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 that an equivalent strategy is already deployed. Overlooking such price discrimination may have large implications.

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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 inherently search for ways to extract more surplus from consumers. One 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 and policymakers. Personalized pricing is viewed as unfair (Campbell, 1999; Kahneman et al., 1986); its use reduces disgruntled consumers' purchase intentions (Leibbrandt, 2020) and risks negative publicity. Furthermore, a literature has developed with the stated intent of searching for use of personalized pricing (Hannak et al., 2014; Hupperich et al., 2018; Iordanou et al., 2017; Mikians et al., 2012), and such pricing has increasingly been scrutinized by policymakers (e.g., Executive Office of the President 2015). Not surprisingly, firms perceived to personalize prices have reacted strongly to preempt reprisals. Amazon, for example, called their pricing strategy a mistake and promised never again to simultaneously charge consumers different prices (Salkowski, 2000).

Although firms are concerned about a possible backlash, they have not abandoned personalized pricing altogether.[2] Instead, firms have found 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. Others have

[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).

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 well disguised nor as effective as hoped.

An alternative, and thus far understudied, strategy is to disguise personalized pricing as dynamic pricing. 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 surplus from the consumer that has just arrived. However, by privately committing to keeping the new price for some length of time, making prices sticky, the firm substantially complicates consumers' efforts to detect finely targeted pricing. I call this strategy *optimized sticky targeted pricing.*

Would this strategy effectively avoid detection? Consider how consumers might try to verify personalized pricing. 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.[3] It would be difficult, if not impossible, for consumers to distinguish whether price changes arise from personalized pricing or traditional dynamic pricing, the latter of which is common and tolerated by consumers.[4] The same reasoning implies that researchers and regulators looking for personalized pricing would fail to detect sticky personalized pricing.

This paper examines 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 extracting surplus from the arriving consumer and profiting from later arrivals who must be charged the same price.

[3] The price may change just before an acquaintance checks price. But then the first consumer would likely recheck price, this time observing the same price as their acquaintance, thus inferring that the previous price change was due to dynamic pricing.

[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. Static individual-level demand is estimated as a function of 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 percentage increase in profits 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 is currently used. A new relationship between prices and popularity emerged at Amazon around 2017, and these new patterns match those from simulations of sticky personalized pricing. However, these patterns are not found in places where sellers lack the means to personalize prices to arriving consumers: brick-and-mortar grocery stores.

Increasing use of inconspicuous but sophisticated pricing methods has substantive implications spanning the economics literature. For example, overlooking 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 prices (Thisse and Vives, 1988). However, because its use is not readily apparent, it may be used widely without academics and regulators being aware. These issues become more problematic as use of sophisticated pricing intensifies. Thus, it may be necessary to incorporate sticky personalized pricing in economic models, even when the research question is not directly related.

2 Background

Consumers, regulators, researchers, and competing firms have been interested in determining whether firms are personalizing prices, conspicuously or not.[5] Searching for straightforward (non-sticky) personalized pricing is simple; one can examine whether two individuals are offered different prices for the same product at the same point in time. However, it is more challenging to verify use of sticky targeted pricing.

Unless they leave long time lags—longer than the price-commitment period—between checking prices for different spoofed consumers, regulators, researchers, and competitors would infer that the same price is offered to nearly all consumers. However, 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 arrivals of 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 various 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 apparent. For example, Shiller (2020) found that income and other demographics revealed relatively little about

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

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 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 its use. If simultaneously effective at extracting surplus, it may be an enticing strategy for online retailers.

3 A Model of Optimized Sticky Targeted Pricing

It is assumed that myopic consumers arrive at the marketplace randomly over time and interarrival times are independent and identically distributed (i.i.d.).[6] Following a price change, the firm privately commits to maintaining the same price for an interval of length s. Time is measured in units of s. Hence, $s = 1$.

The firm's value function is specified only at points in time when two conditions are met: (i) the firm is able to change price (the price-commitment period has elapsed), and (ii) a new consumer is arriving but their type has not yet been revealed. Note that even though the value function is defined before the consumer's type is revealed, the firm does observe the consumer's type before choosing the offer price. The value function is:

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

where the state variable P denotes the price last offered by the firm, P' is the price offered to the newly arriving consumer of then-known type ψ, and $g(\psi)$ denotes the distribution of consumer types. $W^{P'=P}(P, \psi)$ and $W^{P' \neq P}(P', \psi)$ denote expected discounted profits given the chosen offer price. Note that two functions are specified because the formula for

[6]i.i.d. arrivals imply consumer interarrival times follow the exponential distribution and the count of consumer arrivals during a specified interval follows the Poisson distribution. 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 consumers' types.

discounted profits depends on whether the new offer price is the same as the last.

If the firm does not change price, then expected discounted profits are:

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

where $\pi(P,\psi)$ represents 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. Finally, $f(\tau;\lambda)$ is the probability mass function for interarrival times, given arrival rate parameter λ.

