categories and list prices. Data were collapsed to the monthly

[19] Another pattern, between price change frequencies and popularity, is not a useful diagnostic tool due to confounding factors. In particular, for popular products, small changes in aggregate demand are measurable from real-time sales data, leading firms to change prices of these products frequently. See Appendix Section A.3 for details.

[20] `tinyurl.com/2brca24c`.

[21] The selection process prioritized finding similar counts of products (sold by Amazon) from various points in the distribution of sales ranks (as of February 2021), to compensate for the fact that many products with poor ranks were not available from Amazon directly, but rather only from third-party sellers.

[22] The data collection process resulted in fewer observations in earlier years. To be included, products—defined by ASINS/UPCs—must be available in directly from Amazon in February 2021. Some products(ASINS/UPCs) were unavailable in prior years, for example, because new generations of products have different ASINS/UPCs than their predecessors. See Section A.2 for details.

level, yielding average sales ranks and ranges of prices offered over the month, defined as the maximum minus the minimum price. Price ranges are then regressed on indicators for various lagged-sales rank intervals. Specifically:

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

where $\max_{t\in m}(P_{it})-\min_{t\in m}(P_{it})$ is the range of prices offered in month m, 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 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 inverted U-shaped pattern.

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 optimized sticky personalized pricing would be challenging to implement but other traditional forms of dynamic pricing are common. 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.[23] The restricted data include 792,162 product/store pairs. As with the Amazon price data, the grocery scanner data were collapsed to the monthly level. The collapsed data contain price ranges, average prices, and

[23]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).

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 January/February unit sales across product/store pairs is highly skewed. The 10th percentile is 2, the median is 16, the 75th percentile is 41, and the 99th percentile is 371.

Monthly 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.[24] 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 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 low and medium popularity products, and

[24]The data used in these regressions includes seasonal products. Similar (unreported) results were found when restricting the data to a balanced panel.

pricing patterns at Amazon are consistent with its use.

These findings are novel, to my knowledge, but perhaps not surprising. Recent anecdotes suggest a trend towards more sophisticated pricing strategies that simultaneously allow finer targeting while assuaging consumer concerns. 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.

