Intertemporal Pricing of New Products: Incentivizing Consumer Learning and Inertia

Dan Zou*

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Abstract

When a new brand is launched, consumers are initially both uncertain of and not inertial to the new brand. Though these barriers may disappear on their own over time, a savvy brand manager who knows the relative importance of both can use relevant marketing levers to increase profits in the long run. This paper studies exactly these barriers and measures their relative effects on the launch of new brands. In particular, I focus on how the new brand’s optimal prices are affected intertemporally in order to pin down which effect is larger. I start with evidence that prices for new products are indeed atypically low compared to later in their life cycle and compared to mature products. Motivated by this, I try to isolate the effects of consumer learning and inertia through a simple yet flexible structural model of demand. For simplicity, I limit the consumer learning and inertia processes to only be affected by actual purchases. As a practical example, I estimate this model using data from the yogurt category which includes purchases before and after the entry of Chobani. In counterfactuals, I find optimal prices in scenarios with different parameters for consumer learning or inertia. These counterfactuals reveal that, for Chobani, incentivizing consumer loyalty is the larger motivation for the firm to price low at launch. Though I only estimate and simulate one brand launch, the methodology for studying these relative effects is generally useful for any brand manager seeking to incentivize consumer learning or inertia for new brands.

1 Introduction

The existence of consumer uncertainty and consumer inertia can handicap new brands’ profitability. If consumers are risk averse and uncertain about their preferences for a new

*University of Chicago - Booth School of Business, PhD student in Marketing. Please direct all correspondence to zou@chicagobooth.edu. I would especially like to thank Günter Hitsch, Jean-Pierre Dubé, and Pradeep Chintagunta for their advice throughout the course of this project.
brand, they will be willing to pay less for the new brand than if they had more information. And, if consumers exhibit inertia in that they are more likely to buy brands they bought in the past, the fact that a new brand is unavailable before it is launched weakly reduces consumers’ willingness to pay relative to later, when consumers have actually had a chance to purchase the brand. These handicaps are not necessarily permanent: even without any additional incentives, consumers over time may purchase and learn about the new brand, increasing their willingness to pay by inducing inertia or reducing uncertainty. Depending on consumers’ preferences, however, this unaided process could be slow. Generally speaking, by speeding up learning or the rate at which new customers purchase the brand, the new brand’s manager can increase long-run profits by investing in consumers early and reaping a higher willingness to pay later. By how much these investments will or will not pay off critically affects the manager’s marketing decisions at product launch. For example, if free samples affect consumer learning but have no effect on inertia, they would only be warranted if consumer uncertainty posed a large enough disadvantage. Or, if low introductory prices affect consumer uncertainty and inertia by incentivizing consumers to purchase, they might be more cost-effective if both handicaps are large.

These payoffs to incentivizing consumer learning and inertia are exactly the focus of this paper. Should a new brand’s manager focus on informing consumers, getting consumers to buy, both, or neither? In order to answer this question, I look to the effects these processes have on new brands’ profits and optimal prices over time. Differences in prices and profits among scenarios where consumer learning or inertia are turned on or off directly speak to the short-run profits the new brand foregoes for greater longer-run profits. Because I do not have reliably exogenous variation which changes consumers’ learning or inertia in the real world, I take two approaches. First, I examine pricing patterns over time and across brands in observed data. Second, I simulate a model where I change the impact consumer learning or inertia have on purchase decisions and then calculate how profits and optimal prices change.

I use two data sets in these approaches: a household scanner panel and a retailer scanner panel; Nielsen’s Homescan Consumer Panel and Retailer Scanner Panel. These data are novel in their breadth, covering households and retailers across the United States and including information on all goods purchased by households or sold by retailers. My exploratory analysis focuses on a subset of this data, looking into a handful of categories sold at grocery store retailers (yogurt, refrigerated pudding, toothpaste, and vodka) in order to figure out whether new brands are priced differently. I find that, across my four product categories, new brands’ prices increase over their first year faster than over their second year. For yogurt, refrigerated pudding, and toothpaste, I also find that price changes for new brands in their
second year are comparable to price changes for existing brands. These findings suggest that firms indeed price new brands low, consistent with a response to consumer uncertainty or consumer inertia.

Knowing this, I move to the questions of how much and whether a new brand should invest in making consumers more inertial or more informed. In order to link consumer uncertainty or inertia with prices or profits, I model both demand and supply of the new brand. For the sake of real-world relevance, I examine the entry of Chobani in 2007-2008. In order to try to improve identification of household learning separate from other forms of state dependence, I include controls for household state dependence in brands and unobserved household heterogeneity. Separating out household state dependence from consumer learning relies on an assumption that households do not learn about old yogurt brands but do learn about Chobani and on the fact that my data span pre- and post-launch periods. In the interest of parsimony, I model myopic, heterogeneous households that are only affected by their brand-specific match values, learning about Chobani’s match value, brand-level state dependence, and brand-level prices. I estimate the parameters of this demand model using a hierarchical Bayesian Markov chain Monte Carlo algorithm.

I do not use observed price patterns when I simulate counterfactual consumer behavior. This is because, in a counterfactual world where brands’ payoffs are different, it is unclear that brand managers would play the same pricing strategies. Therefore, exploring the effect different consumer behavior has on prices and profits requires structural assumptions on the supply side. I simplify the problem to one of a monopolist that cannot price discriminate, has no agency problems, and faces only marginal costs. I believe that these simplifications preserve the effects I am interested in, how firm prices and profits change, without making my problem unnecessarily complex. Even in this very simple case, however, the firm’s problem is difficult to solve without further assumptions. In the general case, the firm is allowed to condition its pricing decisions on the realized distribution of household learning across households (possibly conditional on some information set). Because this distribution has effectively infinite degrees of freedom and evolves nontrivially, incorporating any information about revealed household demand into the monopolist’s policy function quickly becomes intractable.

Drawing from the macroeconomics literature, I simplify the problem using what I think is a reasonable assumption on how the consumers are aggregated. In particular, I examine the case where aggregate profits integrate over a continuum of consumers. By a continuum, I mean that, rather than facing a finite number of discrete consumers, there are infinitely many infinitely small consumers. Rather than summing over demand from a finite number of consumers and their random realizations, aggregate profits instead integrate out the joint
distribution of these random draws when calculating demand. This preserves the richness of my demand model while making the firm’s problem solvable. With all random variables integrated out, aggregate profit becomes a deterministic function of prices, meaning the firm only needs to choose an optimal price path rather than solve for an optimal pricing policy function. Since I assume idiosyncratic utilities to be drawn from a type-1 extreme value distribution, I do not have to resort to a pure Monte Carlo simulation in order to evaluate aggregate profits. Instead, I analytically integrate out idiosyncratic utilities. This makes aggregate profits a smooth function of prices, which, in turn, allows for the use of efficient optimization tools. Because I allow the firm to set different prices at different time periods, having a non-smooth objective function would dramatically increase the computational burden of optimization.