If the offer price changes, then expected discounted profits instead equal:

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

Component A represents expected static profits from the arriving consumer at price P'. Components B and C together represent expected discounted profits at that same price during the price-commitment period. Component B is the expected profits earned from a random subsequent consumer, whose yet-to-be-revealed type is denoted by ψ'. Component C is the expectation of the product of consumer arrivals (n) and the average time discounting per arriving consumer ($\delta(n)$), given arrival-count mass function $h(n;\lambda)$.[7] Component D equals expected discounted profits earned after the price-commitment period ends. Note that $\exp\left(-r \times (s+\tau)\right)$ represents time discounting until the firm has another opportunity

[7] $\delta(n)$ can be simulated to arbitrary precision.

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 the firm faces 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 who arrive shortly thereafter (if it intends to use optimized sticky targeted pricing), which may lower expected profits from these later arrivals.

For example, suppose the firm raises the posted price to extract surplus from a high-value arriving consumer. Then it must offer the same high price—higher than the optimal uniform price—to subsequent consumers arriving soon thereafter. However, the price that maximizes expected profits from later arrivals—whose types are not yet known—is the optimal uniform price. Any higher (or lower) price reduces expected profits from these 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 extremely 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

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

and whether the firm chooses to change price for a new arrival. In regards to the latter point, note that the firm may forgo changing the posted price when the static gains are low. Keeping the price the same maintains the flexibility to change the 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 individual-level profit functions $\pi(P, \psi)$. In this section, they are estimated in the context of Netflix, using data and methods closely following Shiller (2020).

4.1 Data

Data were obtained from ComScore via the Wharton Research Data Service (WRDS). The dataset contains demographics and browsing histories during 2006 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 the 4,600 most popular websites during 2006, (2) total visits to all websites, 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.

[9] Initially, the 5,000 most popular websites were selected. Then, some categories of websites were excluded: movie rental chains, pornography, 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 viewed more than 2 subpages per visit to the Netflix domain, on average. A non-subscriber would be unlikely to do so, because a non-subscriber is unable to log in and view subpages available only to subscribers.

4.2 Empirical Model

The estimation procedure includes demand- and supply-side models. Typically, a supply-side model is included to identify 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 from 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 a 3 DVDs at-a-time plan for $17.99. The conditional indirect utility consumer i receives from tier j of Netflix's services is:

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

where P_j denotes tier j's price, and α and $\nu_i + \delta_j$ denote individual i's price sensitivity and intrinsic utility for product tier j, respectively. I normalize δ_1 to zero, because otherwise there are infinite combinations of $\delta_1, ..., \delta_J$ and $\nu_1, ..., \nu_N$ which imply the same intrinsic utilities, implying the model would not be identified. The error term ϵ_{ij} is assumed to follow the type 1 extreme value distribution.

The probability consumer i selects tier 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-side model is used to construct two sets of moment conditions: (1) ex-ante estimates of subscription probabilities ($\hat{s}_{ij\neq 0}\left(X_i\right)$; described in Section 4.2.4) less the corresponding model predictions from Equation 7 ($s_{ij\neq 0}\left(\nu_i, \alpha, \delta, P\right)$), and (2) the aggregate share of consumers choosing each tier ($\hat{s}_j$) less the model's prediction $\left(\int_\nu s_{ij}\left(\nu, \alpha, \delta, P\right) f\left(\nu\right) d\nu\right)$.

4.2.2 Supply

Firm profits are:

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

where c_j is the marginal cost of tier j, θ is a markup parameter, $P_j(\theta) = (1+\theta)\, c_j$ is the price of tier j, s_j is the aggregate share of consumers 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. This assumption follows a conversation with a former Vice President of Marketing at Netflix, who indicated that this was approximately true, by design.

The corresponding first-order condition is:

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

This first-order condition comprises the final moment condition.

4.2.3 Objective Function and Identification

Consumer preference parameters are estimated by minimizing an objective function comprised of the demand- and supply-side moment conditions. Specifically, the objective function is:

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

The first component of the objective function is the squared difference between the ex-ante probability consumer i subscribes to Netflix and the corresponding model prediction, summed across consumers. This first component identifies ν_i: It is apparent from Equation 7 that consumer i's probability of selecting the inside good monotonically rises with ν_i. The second component is the squared difference between the aggregate share known to choose tier j and the corresponding model prediction, summed across tiers. It identifies δ_j: The implied share choosing tier j rises monotonically with δ_j. The last component is the squared first-order condition, from the supply-side model. As explained next, it identifies the mean price sensitivity α.[12]

Note that there are four sets of terms in the last component of the objective function: 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 is estimated from annual financial reports: $\theta = 0.59$.[13] 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.[14]

The only remaining terms are $\frac{ds_j}{d\theta}, \forall j$. They depend on consumer preference parameters from the demand-side model, in particular on price sensitivity α. Note that $\frac{ds_j}{d\theta}$ monotonically increases with α, implying that α is identified.[15]

Finally, note that as the scale of α, ν_i, and δ_j jointly increase, the error draws ϵ become less likely to impact a 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 data that allow precise predictions

[12]Note that the model is exactly identified.