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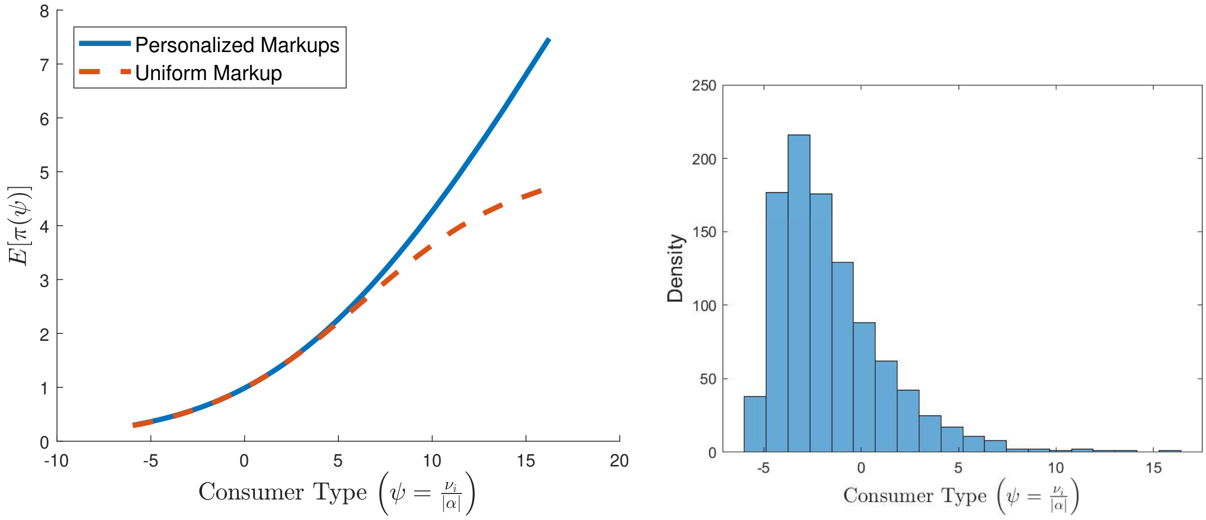
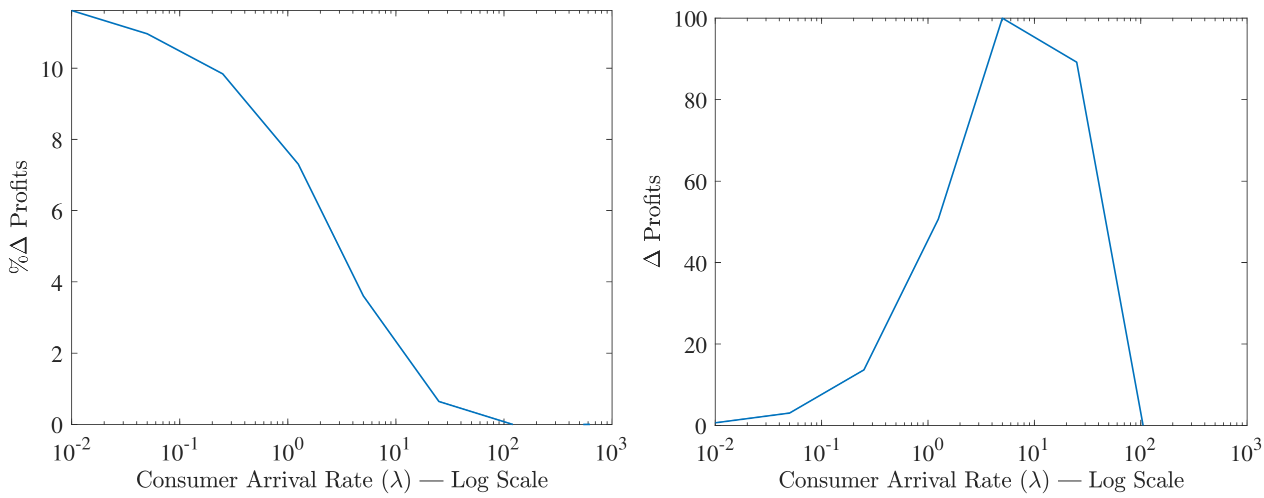
Figure 1: Profits by Type: Static Personalized Pricing



(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 Optimized Sticky Targeted Pricing v. Consumer Arrival Rate

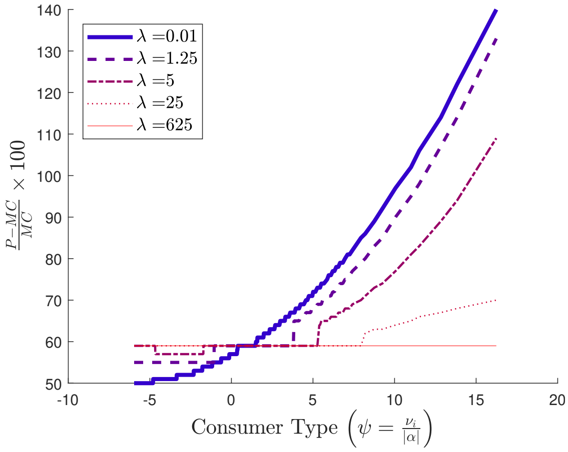


(a) Percent Change **(b)** Absolute Change

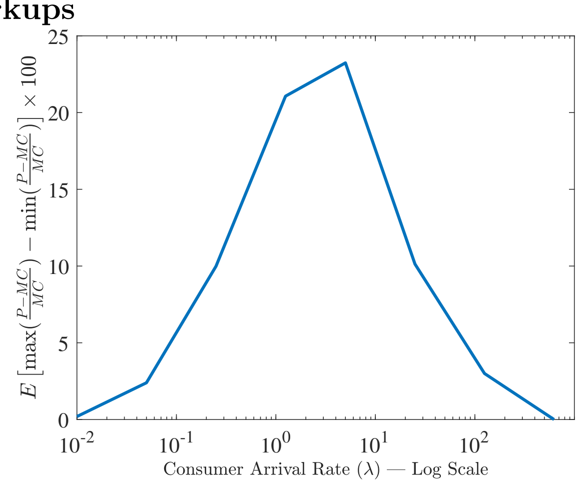
Notes: Figure 2a shows the percent increase in profits from implementing optimized sticky targeted pricing. Under optimized sticky targeted pricing, expected discounted variable profits equal $V(\hat{P})$ whereas under uniform pricing profits are $\frac{\lambda}{r}\int_{\psi}\pi(\hat{P},\psi)g(\psi)d\psi$, where $\hat{P}$ denotes the optimal uniform price. 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