To study whether the new brand wants to incentivize consumer learning or inertia, I start by calculating baseline profits and optimal prices without changing any demand parameters. In counterfactuals, I turn off consumer learning or inertia and recalculate profits and optimal prices. Comparing the results of these counterfactuals with the baseline indicates whether incentivizing consumer learning or inertia is a good idea. In particular, I find that in the baseline case and in the counterfactual with no learning, prices increase roughly 8% over the first year. In the counterfactual with no consumer inertia, however, prices barely increase at all. This suggests that, for Chobani, consumer inertia is the greater force causing Chobani to price low at introduction.

The rest of the paper proceeds as follows. Section 2 outlines related research and discusses the contribution of my work. Section 3 describes the data and my construction of the panel. Section 4 details the demand model, with Section 5 detailing estimation of the demand model. I discuss my counterfactuals in Section 6. Section 7 concludes.

2 Past Literature

There has been a vast amount of research done studying the pricing of new products, consumer learning through purchase, and consumer inertia. More generally, there has also been research in economics discussing the problem of aggregating heterogeneous agents. In this section, I try to describe these streams of research and explain where my work contributes.

The theory on new product pricing is prescriptive and relatively restrictive. This is because models of firm pricing require many assumptions in order to calculate optimal behavior analytically. Though the comparative statics of any individual new product pricing model are straightforward, understanding these threads jointly is difficult without empirical evidence on the magnitude of their relevance. So, in the absence of good data, the early theory
literature offered the insights it could into why we might observe different price patterns in real life. For example, Robinson and Lakhani (1975) talks about the implications of forward-looking rather than myopic firms, and Dolan and Jenland (1981) describes optimal pricing under simple models of market evolution. Somewhat more recently, Krishnan et al. (1999) takes some of these pricing models and shows that patterns produced by these models are similar to those found in data. Due to enormous advances in computing power since these models were developed, it has become possible to search for optimal prices without a fully analytic formulation of the firm’s problem. I try to accomplish this in my research here.

An extensive body of work studies how learning through purchase can enter the decision functions of different types of agents. Given my focus on implications of consumer learning, the most relevant subset of this work was started by Erdem and Keane (1996). Erdem and Keane (1996) rationalizes households’ purchases of laundry detergent using a model involving forward-looking agents who learn both by purchasing and by viewing advertisements. In a counterfactual which holds all firm behavior constant except one firm’s advertising, they find that sustained advertising has meaningful, positive long-run effects, with consumer learning causing a stronger effect on new products. For a detailed review of this paper and other papers which have studied different types of consumer learning, see Ching et al. (2013).

Worth mentioning here are Ching (2010a) and Ching (2010b), both of which control for the fact that pricing is endogenous in counterfactual simulations. This type of control is important to my work because I am interested in counterfactual worlds which are not observed in the data. In other words, I want to avoid the Lucas critique as best I can, especially since I am fundamentally changing the parameters that affect demand. Ching (2010a) and Ching (2010b), however, consider a very different research setting: aggregate learning for new, generic pharmaceuticals using aggregate data. With household-level panel data, I am able to allow households to be fully heterogeneous in my demand estimation. Furthermore, whereas Ching is interested in price elasticities along the observed equilibrium path and the effect of policy changes, I focus on firms’ tradeoffs in unobserved cases where consumers are more or less informed. The main simplification of Ching’s models enters through the idea of aggregate learning: every agent in the market shares beliefs about new products. I instead allow for heterogeneity in beliefs across agents (consumers, in my case). This means that the distribution of beliefs across consumers is not easily summarized, a significant departure from Ching (2010a) and Ching (2010b), which summarize the amount of learning using one distribution.

Also worth mentioning here is Goettler and Clay (2011), which studies the role of fixed two-part tariffs as a price discrimination tool when consumers learn about their idiosyncratic preferences for different products. Their model of consumer behavior is very similar to the
consumer behavior I am interested in, but the examination of fixed tariffs applies to very different settings. Because I am per se interested in intertemporal pricing in a retail setting, and because prices for retail goods change over time, I cannot simplify my supply model to one with only fixed prices. Although they briefly demonstrate a counterfactual which searches for optimal tariffs under different scenarios, it is unclear whether their method would be able to optimize over intertemporally differing prices, as this would greatly increase the dimensionality of the search space.

The interactions between consumer learning and firm decisions have also been studied from a theoretical perspective. These papers examine a variety of effects that consumer learning, more generally, have on equilibrium outcomes. Some examples include common values and common information (Kalish (1983), Bergemann and Välimäki (1997), Bergemann and Välimäki (2000)), “mass” versus “niche” markets (Bergemann and Välimäki (2006)), or the case where consumers have to learn about multiple products (Bergemann and Välimäki (2000), Villas-Boas (2004)). My work here, however, does not consider these effects, instead taking a small step towards understanding empirically the basic underlying relationship between consumer learning through purchase and firm pricing.

The existence and impact of consumer inertia has also been extensively studied. Dube et al. (2008), which solves for optimal steady-state pricing policies in the presence of consumer inertia and consumer heterogeneity, examines how inertia affects long-run pricing. The main distinction from my research is that “structural state dependence” (Heckman (1981)) and consumer learning have different implications for the new brand’s launch. This means that knowing the relative magnitudes of the two effects is important in choosing the marketing mix from launch onward, the focus of this paper. Dube et al. (2010) finds that structural state dependence is robust to alternative explanations for inertia, specifically preference heterogeneity, autocorrelated taste shocks, search, or learning. This work leads me to believe that structural state dependence may have a meaningful impact on a new brand’s launch decisions.

Because consumers are heterogeneous and because this heterogeneity evolves over time due to consumer learning and inertia, solving the new brand’s pricing problem is not so easy. Although not directly related to my work, research about heterogeneous agents in macroeconomics models has studied methodological techniques of summarizing heterogeneity tractably so as to study movements in macro-variables. Because consumer learning leads consumers to be heterogeneous even if they are ex ante identical, and because I am essentially interested in aggregate demand, this macroeconomics research is qualitatively very similar. My main simplification here will involve an assumption that profits are maximized over demand from a continuum of consumers. Under this assumption, a sort of “law of large
numbers” holds, permitting tractable solutions of the profit maximization problem. Uhlig (1996) and Al-Najjar (2004) discuss this generally and formally. Because the details are reasonably technical, I leave my application of this work for Section 6.