[13]According to Netflix's 2006 financial statement, the costs of subscription and fulfillment were 62.9% of revenues, implying the (constant marginal cost) markup equals $\frac{1}{0.629} - 1 = 0.59$.

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

[15]The explanation relies on the point that $s_{ij}(\nu_i, \alpha, \delta, P(\theta))$ is determined by the moment conditions from the demand-side model. As α changes, other parameters in the model adjust to keep these two moment conditions satisfied, leaving $s_{ij}(\nu_i, \alpha, \delta, P(\theta))$ unchanged. With s_{ij} fixed, $\frac{ds_j}{d\theta}$ is monotonic in α when there is a common percent markup over costs. See Shiller (2020) for details.

of individuals' choices (i.e., ex-ante individual subscription probabilities $s_{ij\neq0}(X_i)$ are close to either 0 or 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 the objective function is the sum of squared differences between ex-ante estimates ($\hat{s}_{ij\neq0}(X_i)$) and model predictions ($s_{ij\neq0}(\nu_i, \alpha, \delta, P)$) of individual subscription probabilities. Hence, before estimating the model, one must first estimate the probability each consumer subscribes.

The probability that each individual subscribes to Netflix is estimated using a lasso-penalized logit model. Specifically, the penalized log-likelihood function equals:

$$\ell(\phi, \beta) = \sum_{i=1}^{N} \ln\Big(s_{ij\neq0}(X_i) \times 1\,(buy) + \big(1 - s_{ij\neq0}(X_i)\big) \times \big(1 - 1(buy)\big)\Big) - \omega \sum_{k=1}^{K} |\beta_k|, \quad (11)$$

where $1(buy)$ is an indicator for subscription, and $s_{ij\neq0}(X_i)$ denotes the predicted probability of subscribing:

$$s_{ij\neq0}(X_i) = \frac{\exp(\phi + X_i\beta)}{1 + \exp(\phi + X_i\beta)}. \quad (12)$$

Parameters to estimate include ϕ, β, and the lasso penalty parameter ω. ϕ, β are estimated by maximizing the in-sample penalized likelihood, and ω is estimated by maximizing the out-of-sample likelihood, using two-fold cross-validation.

The lasso model is estimated on a set of 4,633 normalized variables, including individual's web-browsing and demographic variables. See Shiller (2020) for a detailed analysis of variable importance and additional estimation details.

4.3 Individual Demands

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 markup θ:

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

Figure 1 shows expected profits from each consumer type, both when the firm personalizes the markup for each consumer, and under uniform pricing. Note that the profit gains from personalizing the markup are large for captive consumers (with large $\psi = \nu_i/\ |\alpha|$). The density of consumer types is shown in Figure 1b. Overall, personalizing markups raises profits by 12.99% relative to status-quo uniform pricing, if ignoring impacts of personalized pricing on consumer backlash.[16]

5 Results

Counterfactual outcomes under optimized sticky targeted pricing are simulated using individual-level profit functions $\pi(P, \psi)$ and the distribution of types $g(\psi)$, from Section 4. To isolate the impact of product popularity, an array of different consumer arrival rates (λ) are considered.

Counterfactual simulations proceed in several steps, which are repeated for each assumed consumer arrival rate. First, the firm's value function is approximated using value function iteration, by iterating on the Bellman equation in Equation 1, until it converges. Then, the value function is used to determine the firm's policy function. Some outcomes directly follow. For example, 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, the per-period (length $= s$) interest rate is assumed to be 0.1/365.

[16] The percent profit increase, 12.99%, incorporates Netflix's fixed cost. Variable costs are assumed to equal the "cost of revenues" from Netflix's 2006 Annual Report, about \$627 million. Fixed costs are assumed to equal "operating expenses," 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.

If the price-commitment interval s lasts one day, this corresponds to a 10% yearly interest rate.

5.1 Comparative Statics

Figure 2 compares discounted profits from optimized sticky targeted pricing and from status quo 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 relationship between the absolute change in profits and the arrival rate is more nuanced. 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, reversing this pattern. 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.

A similarly nuanced relationship is apparent for the range of prices offered over time—rather than across different consumer types—because of two competing forces. First, as the arrival rate increases, the firm offers a smaller range of prices across different types of arriving consumers (see Figure 3a). 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 the range of prices offered over a given time interval (longer than s) increases in the rate of consumer arrivals. However, for very high consumer arrival rates, the firm forgoes changing prices altogether. Overall, the relationship between the price range over a longer interval and the consumer arrival rate has an inverted U-shape (see Figure 3b).