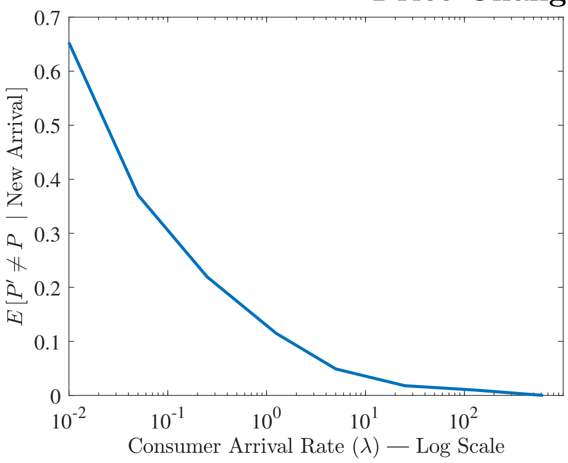


(a) Range of Markups Across Consumers

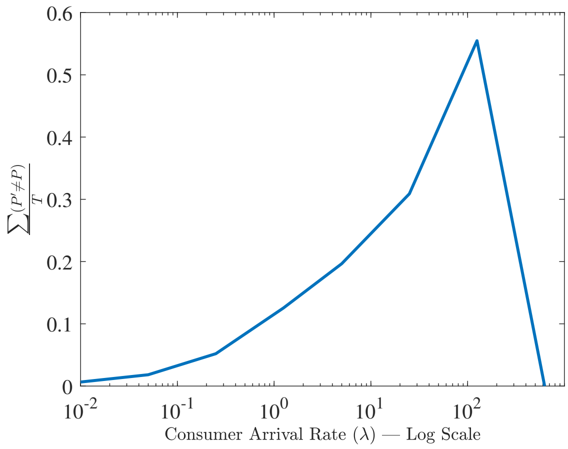


(b) Expected Range of Markups, $t = 30s$

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: $\max_{t\in m}(P_{it}) - \min_{t\in m}(P_{it})$					
	Amazon (first party)			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: In columns (1-3), the dependent variable is the range of first-party Amazon prices offered over a month. In Columns (4-6), the dependent variable is the range of third-party prices over time, where the price at any given moment in time is the lowest price offered across all third-party sellers. Standards errors, clustered by product ID, are reported in parentheses.