3 Data

My data come from two sources: Nielsen’s Homescan Consumer Panel (hereafter, “Homescan”) and Nielsen’s Retailer Scanner Panel (hereafter, “RMS”). Because I only use a subset of the available data, I describe this subset here. My Homescan extract is a household scanner panel over households in the United States from 2006 through 2011, containing information on whether the household took a trip to a grocery store, characteristics of visited stores (identity and Zip-3 location of the store), and prices, characteristics, and quantities purchased for purchased UPCs. My RMS extract is a weekly retailer scanner panel over a subset of United States grocery retailers from 2006 through 2011, containing characteristics of the stores (hidden retailer identity and Zip-3 location) as well as prices, characteristics, and quantities sold of all UPCs sold by every store owned by each retailer.

An important limitation of the raw data when using it to estimate discrete choice models is that only prices for purchased products are observed. This is true in the Homescan at the household level and in the RMS at the store level. In both my exploratory analysis and structural estimation, I am concerned about selection bias arising from not observing prices when products are not purchased. In order to combat this bias, I impute prices in both the RMS and the Homescan. The treatment of these missing prices in itself has been a topic of research (see, e.g., Erdem et al. (1999)), but I believe that my approach is both reasonably believable and testable. Very briefly, in the RMS, I impute UPCs’ missing weeks’ prices by using the observed price series for those UPCs. I then take ACV-weighted averages of these prices at the brand level in order to impute the prices for products the Homescan households did not purchase. For a much more detailed description of my procedure, see Appendix A.

3.1 Lower Prices for New Brands

I first explore the data to see whether brands’ prices are consistent with the story that brands are trying to incentivize purchase when the brands are new. By incentivizing purchase at launch, a brand trades off short-run profits in exchange for consumers who are willing to pay more for the brand in the future. In particular, I look for evidence that firms price new products lower at introduction than later in their life cycle. To do so, I examine the

1These data are available through the Kiits-Nielsen Data Center at the University of Chicago Booth School of Business. Visit http://research.chicagobooth.edu/nielsen for more details.

2Prices in the RMS are imputed to be expenditure divided by quantity. Since Nielsen’s week definition does not necessarily correspond to when retailers change prices, Nielsen’s “prices” should be understood as an expenditure-weighted average price per week.
Figure 1: Yogurt category. One observation is a (new) UPC-store; means are unweighted and within-UPC-store. Only UPC-stores that exist for at least two years included in order to check with Figure 2. Mean: 0.9753, Median: 0.9829, IQR: [0.9260, 1.0223], 134,336 UPC-stores. Histogram is basically identical if all UPC-stores that exist for one year included. X-axis is truncated at 0.5 and 1.5.

ratio of a new product’s average price in its first two months compared to its average price in the rest of its first year. I do this calculation for all UPC-stores for new brands, and define a brand’s launch date to be the first week it is sold in the RMS in a Zip-3. I do this to account for the fact that brands are often not released simultaneously across the entire United States.

Figure 2 shows a histogram of this average price ratio for UPCs of new brands in the Yogurt category. Note that both the mean and median are less than 1, implying that prices increase over the first year when a new brand is launched. It is important to verify that this increase is atypical for new brands, since if prices continued increasing at this rate, then this would not be evidence for new brands specifically incentivizing purchase. Figure 2 addresses this by plotting the CDFs of the distribution of this average price ratio for new brands, new brands in their second year, and old brands. Notably, the distribution has, in some sense, shifted to the right; prices for new brands of yogurt do not, in aggregate, continue increasing as rapidly in their second year as in their first year. As a second check, the distribution of price ratios for old brands’ UPCs suggests that this rightward shift in pricing patterns

\[3\text{Here, I use Nielsen’s definition of a brand to find new brands.}\]
Figure 2: Yogurt category. See Figure 1. Comparing the distribution of price patterns for new brands’ UPC-stores in their first year with their second year and with old brands’ UPC-stores. Vertical lines indicate distribution means. Second year mean: 1.0000, median: 1.0000, IQR: [0.9614,1.0250]. Old UPC-stores’ mean: 1.0000, median: 0.9949, IQR: [0.9485, 1.0335], 2,201,778 UPC-stores.
Figure 3: Toothpaste category. Comparing the distribution of price patterns for new brands’ UPC-stores (483,634 UPC-stores) in their first year with their second year and with old brands’ UPC-stores (3,763,124 UPC-stores). Vertical lines indicate distribution means. First year mean: 0.9761, median: 0.9898, IQR: [0.9312, 1.0223]. Second year mean: 1.010, median: 1.000, IQR: [0.9652, 1.0270]. Old UPC-stores’ mean: 0.9874, median: 0.9921, IQR: [0.9539, 1.0076].

persists past the second year.

I extend this analysis to other product categories in the RMS as well: toothpaste, refrigerated pudding, and vodka (Figures 3 through 5). I choose these categories because I suspect that they have relatively frequent new brand launches. I find that for toothpaste, the price patterns are very similar; for refrigerated pudding, the mean moves in the same direction but the median does not; for vodka, the mean also moves in the correct direction (but not the median) with the pattern actually somewhat reversing for old brands.

On the whole, I take this to be evidence that firms are pricing new brands differently than old brands. This increases the likelihood that consumers will buy these brands at launch, which can incentivize consumer learning and consumer inertia. By compensating risk averse consumers or by making consumers inertial at launch through lower prices, firms can reap higher profits sooner rather than later. Importantly, as is seen in distributions, the price difference is persistent across categories, but is not large on average (e.g. a 2.5% difference in first year prices for yogurt).