Finally, the relationship between the consumer arrival rate 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 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 for searching for personalized pricing are likely to fail to discover use of sticky personalized pricing. This section uses an alternate method: Comparing pricing patterns implied by the model of optimized sticky targeted pricing to empirically observed pricing patterns. With optimized sticky targeted pricing, the relationship between the consumer arrival rate and the range of prices offered over a longer interval 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.[17]

5.2.1 Amazon's Pricing Patterns

Amazon provides an auspicious context for searching for optimized sticky targeted pricing. Amazon has both consumer 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%.[18]

To investigate, Keepa's API was used to collect Amazon price and (category-specific) sales-rank histories for a random set of products sold directly by Amazon in February 2021.[19] Some static product characteristics were collected as well, including product categories and list prices. I collapsed the data to the monthly level, yielding average sales ranks and price

[17]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.2 for details.

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

[19]The product selection process prioritized finding similar counts of products from various points in the distribution of sales ranks, to compensate for the fact that many products with poor ranks were not available from Amazon directly, but rather only from third-party sellers on Amazon Marketplace who were excluded from analyses.

ranges during each month m $\left(\max_{t\in m}(P_{jt}) - \min_{t\in m}(P_{jt})\right)$.[20]

Price ranges are regressed on indicators for various ranges of lagged sales ranks. Specifically:

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

where $1(Sales\ Rank_{j,m-1} \in Range\ \ell)$ indicates whether the lagged sales rank of product j falls within the range denoted by ℓ. The results are reported in Table 1.

Amazon's pricing patterns, in Columns (1-3), match the simulated pricing patterns under 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. The increase for products with sales ranks between 500 and 1000, about \$1 to \$2 (depending on the set of controls), is large compared to the average price fluctuation over a month (\$3.92). Much less popular products, however, have smaller price ranges. This apparent inverted U-shaped pattern persists after controlling for product category, list price ranges, and date.

Columns (4-6) examine whether this pricing pattern is a relatively new phenomenon. Each column repeats the estimation model from Column (3), but restricts the estimation sample to non-overlapping time periods. Note that in earliest years (2015-2016), there appears to be a roughly monotonic relationship between price ranges and sales ranks: More popular products have larger price fluctuations. As will be shown shortly, this same monotonic relationship is apparent in a context where sticky targeted pricing is infeasible. However, there was a dramatic change at Amazon in later years. In the latter set of year pairs, in 2017-2018 and particularly in 2019-2020, the inverted U-shaped pattern appears. Hence, there is evidence that Amazon substantially changed its pricing strategies in recent years, and their new strategy generates pricing patterns which match the patterns expected under optimized sticky targeted pricing.

[20] The data collection process resulted in fewer observations in earlier years. To be included, products—defined by Amazon's proprietary version of UPCs called ASINs—must be available directly from Amazon in February 2021. Some ASINs were unavailable in prior years, for example, because new generations of products have different ASINs than their predecessors. See Section A.3 for details.

5.2.2 Brick-and-Mortar Grocery Pricing Patterns

This section explores whether the inverted U-shaped pattern between popularity and 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. Brick-and-mortar grocery stores do not recognize the consumer's type before the consumer sees prices, rather their type is revealed only at checkout via loyalty/reward cards. Additionally, the store does not observe which products the consumer is considering buying—unlike at e-commerce sites where consumers explicitly enter search keywords—implying the store would need to change prices for all (or most) products each time a new consumer enters the store.

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.[21] The restricted data include 792,162 product/store pairs. As with the Amazon data, the grocery data are collapsed to the monthly level for analyses. The collapsed data contain price ranges, average prices, and unit sales separately for each combination of product, store, and month.

The panel dataset is divided into two time periods: (i) January and February 2019, and (ii) the remainder of 2019. The latter set, months March through December, are used for analyses. Data from the first two months are used to construct ex-ante 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 popularity. 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.[22] Note that price fluctuation ranges are typically lower for less popular products,

[21] Dry foods include: baby food, baking mixes, beverages, candy, cereal, coffee, condiments, crackers, pet food, prepared foods, snacks, soup, and canned vegetables.

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

compared to the omitted category with pre-period sales exceeding 500 ($< 1\%$ of product/store pairs). There appears to be a monotonic relationship—not an inverted U-shaped relationship—between price range and popularity at brick-and-mortar grocery stores.

6 Conclusion

This paper first examines the effectiveness of optimized sticky targeted pricing, then finds evidence suggesting that it is currently used in practice. Specifically, ricing patterns expected with optimized sticky targeted pricing arise at a seller that can plausibly implement such pricing (Amazon), but not in a context where such pricing is infeasible (grocery stores). However, optimized sticky targeted pricing is difficult to conclusively verify: Evading detection is the primary motive for using optimized sticky targeted pricing instead of straightforward personalized pricing.

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?