Table 2: Grocery Store Price Patterns

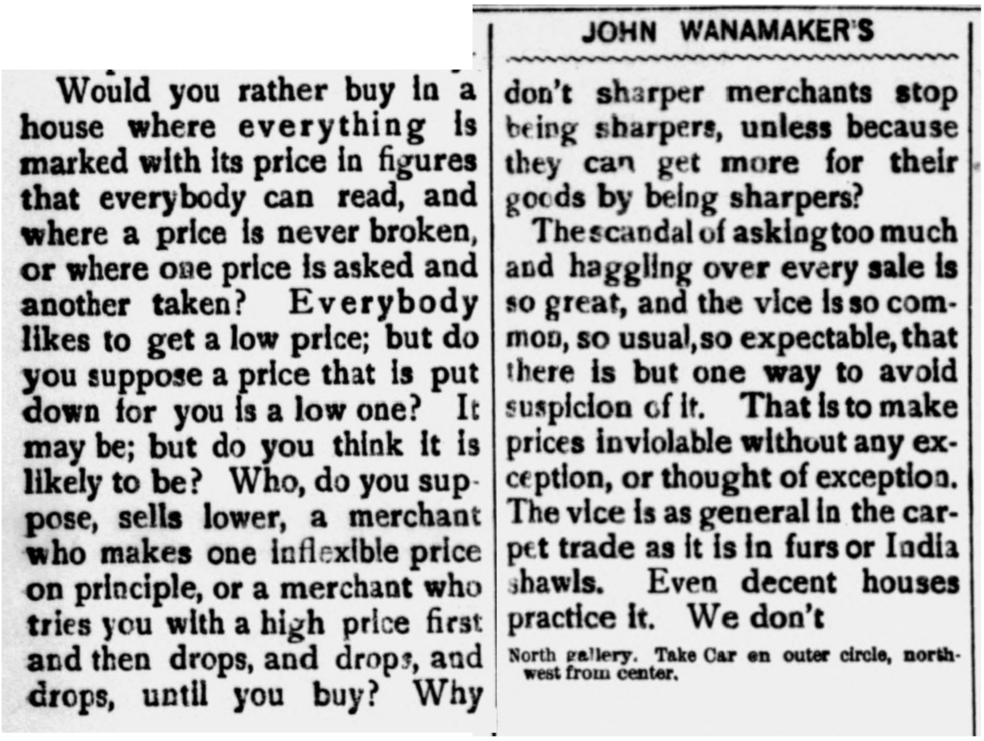
	The dependent variable is monthly price range: $\max_{t\in m}(P_{it}) - \min_{t\in m}(P_{it})$			
	(1)	(2)	(3)	(4)
Jan-Feb Unit Sales:				
sales< 10	-0.527***	-0.496***	-0.497***	-0.524***
	(0.0377)	(0.0352)	(0.0352)	(0.0352)
$10 \leq$ sales < 25	-0.361***	-0.348***	-0.348***	-0.370***
	(0.0375)	(0.0352)	(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.

A Online Appendix

A.1 Background

A.1.1 Supplementary Image



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 A1: 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.1.2 Feasibility of Personalized Pricing Online

The process of visiting a website involves two broad steps, depicted in appendix Figure A2. 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.[25] Consumers can also be required to provide login credentials to access the requested domain.

[25] 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`

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 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.

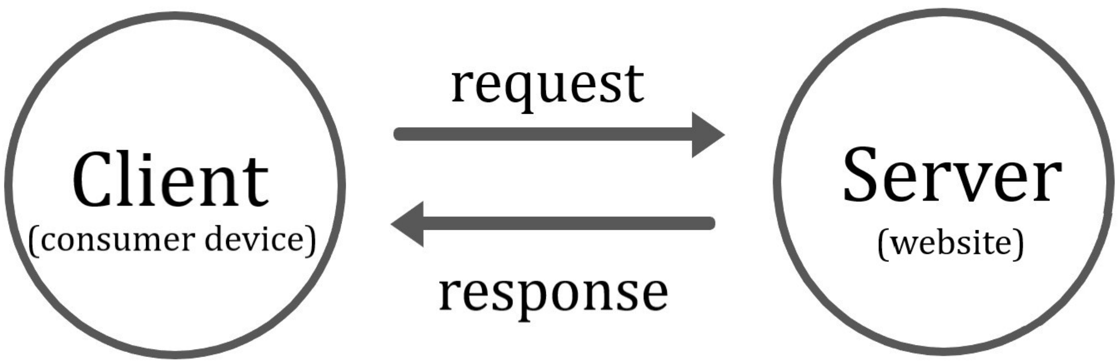


Figure A2: Consumers' Interactions with a Website

A.2 Amazon Pricing: Detailed Timing

This section examines whether the inverted U-shaped pattern between product popularity and the extent of price fluctuations at Amazon, which is consistent with optimized sticky targeted pricing, is a relatively new phenomenon. To this end, I explore Amazon's pricing patterns separately for various non-overlapping time periods.