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4Given the observed price patterns, however, this statement likely does not hold for vodka.
Figure 4: Refrigerated pudding category. Comparing the distribution of price patterns for new brands’ UPC-stores (24,572 UPC-stores) in their first year with their second year and with old brands’ UPC-stores (297,700 UPC-stores). Vertical lines indicate distribution means. First year mean: 0.9792, median: 0.9909, IQR: [0.9159, 1.1147]. Second year mean: 0.9934, median: 0.9837, IQR: [0.9491,1.1191]. Old UPC-stores’ mean: 0.9883, median: 0.9870, IQR: [0.9469, 1.0217].
Figure 5: Vodka category. Comparing the distribution of price patterns for new brands’ UPC-stores (46,710 UPC-stores) in their first year with their second year and with old brands’ UPC-stores (426,139 UPC-stores). Vertical lines indicate distribution means. First year mean: 1.0048, median: 1.0000, IQR: [0.9791, 1.0304]. Second year mean: 1.0105, median: 1.0000, IQR: [0.9848, 1.0270]. Old UPC-stores’ mean: 0.9956, median: 0.9965, IQR: [0.9654, 1.0152].
3.2 Alternative Explanations

Though this evidence is consistent with brand managers incentivizing consumer learning or inertia, low introductory prices may be a result of other explanations which I cannot rule out. For example, if the cost of producing a brand decreases when the brand is new and stays flat when the brand is old, this might be reflected in the retail price. On the consumer side, it may be that consumers’ match value beliefs about the new brand are systematically biased lower than their true match values. The brand’s manager would want to incentivize learning at launch (in the same way as if consumers were risk averse), and one way to do this would be to offer lower prices. I cannot directly test to see whether these effects exist, but my methodology will let me simulate these cases as robustness checks.

Knowing all of this, I move to developing and estimating a model of consumer demand which captures consumer learning through purchase and controls for potential confounds using the yogurt data. I use the yogurt data because of the launch of a large, new brand, Chobani, in the middle of my panel. I try to study household learning of Chobani at the brand level, looking at households choices among brands. I control for some confounds in the way I select households in the Homescan data; I leave the details (and discussion) of this to Section 5, where I discuss identification.

4 Household Demand

I assume households are myopic and face a discrete choice problem, maximizing their per-period utility by choosing among a discrete set of brands. I also assume that they take prices as given. Let $h \in H$ index over households, $j \in J$ index over brands, and $t$ index over purchase occasions. Let there be a subset $J_L \subset J$ of brands over which consumers learn and a subset $J_0 \subset J$ of brands over which consumers do not learn.

4.1 Household Learning

Households possess true match values for brands, $Q_j$ (household-specific subscript suppressed). I assume that $\{Q_j\}_{j \in J_0}$ are known and that $\{Q_j\}_{j \in J_L}$ are not known to each household. Furthermore, I assume that households receive normally distributed signals $\hat{Q}_{jt} \sim N(Q_j, \sigma^2_L)$ upon choosing brand $j \in J_L$ at $t$, and that the household is endowed with one such signal before new brand $j$ becomes available.6

Because of the convenient choice of prior and signal distributions, the household’s beliefs

5Specifically, among Dannon, Chobani, Fage, Stonyfield, Yoplait, store brands, and other brands. See Appendix A for details.

6Without more information about consumers’ beliefs, e.g. from survey data, I do not believe that households’ priors are separately identifiable in the data. Instead, in robustness checks, I change the distribution of consumers’ priors to see whether this assumption significantly changes the results. Because I do not have a formal identification argument here, I impose the aforementioned assumption.
for brands \( j \in J_L \) at any point in time \( t \), are given by

\[
\bar{Q}_j \sim N(Q_{jt}, \sigma_{jt}^2),
\]

where \( Q_{jt} \) and \( \sigma_{jt}^2 \) evolve as

\[
\begin{align*}
\sigma_{jt+1}^2 &= \left( \frac{1}{\sigma_{jt}^2} + \frac{1}{\sigma_L^2} \right)^{-1} \\
\bar{Q}_{jt+1} &= \frac{\sigma_{jt+1}^2}{\sigma_{jt}^2} \bar{Q}_j + \frac{\sigma_{jt+1}^2}{\sigma_L^2} \bar{Q}_{jt}
\end{align*}
\]

if the household chose \( j \) at \( t \), and \( \sigma_{jt+1}^2 = \sigma_{jt}^2, \bar{Q}_{jt+1} = \bar{Q}_{jt} \) if not.

### 4.2 Per-Period Household Utilities

I assume households’ utility from purchasing a brand \( j \in J_0 \cup J_L \) follows the functional form

\[
U_{hjt,Q} = -e^{-r_h \bar{Q}_{hj}}.
\]

Households make decisions, however, using their expected utility \( E[U_{hjt,Q}] \). For \( j \in J_0 \), \( E[U_{hjt,Q}] = -e^{-r_h Q_{hj}} \), trivially. For \( j \in J_L \), households instead make decisions using the familiar expected utility when utility follows a CARA functional form,

\[
E[U_{hjt,Q}] = -e^{-r_h Q_{hj} + \frac{\gamma^2 h^2 s_{ht}}{2}}.
\]

In order to capture the effect of the price of \( j \) for \( h \) at \( t \), \( p_{hjt} \), on consumers’ decisions, I assume that price enters into utility simply as \( U_{hjt,p} = \beta_{h,p} p_{hjt} \).

To account for the presence of consumer inertia, I allow households to have utility which depends on purchases in past periods through some state \( s_{ht} \). In this paper, I only allow \( s_{ht} \) to contain information on the last brand purchased and assume it enters consumers’ utility linearly: \( U_{hjt,s} = \gamma_h \mathbf{1}\{s_{ht} = j\} \). Note that this is a simple form for consumer inertia. In this paper, I do not consider higher-order inertia processes, but the demand model could be extended in this way.

Finally, I assume households possess an idiosyncratic utility \( \epsilon_{hjt} \), which I do not observe, and which is i.i.d. across time and across brands. I assume that households observe \( \epsilon_{hjt} \) before making their decision. The consumer’s full expected utility function for brand \( j \) is the sum of these components:

\[
E[U_{hjt}] = E[U_{hjt,Q}] + U_{hjt,p} + U_{hjt,s} + \epsilon_{hjt}.
\]
Note that, through all of this, households’ parameters vary at the household level. In my estimation, I will allow flexibly for household-level heterogeneity in these parameters.

5 Demand Estimation

5.1 Hierarchical Bayesian MCMC Algorithm

The estimation technique follows primarily from Rossi et al. (2004). I assume the distribution of $\epsilon_{hjt}$ to be Type 1 Extreme Value distributed and estimate a hierarchical multinomial logit where households’ parameters have a mixture of normals prior distribution. I also do not include observable heterogeneity in my estimation, though this would be a straightforward step. I do this because I am mainly interested in the overall effects of consumer learning and inertia rather than how these effects interact with observables. My main departures from a simple hierarchical multinomial logit follow; for further details on the algorithm, see Rossi et al. (2004) and Appendix B.