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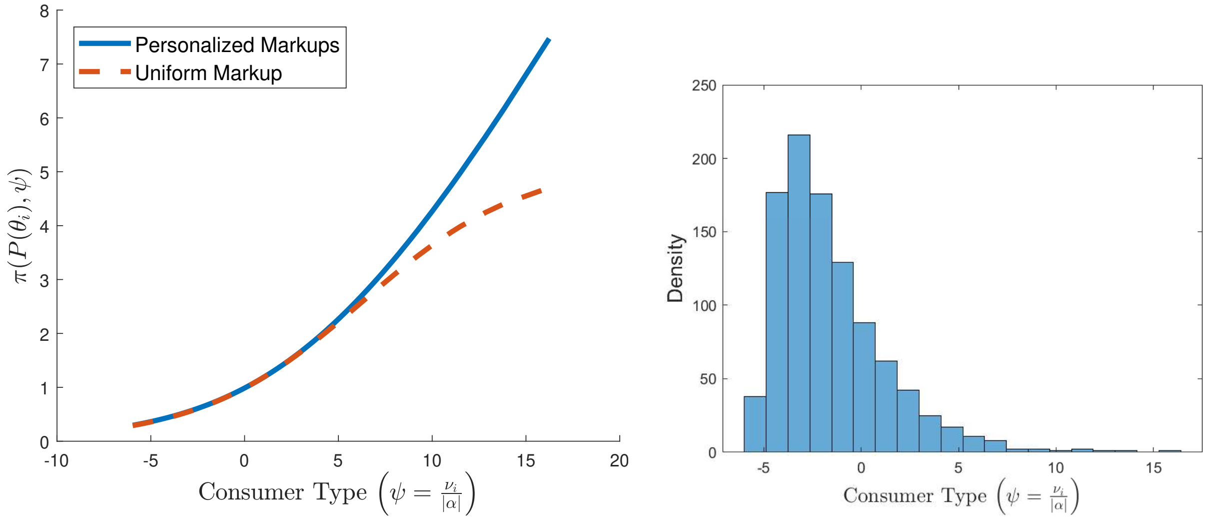
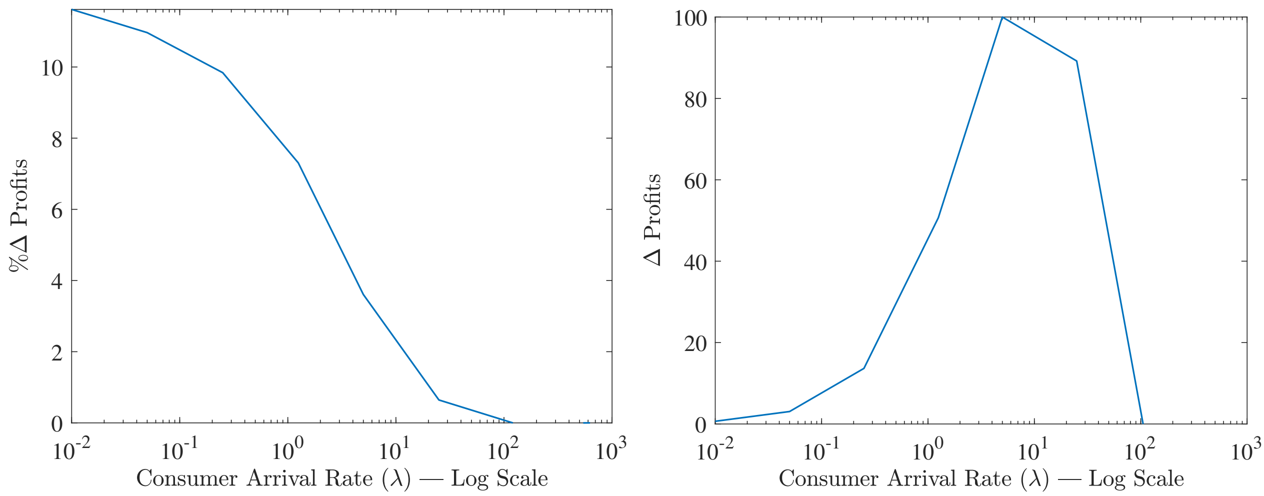
Figure 1: Profits by Type: Static Personalized Pricing



(a) Profits by Consumer Type **(b)** Distribution of Consumer Types

Notes: Figure 1a shows the expected profits earned from each consumer type under static personalized pricing (solid line) and uniform pricing (dashed line). Figure 1b shows a histogram of consumer types.