Table A1 shows summary statistics for the main variables of interest, separately for three pairs of years: 2015-2016, 2017-2018, and 2019-2020. Panel A reflects the entire estimation sample (for each period). Panel B shows summary statistics for a restricted sample of products which were available in 2015-2016 (and had consistent ASIN/UPC codes between 2016 and 2021). Note that both panels show that price fluctuations increased substantially around the beginning of 2017, thus showing a general trend that is not due to an evolving sample of products. In 2015-2016, a product's price typically fluctuated by about \$2.8 over a month. In later years, the typical price fluctuation exceeded \$4.7, about a 70% increase. Hence, there is strong evidence that Amazon's pricing became more sophisticated around the beginning of 2017, which may reflect implementation of optimized sticky targeted pricing.

Table A1: Summary Statistics Over Time — Amazon

Panel A

	2015-2016		2017-2018		2019-2020	
	Mean	SD	Mean	SD	Mean	SD
Amazon Price	33.9	38.2	37.6	40.8	39.0	44.7
$\max_{t\in m}(P_{it}) - \min_{t\in m}(P_{it})$	2.8	7.8	4.8	9.8	5.7	12.8
Sales Rank$_{t-1}$ (in 1000s)	90.6	245.2	117.1	411.3	72.4	358.2
Distinct UPCs	2,416		4,181		6,771	

Panel B:
Restricted to Products Available in 2015-2016

	2015-2016		2017-2018		2019-2020	
	Mean	SD	Mean	SD	Mean	SD
Amazon Price	33.9	38.2	36.1	38.4	36.3	35.4
$\max_{t\in m}(P_{it}) - \min_{t\in m}(P_{it})$	2.8	7.8	4.7	9.7	5.2	10.2
Sales Rank$_{t-1}$ (in 1000s)	90.6	245.2	88.6	332.4	40.6	195.3

Notes: The table shows summary statistics for the main variables of interest, separately for different date ranges. Panel A shows summary statistics for the entire estimation sample. Panel B restricts the sample to products available in 2015-2016 (and with consistent ASINS/UPCs between 2016 and 2021).

To investigate further, Table A2 repeats the estimation model (from Equation 14), separately for each pair of years. Like in the summary statistics table, there are two panels. Panel A includes the full estimation sample each period, and Panel B uses a restricted sample of products which were available in 2015-2016. In early years (2015-2016), monthly price ranges increase in popularity (decline in sales rank), which is the same pattern that is observed at Grocery stores in 2019 and for third-party sellers at Amazon, contexts where one should not expect optimized sticky targeted pricing to be feasible. However, there was a dramatic change in the relationship between popularity and price fluctuations in later years. In the latter set of year pairs, in 2017-2018 and particularly in 2019-2020, the pattern of prices at Amazon follows the inverted U-shape expected when a firm is using optimized sticky targeted pricing.

A.3 Amazon Pricing: Price Change Frequencies

Figure 3d suggests that optimized sticky targeted pricing causes an inverted U-shape pattern between product popularity and price change frequencies. However, other factors strongly impact the relationship between price changes and popularity. In particular, price change frequencies may monotonically increase in popularity: Firms can measure small demand shocks more quickly for popular products, and the profit gains (in absolute terms) of reacting to small changes in demand are bigger for more popular products. Due to these other reasons, one should expect firms to frequently make small price changes for popular products, possibly at every opportunity (i.e., the end of every fixed-price interval s). Hence, price changes for this unrelated reason may obscure the inverted U-shape patterns that would otherwise arise from sticky personalized pricing.

Despite these concerns, the remainder of this section examines whether the inverted U-shape between popularity and price change frequencies is observable.

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. Specifically:

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

The results are shown in Table A3. Note that the inverted U-shaped pattern is not readily apparent. Rather, it appears that the most popular set of products change price most frequently.[26] However, this pattern is consistent with simultaneous use of optimized

[26] Similar results were found when normalizing price change frequencies by the fraction of the month the product was in stock, as opposed to out of stock.