5.1.1 Initial conditions

The state dependence variable is unobserved for my households’ initial purchase decisions. This leads to an identification problem in that each household’s initial state variable is endogenously determined. Heckman (1981) discusses this at length. Essentially, I am worried that, without the correct treatment of this endogeneity, my estimation will not properly separate unobserved heterogeneity from households’ state dependence parameter.

I try to deal with this problem by assuming that households’ initial state variables are drawn from their stationary distribution, conditional on households’ parameters. This assumption is restrictive, but could be tested against other distributions of initial state variables. Practically, I assume a uniform distribution over states at some initial time period and then simulate the model (drawing prices from the observed joint distribution of prices) for fifty trips for each household. I use Monte Carlo integration to integrate over this distribution in my likelihood, simulating over 100 draws.

5.1.2 Unobserved match value signals

Since I do not observe the match value signals observed by households, I instead use data augmentation to draw households’ beliefs. Because of the structure of belief evolution in Equations 1 and 2, $\sigma^2_{jt}$ evolves deterministically, given households’ parameters, meaning I only need to draw households’ mean match value beliefs in each iteration of my algorithm. Because I do not know of a conjugate distribution to draw these mean match value beliefs, I use a Metropolis-Hastings step to draw these values.
5.2 Identification

5.2.1 Match values

Note that absolute match values are not identified in this formulation of consumer utility. This is because $-r_h Q_{hjt} + \frac{r^2 \sigma^2_{Qjt}}{2}$ can take the same value for different parameter values. The relevant identified metrics are the relative match values (i.e. whether the consumer likes brand $j$ more or less than brand $k$, and by how much). As a result, I fix the location and scale of $Q_{hjt}$ by arbitrarily setting the match value for Yoplait to be $-0.6$.

5.2.2 Outside option

I cannot fix the mean utility for the outside option at some value. Because of the form of the exponential function using a type 1 extreme value distribution, this would impose an implicit restriction on purchase probabilities. Under reasonable parameters, specifically that households do not prefer higher prices and examining the case of no state dependence, the maximum mean utility for some brand is $0$ and the minimum is $-\infty$. Supposing that the outside option mean utility were fixed at $0$ would mean that the maximum purchase probability for any brand is $\exp(0) = 0.5$. This is only one example of a restriction imposed by fixing this value. To deal with this, I instead estimate a household-specific parameter $U_{h0}$, where $U_{h0t} = U_{h0} + \epsilon_{h0t}$.

5.2.3 Data selection

In order to control for potential confounds which may affect estimates of consumer learning or inertia, I limit the scope of the data I use in my demand estimation. In my Homescan extract are a total of around 40,000 households. First, I only consider households whose size does not change, who consist of a maximum of four members, who do not move into a different Zip-3, and who stay in the panel from 2006-2011. This restricts my sample to 9,114 households and 1,006,251 purchases of yogurt.

Second, I limit the scope of my data to just single-serving yogurt purchases. In particular, I exclude purchases of containers larger than 10 ounces, leaving me with 9,025 households. I exclude these large container purchases because I believe that people purchase large containers of yogurt for different reasons than single-serving yogurt.

Third, I exclude households that purchase multiple brands of yogurt in one purchase occasion. This leaves me with 4,308 households. Although I could expand the space of discrete choice decisions to include combinations of brands, identification for these combinations would be thin: the average household purchases multiple brands at only 4.2% of trips (conditional on being a household that ever purchased multiple brands of yogurt, the household purchases multiple brands at 8.0% of trips). Cutting out these households is crude
but still leaves many households, though they are possibly now non-representative. It may be possible to instead keep multiple brand households in the data, but this would require an assumption on how to deal with these multiple brand purchases. Because households may be purchasing multiple brands for many different reasons, e.g. variety seeking or differing preferences within-household, and because I want to focus on consumer learning, I leave this for future work.

Fourth, I exclude households that purchase multipacks of yogurt. Out of the 9,025 households that purchase single-serving yogurt, 1,980 households do not purchase multipacks. Combining this cut of households with the cut of multiple brand households, I am left with 1,509 households. I do this because these households are likely stockpiling. This interferes with estimation of consumer learning mainly because it is much less likely that a stockpiling household consumes its purchase of yogurt before the next shopping trip. This means that tracking how much household learning happens over time would be a lot noisier. In the best case, it would bias my estimates of consumer learning towards 0 (via standard measurement error bias). A richer model of consumer behavior might be able to properly spread out household learning depending on when consumption actually occurs, but I am not aware of research that has done this.

Fifth, I exclude households who purchase yogurt fewer than six times from 2006-2011. This is because I do not believe that a model of consumer learning applies to these households. Probably of greater concern is what drives these consumers to buy yogurt at all, which I do not explicitly model. Although these households’ behavior would be captured by a relatively higher utility for the outside option, I do not believe this would be accurate in a counterfactual. This exclusion leaves me with 838 households who purchase yogurt 28,861 times (the other 671 households only purchase yogurt 1,551 times).

Finally, I define a household to be in the market for yogurt if the household makes a trip to a store where the household ever bought yogurt from 2006-2011. This results in 406,720 total trips (approximately 1.56 trips per household per week). Again, for details on the construction of prices for unpurchased products, see Appendix A.

5.2.4 Identifying learning

In identifying household learning, I rely on the assumption that households only learn about Chobani and not about other brands of yogurt. This is motivated by the fact that the other large brands of yogurt have been around for a much longer time; the newest, Fage, has been available in the United States since 2001. Given this assumption, I argue that non-learning state dependence is identified by pre-Chobani purchase behavior. I could potentially separate out even more complex models of non-learning state dependence using
this assumption and a more complex model of state dependence, but I leave this for future work.

If households are new to the yogurt category, they may still be learning about yogurt. I try to deal with this in my inclusion only of households that purchased yogurt six or more times. Since yogurt is so ubiquitous, I do not think my assumption is too strong. For this to be a problem, effects from household learning of old brands need to be large relative to other household state dependence processes. I do not think this is the case.

5.3 Demand Estimation Results

After 30,000 burn-in iterations, I draw 10,000 posterior draws. As I mention in Appendix A, the price I use is, roughly speaking, the ACV-weighted average price per ounce for a brand of yogurt. Figures 6 and 7 are histograms over households’ median posterior parameter draw.