Figure 2: Counterfactual Profit Gain v. Consumer Arrival Rate

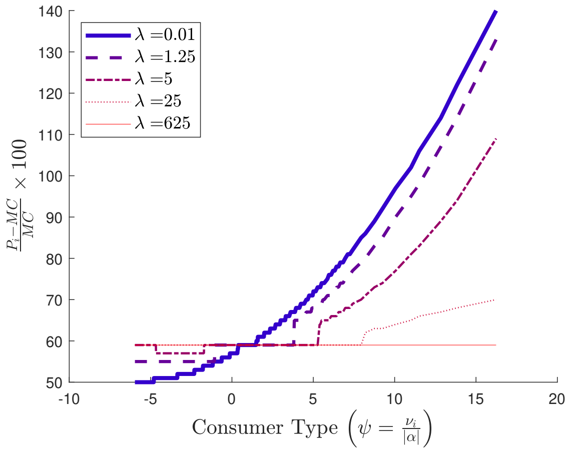


(a) Percent Change **(b)** Absolute Change

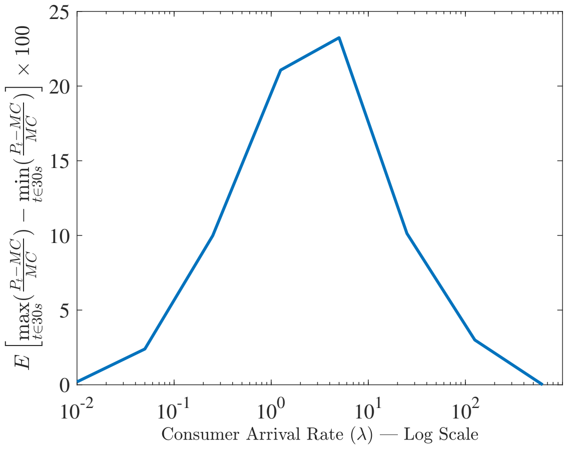
Notes: Figure 2a shows the percent increase in profits from implementing optimized sticky targeted pricing. Under optimized sticky targeted pricing, expected discounted profits equal $V(\hat{P})$, whereas under status quo uniform pricing discounted profits are $\frac{\lambda}{r}\int_{\psi}\pi(\hat{P},\psi)g(\psi)d\psi$, where $\hat{P}$ denotes the optimal uniform price. The consumer arrival rate (λ) denotes the expected number of consumer arrivals during a period of length s. Figure 2b shows the absolute increase in profits against the consumer arrival rate. Absolute profits are normalized so that the highest value across the various arrival rates is 100.

Figure 3: Simulated Pricing Patterns

Markups

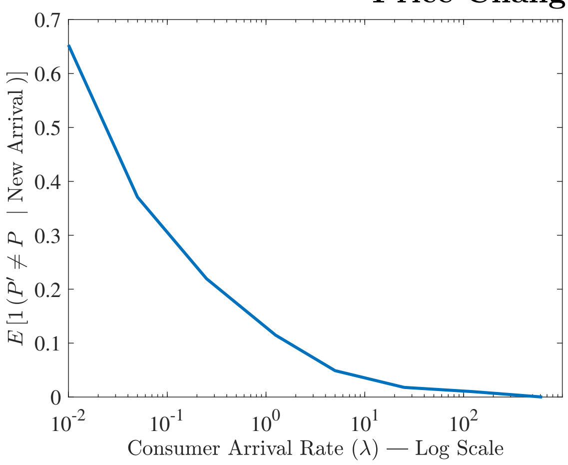


(a) Across Consumers

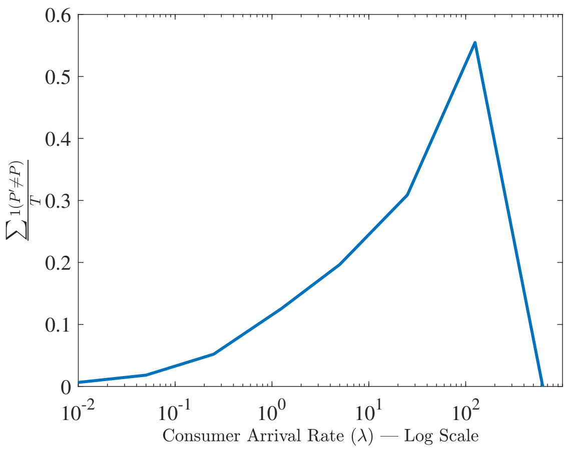


(b) Range over Time

Price Change Frequencies



(c) Conditional on Consumer Arrival



(d) Time-Normalized

Notes: Figure 3a shows the range of percent markups across consumer types, assuming the previous markup was the optimal uniform markup. Each line on the graph shows the range of markups across consumers for a specific arrival rate (λ). Figure 3b shows the expected range of markups offered over a time interval of length $30 \times s$ against the consumer arrival rate. Figure 3c shows the likelihood the firm changes the price when a new consumer arrives, conditional on the price-commitment period having ended. Figure 3d shows the expected number of price changes occurring during an interval of length s.

Table 1: Pricing Patterns at Amazon

	The dependent variable is monthly price range: $\max_{t\in m}(P_{jt}) - \min_{t\in m}(P_{jt})$					
	Entire sample			Detailed timing		
				2015-2016	2017-2018	2019-2020
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged sales rank:						
1(Btw. 100 & 500)	0.449	0.271	0.328	-3.201	0.716**	0.484***
	(0.336)	(0.243)	(0.247)	(2.430)	(0.332)	(0.185)
1(Btw. 500 & 1000)	1.999***	1.151***	1.138***	-3.499	0.0938	1.363***
	(0.358)	(0.256)	(0.259)	(2.434)	(0.363)	(0.206)
1(Btw. 1000 & 2000)	1.278***	0.683***	0.618**	-3.892	0.541	1.010***
	(0.357)	(0.256)	(0.260)	(2.403)	(0.389)	(0.224)
1(Btw. 2000 & 5000)	0.517	0.0675	0.184	-4.601*	0.191	0.494**
	(0.349)	(0.250)	(0.255)	(2.414)	(0.374)	(0.207)
1(Btw. 5000 & 10,000)	0.387	-0.274	-0.112	-4.854**	0.123	-0.116
	(0.348)	(0.249)	(0.255)	(2.408)	(0.380)	(0.193)
1(Exceeding 10,000)	-0.118	-1.229***	-0.382	-5.111**	-0.569*	0.118
	(0.343)	(0.243)	(0.260)	(2.469)	(0.322)	(0.211)
Fixed effects:						
Category	Y	Y	Y	Y	Y	Y
List price decile		Y	Y	Y	Y	Y
Date			Y	Y	Y	Y
Observations	274,953	27,4953	274,953	40,266	74,126	123,113
Adjusted R^2	0.041	0.131	0.143	0.163	0.180	0.131