Table A2: Amazon's Pricing Patterns — Changes over Time

Panel A

	The dependent variable is: $\max_{t\in m}(P_{it}) - \min_{t\in m}(P_{it})$		
	2015-2016	2017-2018	2019-2020
	(1)	(2)	(3)
Lagged Sales Rank':			
1(Btw. 100 & 500)	-3.201	0.716**	0.484***
	(2.430)	(0.332)	(0.185)
1(Btw. 500 & 1000)	-3.499	0.0937	1.363***
	(2.434)	(0.363)	(0.206)
1(Btw. 1000 & 2000)	-3.892	0.541	1.010***
	(2.403)	(0.389)	(0.224)
1(Btw. 2000 & 5000)	-4.601*	0.191	0.494**
	(2.414)	(0.374)	(0.207)
1(Btw. 5000 & 10,000)	-4.854**	0.122	-0.116
	(2.408)	(0.380)	(0.193)
1(Exceeding 10,000)	-5.111**	-0.569*	0.118
	(2.469)	(0.322)	(0.211)
Observations	40,266	74,126	123,113
Adjusted R^2	0.163	0.180	0.131

Panel B:
Restricted to Products Available in 2015-2016

	2015-2016	2017-2018	2019-2020
	(1)	(2)	(3)
Lagged Sales Rank':			
1(Btw. 100 & 500)	-3.201	1.468***	1.374***
	(2.430)	(0.530)	(0.338)
1(Btw. 500 & 1000)	-3.499	0.419	2.093***
	(2.434)	(0.557)	(0.370)
1(Btw. 1000 & 2000)	-3.892	0.870	1.122***
	(2.403)	(0.586)	(0.350)
1(Btw. 2000 & 5000)	-4.601*	0.560	0.892**
	(2.414)	(0.570)	(0.363)
1(Btw. 5000 & 10,000)	-4.854**	0.725	0.131
	(2.408)	(0.584)	(0.335)
1(Exceeding 10,000)	-5.111**	-0.193	0.142
	(2.469)	(0.527)	(0.353)
Observations	40,266	54,849	54,692
Adjusted R^2	0.163	0.200	0.170

Notes: Each column denotes a different estimation sample, delineated by time. All models included fixed effects for category, date, and deciles of list price. Standards errors, clustered by product ID, are reported in parentheses. Panel A uses the full estimation sample in each period. Panel B restricts analysis to the set of products available in 2015-2016 and used to estimate column (1).

targeted sticky pricing and automated responses to changes in aggregate demand. For popular products, there may be enough information from recent purchase decisions to identify small changes in aggregate demand, implying that for popular products firms may change prices at nearly 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. Thus, the lack of an inverted U-shaped pattern does not bolster evidence of sticky targeted pricing, but nor does it rule out sticky targeted pricing.

Table A3: Price Change Frequency Patterns on Amazon.com

	The dependent variable is monthly price change frequency					
	Amazon (first party)			Third-party seller		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Sales Rank:						
1(Btw. 100 & 500)	-0.591	-0.614	-0.637	-2.371*	-2.430*	-2.439*
	(0.581)	(0.581)	(0.583)	(1.392)	(1.380)	(1.378)
1(Btw. 500 & 1000)	-0.914	-1.113*	-1.150*	-2.888**	-3.166**	-3.088**
	(0.584)	(0.592)	(0.589)	(1.413)	(1.411)	(1.406)
1(Btw. 1000 & 2000)	-0.126	-0.370	-0.360	-2.159	-2.599*	-2.541*
	(0.594)	(0.597)	(0.594)	(1.430)	(1.432)	(1.429)
1(Btw. 2000 & 5000)	-1.308**	-1.509**	-1.499**	-3.029**	-3.364**	-3.395**
	(0.600)	(0.603)	(0.600)	(1.449)	(1.448)	(1.449)
1(Btw. 5000 & 10,000)	-0.893	-1.179*	-1.201*	-3.681**	-3.943***	-4.060***
	(0.649)	(0.652)	(0.653)	(1.436)	(1.435)	(1.442)
1(Exceeding 10,000)	-3.989***	-4.308***	-3.796***	-6.558***	-7.060***	-6.768***
	(0.560)	(0.562)	(0.578)	(1.407)	(1.403)	(1.433)
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	0.019	0.025	0.031	0.035	0.043	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 lowest price. Standards errors, clustered by product ID, are reported in parentheses.