The parameters themselves are of some interest. Households exhibit a considerable amount of heterogeneity in brand preferences, price sensitivity, and learning. Beyond these observations, interpreting these raw estimates on their own, however, is difficult, so I turn to real-world quantities. Here, I calculate aggregate own price elasticities for Chobani and Yoplait over time. These elasticities are evaluated at the prices faced by each household at each trip. I then take the mean aggregate own price elasticities over each month and over over all households and trips from 2006-2011. Time series plots for these are in Figures 8
In order to understand how prices are affected by consumer learning and inertia, I model the supply of yogurt in my counterfactuals. This is especially true when demand parameters change, since, based on demand estimates alone, it is unclear how the supply of yogurt would react.

6 Counterfactuals

In my counterfactuals, my goal is to elaborate on the effect of consumer learning and inertia on firms' pricing and profits. In order to do so, I use a more structural and stripped-down supply-side model which still considers what I think are the important features of this relationship. I first discuss my assumptions and my motivations for making them. Using these assumptions, I then run the simulations relevant to understanding how a firm ought to change its decisions in response to different household learning or inertia behaviors.

6.1 Assumptions

6.1.1 Preliminary Simplifying Assumptions

I begin by describing some assumptions I make in order to make the supply setting as simple as possible while preserving the fact that consumer learning affects intertemporal pricing decisions. First, broadly speaking, I only examine a monopolist’s problem. Solving
Figure 8: Mean Chobani own price elasticity over time, with the mean taken over all household draws at all observed prices within a month.

Figure 9: Mean Yoplait own price elasticity over time, with the mean taken over all household draws at all observed prices within a month.
for pricing equilibria in a pricing game with two or more firms is highly nontrivial, especially because payoffs are changing over time. Though there are techniques to try to solve these equilibria, my paper is not per se about solving dynamic games. As a result, I only model and simulate a monopolist’s problem. Though I do not consider interactions between consumer learning, inertia, and competition, these simulations still explore the effects of consumer learning and inertia on a firm. Specifically, I model the pricing decisions of a monopolist firm that is launching one new brand.

I assume that the monopolist in my counterfactuals is a single-brand monopolist manufacturer that owns the retailer. I do this to abstract from both the agency problem between manufacturers and retailers and the fact that I do not have a model of consumers’ decision over retailers. I also assume that the monopolist cannot price discriminate across households, though this may be feasible in the real world. Furthermore, I assume that the firm has constant marginal costs of production for both brands. I plan on calibrating firms’ costs using data; I do not estimate costs here.

I do not account for the fact that the households in my panel may not be representative of the population of households across the United States. Although the original ~40,000 Homescan households have projection factors which are meant to make these households representative, my demand estimates only use a small subset of 838 of these households. In my model, the monopolist only makes pricing decisions based on the households for whom I have demand estimates. I do not believe I would be able to project these households up to a higher level of aggregation in a meaningful way without more information on the demand parameters for households that I do not estimate. One way to extend this analysis to include projection factors would be to multiply each household’s demand by its weight before summing up aggregate demand.

6.1.2 Continuum of Consumers

Even after restricting the counterfactual using the aforementioned assumptions, the household learning process still causes major problems in actually solving for optimal firm prices. Intuitively, this is because the firm can condition its pricing on its beliefs about the distribution of learning states across households. For this reason, I assume the firm faces a continuum of consumers with mass equal to the observed number of households in my data and with parameters drawn from my households’ posterior parameter draws. Having a continuum of consumers implies that demand evolves deterministically, given a price path. The monopolist’s optimal pricing decision, therefore, will be the maximum price path, avoiding any need to compute a policy function.

To understand this problem more formally, let the firm’s profit maximization problem be
described recursively as

\[ V(s) = \max_p \{ \pi(s, p) + \beta E[V(s')|s, p] \}, \]

where \( s \) consists of the relevant information observable to the firm, \( p \) are the prices set by the firm (with \( p(s) \) being the firm’s pricing policy function), \( \pi(\cdot) \) is the (possibly expected) per-period profit function, \( \beta \) is the firm’s discount factor for payoffs in the next period, and \( V(\cdot) \) is the firm’s present discounted sum, at state \( s \), of all expected profits.

In the case where \( s \) contains states summarizing a distribution over discrete consumers’ learning processes, solving the firm’s problem suffers from the curse of dimensionality. In any way that this distribution is measured, \( \text{dim}(s) \) increases in the granularity of measurement. This means that the problem very quickly becomes intractable. For any reasonable amount of complexity in this distribution, solving the problem when the firm needs to condition on information about the distribution requires enormous state spaces. As an example, consider the firm’s knowledge about consumers’ beliefs about the new product’s match value. These beliefs vary across consumers because consumers are heterogeneous and because consumers’ learning paths are different. Even conditional on a type of consumer, that consumer may receive different signals or different idiosyncratic utility draws, both of which lead to different beliefs. In the case where the firm has perfect information about its consumers, the state space is far too large: at least one state for each additional individual consumer tracking each consumer’s uncertainty. If instead the firm has limited information, solving for a rational firm’s optimal pricing still requires solving the full model, then taking the appropriate conditional expectation.

I show that a continuum of consumers makes the monopolist’s problem tractable in two steps. The first step involves demonstrating that a continuum of consumers makes demand deterministic, conditional on a price series. The second involves showing that deterministic demand means that I can maximize over price series (unconditional on state variables) rather than pricing policy functions.

In order to show the first step, I apply research by Uhlig (1996) and elaborated more specifically by Al-Najjar (2002). The details are mathematically technical, but the intuition is that, under certain conditions for the idiosyncratic random individual draws, a sort of “law of large numbers” applies. This law of large numbers guarantees almost sure convergence of any empirical frequencies to a certain kind of integral over the agents’ random draws as the number of agents grows (countably) to infinity. In other words, the continuum of consumers model generates demand outcomes almost surely close to a case where the firm faces a large number of discrete consumers. The main condition for applying these results is that the
set of integrated random draws is an element of a certain class of independent stochastic processes. Because each random draw in my demand model is conditionally independent of every other random draw, this condition is satisfied. For a much more detailed discussion of this, see both Uhlig (1996) and Al-Najjar (2004).

The relevant density function in my problem is the transition density \( f(s'|s,p) \) over which the expectation of the value function is integrated. Because of the results from Uhlig (1996) and Al-Najjar (2004), a continuum of consumers implies that the empirical distribution of \( s'|s,p \) converges to \( F(s'|s,p) \), which is known to the firm. Then, because \( s'|s,p \) is deterministically known, for any sequence of prices \( \{p_t\} \), \( \pi(s_t,p_t) \) is deterministic for all \( t \).