Notes: Columns (1-3) include the entire pricing history for available products, from the earliest available date through February 2021. Columns (4-6) estimate the model separately for non-overlapping time periods. Standards errors, clustered by product, are reported in parentheses.

Table 2: Pricing Patterns at Grocery Stores

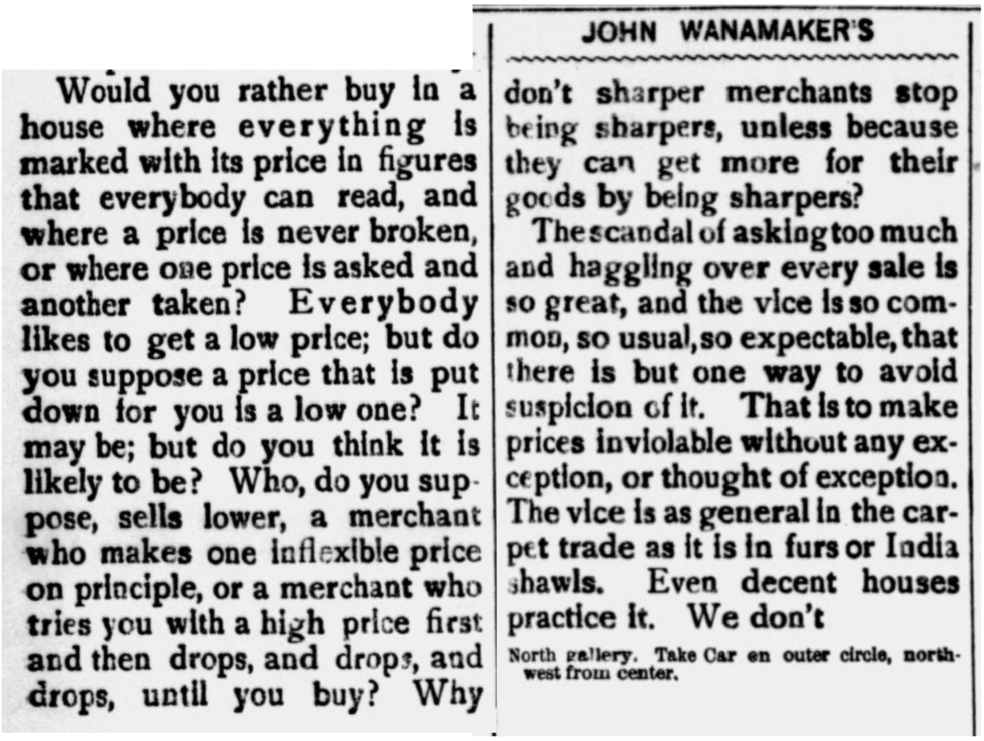
	The dependent variable is monthly price range: $\max_{t \in m}(P_{jt}) - \min_{t \in m}(P_{jt})$			
	(1)	(2)	(3)	(4)
Jan-Feb unit sales (at single store):				
Sales$<$ 10	-0.527***	-0.496***	-0.497***	-0.524***
	(0.0377)	(0.0352)	(0.0352)	(0.0352)
$10 \leq$ sales < 25	-0.361***	-0.348***	-0.348***	-0.370***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

Notes: The data sample used to estimate these models includes months March through December, 2019. The dependent variable is the range of prices offered over a month for a product/store pair. 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

This figure shows an excerpt of an advertisement that originally appeared on the 5^{th} 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 steps. 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.[23] Consumers can also be required to provide login credentials to access the requested domain.

[23] 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.

A.2 Amazon Pricing: Price Change Frequencies

Figure 3d suggests that optimized sticky targeted pricing causes an inverted U-shaped pattern between product popularity and price change frequencies. However, other factors strongly impact the relationship between popularity and the frequency of price changes. In particular, firms can measure small demand shocks more quickly for popular products, and the profit gains (in absolute terms) from 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 obscuring the inverted U-shaped pattern between popularity and price change frequencies that would otherwise arise from sticky personalized pricing. Despite these concerns, the remainder of this section examines whether this inverted U-shaped pattern is observable.

To determine the relationship between price change frequencies and popularity, monthly price change frequency is regressed on indicators for various ranges of lagged sales ranks. Specifically:

$$\sum_{t \in m} 1(P_{jt} \neq P_{j,t-1}) = a + \sum_{\ell} \kappa_{\ell} 1(Sales\ Rank_{j,m-1} \in Range\ \ell) + \epsilon_{jt}. \tag{15}$$

The results are shown in Table A1. Note that the inverted U-shaped pattern is not readily apparent.[24] Rather, it appears that the most popular set of products change price most frequently; the mean number of monthly price changes for the most popular group (ranks < 100) is $\sim$7.4 , which equates to a price change about every four days.[25]

This pattern is consistent with simultaneous use of optimized sticky targeted 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 make small price adjustments at nearly every opportunity (i.e., the end of every fixed-price interval). By contrast, the price change frequency in Figure 3d peaks at about 0.5, suggesting optimized sticky targeted pricing can at most cause price changes about half as often as feasible. Thus, price changes frequencies for other reasons overshadow those attributed to sticky targeted pricing, at least for popular products, thus obscuring patterns that are indicative of sticky personalized pricing. 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.

[24]Similar results were found when normalizing price change frequencies by the fraction of the month the product was in stock

[25]If normalizing price change frequencies by the portion of the month a product is in stock, then the average price change frequency for popular products is $\sim$10.9, which corresponds to a change roughly every three days.

Table A1: Price Change Frequency Patterns — Amazon

	The dependent variable is monthly price change frequency		
	(1)	(2)	(3)
Lagged sales rank:			
1(Btw. 100 & 500)	-0.591	-0.614	-0.637
	(0.581)	(0.581)	(0.583)
1(Btw. 500 & 1000)	-0.914	-1.113*	-1.150*
	(0.584)	(0.592)	(0.589)
1(Btw. 1000 & 2000)	-0.126	-0.370	-0.360
	(0.594)	(0.597)	(0.594)
1(Btw. 2000 & 5000)	-1.308**	-1.509**	-1.499**
	(0.600)	(0.603)	(0.600)
1(Btw. 5000 & 10,000)	-0.893	-1.179*	-1.201*
	(0.649)	(0.652)	(0.653)
1(Exceeding 10,000)	-3.989***	-4.308***	-3.796***
	(0.560)	(0.562)	(0.578)
Fixed effects:			
Category	Y	Y	Y
List price decile		Y	Y
Date			Y
Observations	274,953	274,953	274,953
Adjusted R^2	0.019	0.025	0.031

Notes: The dependent variable is the count of price changes during a month. Standards errors, clustered by product, are reported in parentheses.

A.3 Detailed Timing Supplement

A potential concern with the detailed timing analysis in the main text arises from the unbalanced panel used in estimation. It is possible that the products observed in later years are somehow fundamentally different than the products available earlier. Perhaps these differences explain the emergence of the inverted U-shaped pattern. This section examines this concern more closely.

Table A2 shows summary statistics for the main variables of interest, separately for three pairs of years: 2015-2016, 2017-2018, and 2019-2020. Panel A imposes no restrictions on the sample, except for the time frame. Panel B restricts the sample to products (ASINs) available in 2015-2016. Note that both panels show that price fluctuations increased substantially around the beginning of 2017, thus showing a general trend that persists when restricting the sample to products available early on. In 2015-2016, a product's price typically fluctuated by about \$2.8 over a month. In later years, the typical price fluctuation was at least \$4.7, a roughly 70% increase. These statistics suggest that Amazon's pricing became more sophisticated around the beginning of 2017, which may reflect implementation of optimized sticky targeted pricing.

To investigate further, Table A3 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 places no restrictions on the sample of products (apart from the time frame). Panel B restricts the sample to products available in 2015-2016, yielding similar results. 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), a context 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 at Amazon in later years. In the latter set of year pairs, in 2017-2018 and particularly in 2019-2020, the inverted U-shaped pattern appears, the same pattern that is expected when a firm is using optimized sticky targeted pricing.

Table A2: Summary Statistics Over Time — Amazon

Panel A

	2015-2016		2017-2018		2019-2020	
	Mean	SD	Mean	SD	Mean	SD
$\max_{t \in m}(P_{jt}) - \min_{t \in m}(P_{jt})$	2.8	7.8	4.8	9.8	5.7	12.8
Price (P_{jt})	33.9	38.2	37.6	40.8	39.0	44.7
Sales rank$_{m-1}$ (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
$\max_{t \in m}(P_{jt}) - \min_{t \in m}(P_{jt})$	2.8	7.8	4.7	9.7	5.2	10.2
Price (P_{jt})	33.9	38.2	36.1	38.4	36.3	35.4
Sales rank$_{m-1}$ (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.

Table A3: Amazon's Pricing Patterns — Changes over Time

Panel A

	The dependent variable is: $\max_{t\in m}(P_{jt}) - \min_{t\in m}(P_{jt})$		
	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. Panel A uses all observations in each period. Panel B restricts the sample to the set of products available in 2015-2016. Standards errors, clustered by product, are reported in parentheses.