Since \( s \) evolves deterministically, choosing the optimal \( p(s) \) is equivalent to choosing the profit maximizing price path defined by \( \{p_t \equiv p(s_t)\} \). To show this, I prove both implications. Clearly, if \( p(s) \) is optimal, then \( \{p_t \equiv p(s_t)\} \) is optimal. For the other implication, assume that \( \{p_t \equiv p(s_t)\} \) is not optimal. There then exists \( \{\hat{p}_t\} \) which yields higher profits for the firm. This price path implies some deterministic state path \( \{\hat{s}_t\} \). But then \( p(s) \) cannot be optimal because \( \hat{p}(s) \) which sets \( \hat{p}(s_t) = \hat{p}_t \) yields higher profits, which is a contradiction. In summary, this means I can search for the firm’s optimal price path \( \{p_t\} \) instead of for the firm’s optimal policy function \( p(s) \).

To understand why I do not consider discrete consumers more intuitively, consider a case where the firm has perfect information, all households are identical ex ante, and households do not have brand-level state dependence. The curse of dimensionality very quickly hurts if either the number of households increases or if the maximum number of signals obtainable by households is increased. If each household’s state is another firm state parameter, the state space trivially grows linearly the number of households. Because households are ex ante identical, another possible firm state vector might track the number of households which purchased the new brand a certain number of times. But then the problem grows exponentially in the maximum number of obtainable signals. In either case, solving the firm’s pricing policy function quickly becomes intractable without assumptions which reduce the size of the state space. Conditioning the firm’s decision on limited information is, practically speaking, equally infeasible because it requires solving the full problem, then taking a conditional expectation. Moreover, accounting for household-level heterogeneity on top of this increases the size of the state space even more, since it requires keeping track of of a tensor product of the number of types with the number of learning states.

The assumption of a continuum of consumers avoids this state space explosion handily. With a continuum of consumers, brand shares are equal to purchase probabilities and the “empirical” distribution of consumers’ signal draws is equal to the underlying distribution that signals are drawn from. Given that all the idiosyncratic draws (priors, quality signals,
and idiosyncratic utility draws) are known, the evolution of demand is deterministic given any price series set by the firm. The firm’s maximization problem now only requires maximizing “expected” profits (equivalent to actual profits since demand is deterministic) over all possible price paths.

6.2 Maximization Procedure

6.2.1 Setup

Formally, I would like to optimize over the sum of present discounted profits over the continuum of households and the distributions of idiosyncratic draws $\epsilon$ and $\hat{Q}$,

$$\Pi(\{p_\tau\}; \Theta) = \sum_{t=1}^{T} \delta^t \int \pi_t(\{p_\tau\}, \epsilon, \hat{Q}; \theta_h)f_\epsilon(\epsilon)f_\hat{Q}(\hat{Q}|\theta_h)f_{\theta_h}(\theta_h)d\epsilon d\hat{Q} d\theta_h.$$  

$\theta_h$ is the vector of household parameters; $\epsilon$ refers to a series of idiosyncratic utility draws, $\epsilon \equiv \{\epsilon_{0\tau}, \epsilon_{1\tau}\}_{\tau=1}^{T}$; $\hat{Q}$ refers to a series of match value signal draws, $\hat{Q} \equiv \{\hat{Q}_{h1s}\}_{s=0}^{S}$; $\hat{Q}_{h1s} \sim \mathcal{N}(Q_{h1}, \sigma_{h1}^2)$. Here, $\tau$ indexes over time periods and $s$ indexes over realized match value signals (where $\hat{Q}_{h10}$ is $h$’s prior mean, $\hat{Q}_{h11}$ is the signal realization for $h$’s first purchase, $\hat{Q}_{h12}$ is the signal realization for $h$’s second purchase, and so on). Also, per-period profits $\pi_t(\cdot)$ are period-specific and are given by

$$\pi_t(\{p_\tau\}, \epsilon, \hat{Q}; \theta_h) = 1\{E[U_{h1\tau}] > U_{0\tau}\}(p_t - c),$$

where $c$ is the marginal cost and the utilities are as in the demand model. In other words, the firm’s profits from one household are given by that household’s discrete decision to buy the new brand, $j = 1$, multiplied by the monopolist’s margin on that product.

6.2.2 Analytic integral over $\epsilon$

Note that, given beliefs, prices, the last brand bought, and $\theta_h$, $\pi_t(\cdot)$ does not depend on realizations of $\epsilon_{0\tau}$ or $\epsilon_{1\tau}$ for $\tau < t$. Additionally, given $\hat{Q}$, the number of past purchases of brand 1, $n_{1\tau}$, is a sufficient statistic for beliefs. As a result, $\pi_t(\cdot)|n_{1\tau}$ is independent of $\epsilon_{0\tau}$ and $\epsilon_{1\tau}$ for $\tau < t$. The conditional integral over $\epsilon$, therefore, can be expressed as
\[
\int \pi_t(\{p_t\}, \epsilon, \hat{Q}; \theta) f_\epsilon(\epsilon) d\epsilon =
\]
\[
= \sum_{s=0}^{t-1} \mathbb{E}_{\epsilon_0, \epsilon_1 | \pi_t(\{p_t\}, \{\epsilon_0, \epsilon_1\}, \hat{Q}; \theta)|n_{1t} = s} \mathbb{P}(n_{1t} = s)
\]
\[
= \sum_{s=0}^{t-1} \frac{\exp(E[\bar{U}_{1ts}])}{\exp(E[\bar{U}_{1ts}] + \exp(U_0))} (p_t - c) \mathbb{P}(n_{1t} = s),
\]
where \(E[\bar{U}_{1ts}]\) is the mean expected utility given \(\hat{Q}, \theta, \) and \(s\) signals. For mathematical details, see Appendices C and D.

Though this conditionality on \(n_{1t}\) is specific to the fact that \(\hat{Q}\) specifies the order of draws, the mathematical simplification of integrating out \(\epsilon\) is not limited to this assumption on the order in which consumers receive signals. Appendix E discusses how it is equivalent to integrate over match values which are fixed in time rather than fixed in order. This is because, under both assumptions, match value signals are drawn from the same joint distribution (conditional on \(\theta\)). Any integral over this joint distribution does not change, conditional on a purchase history. Because the joint distribution of random variables does not change, the probability of observing any purchase history also does not change. Applying the law of total expectation over purchase histories gives the desired result.

### 6.2.3 Monte Carlo simulation

Aggregate profits now look like

\[
\Pi(\{p_t\}; \Theta) = \sum_{t=1}^{T} \delta_t \int \sum_{s=0}^{t-1} \frac{\exp(E[\bar{U}_{1ts}])}{\exp(E[\bar{U}_{1ts}] + \exp(U_0))} (p_t - c) \mathbb{P}(n_{1t} = s) f_\Theta(\hat{Q}_h | \theta_h) f_{\theta_h}(\theta_h) d\hat{Q} d\theta_h.
\]

Because there is no analytic integral over the joint distribution of \(\hat{Q}, \theta_h, \) I instead simulate over \(K\) draws from these distributions and approximate the integral using a mean over these draws. For details on how to efficiently evaluate this objective function and its gradient, see Appendix F.

### 6.3 Results

I assume that the monopolist owns and is launching Chobani. The following assumptions I make are somewhat arbitrary but testable. I fix marginal costs for Chobani to be the 0.1-percentile of observed purchases for Chobani in the Homescan ($0.08/oz). I draw 100 replications of the 838 households and simulate these households for 324 purchase trips (roughly corresponding to four years of purchases at 1.56 trips per week), assuming the
<table>
<thead>
<tr>
<th>Date of Price Change</th>
<th>Baseline</th>
<th>No Learning</th>
<th>No Inertia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Launch</td>
<td>0.4732</td>
<td>0.4741</td>
<td>0.5707</td>
</tr>
<tr>
<td>+1 week</td>
<td>0.5426</td>
<td>0.5428</td>
<td>0.5708</td>
</tr>
<tr>
<td>+4 weeks</td>
<td>0.5594</td>
<td>0.5599</td>
<td>0.5708</td>
</tr>
<tr>
<td>+8 weeks</td>
<td>0.5902</td>
<td>0.5911</td>
<td>0.5710</td>
</tr>
<tr>
<td>+52 weeks</td>
<td>0.6051</td>
<td>0.6062</td>
<td>0.5710</td>
</tr>
<tr>
<td>+60 weeks</td>
<td>0.6108</td>
<td>0.6120</td>
<td>0.5710</td>
</tr>
<tr>
<td>+104 weeks</td>
<td>0.6181</td>
<td>0.6195</td>
<td>0.5710</td>
</tr>
<tr>
<td>+156 weeks</td>
<td>0.6236</td>
<td>0.6253</td>
<td>0.5710</td>
</tr>
<tr>
<td>Present discounted profits</td>
<td>$1133.77</td>
<td>$1160.91</td>
<td>$555.85</td>
</tr>
</tbody>
</table>

Table 1: Optimal price series and profits for the counterfactuals described in Section 6.3.

The firm’s discount factor is 0.995. I allow the firm only to change prices eight times, at trips 0, 2, 6, 12, 81, 93, 152, and 243. These correspond to price changes after week 1, week 4, week 8, week 52, week 60, week 104, and week 156. These dates were chosen to relate back to the price ratios I discussed in Section 3 and also to let the monopolist change prices more when beliefs are changing more rapidly.

I run the following counterfactuals. First, I find the firm’s optimal prices without changing any demand parameters, to get a baseline. In order to study the sizes of the impacts that consumer learning and inertia have on the new brand’s prices and profits, I simulate counterfactuals which eliminate the effects of consumer learning or inertia, then re-optimize the new brand’s prices.

I report the optimal prices and resulting profits in Table 1. The baseline results are qualitatively intuitive: prices increase rapidly, then slowly. As a comparison to my price histogram for the entire yogurt category, the ratio of the average price in the first two months versus the price in the remaining first year (see Figure 1) is 0.9188 for the baseline counterfactual, which is lower than the mean observed ratio (0.9753), but only slightly outside the interquartile range of the distribution. This could be, for example, because consumers had more to learn about Chobani than other new brands of yogurt. The same price ratio in Chobani’s second year is 0.9906, which is well within the interquartile range of the distribution from Figure 2. In the counterfactuals, the absence of consumer inertia has a major effect on optimal prices: they no longer increase substantially over any period of time. The absence of consumer learning, however, allows for a small level increase in prices, but does not affect the intertemporal increase in prices.

These results suggest that Chobani should focus on marketing which incentivizes consumer inertia. Some marketing tools may be more suitable for this. For instance, a free
sample, though it would inform consumers and thereby cause them to purchase, would probably not be optimal. On the other hand, something like displays or better shelf placement might more directly increase the likelihood that a consumer purchases, which would be better focused on leading consumer to be inertial.

7 Conclusion

This paper studies the effects of consumer learning and inertia on new brand pricing and profits. The results contribute in two main ways. First, I find evidence in data on prices across the United States that firms price new products differently from old products in a way consistent with consumer learning or consumer inertia. Although this effect is not large, it is measurable and present in four distinct product categories. Second, I find that, for Chobani, consumer inertia had a larger impact on introductory prices than consumer learning did. Given all the computational simplifications I make, a relevant area of future research is to find firm-side informational simplifications that reduce the dimensionality of the firm’s problem in a way that is more consistent with real-world firm information. And, as mentioned in the paper, the demand model could be extended in several ways to ensure robustness of the results I find. Another question is whether the result about the relative magnitude consumer inertia compared to consumer learning is more generally true across other new brands, and whether brand managers agree with the empirical findings.
Appendices

A Price Imputation

The Nielsen Homescan panel only contains information about households’ purchased UPCs in the panel. In other words, I do not directly observe information at any given time period about UPCs the households did not purchase. In order to adequately account for the effect of products in the category that weren’t purchased, I fill in these unobserved prices using both other observations in the Homescan itself and Nielsen’s RMS data. The simplest way to impute prices is to match data directly on the store visited and the date purchased. But since both Homescan and RMS only include information on purchased products, this simple match is fairly incomplete.

Non-purchased brands from trips to RMS stores are relatively simple to fill in, since frequently purchased brands of yogurt (the ones I am interested in) almost always are sold in any given week in a store. Of course, a given UPC within a top brand may not be purchased as often. For example, though we might expect that a UPC with a temporary price reduction will always be sold at a store, that same UPC might not be sold if it does not have a temporary price reduction. This would mean that only using observed prices will cause estimates of price elasticities to be too elastic, since non-purchased prices are observed on average to be lower than they actually are.

To deal with this, I assume that the price for a UPC which was not purchased is the last observed “regular” (without a temporary price reduction) price. Nielsen, however, does not provide information on regular prices, and so these must be imputed as well, using observed paid prices. There has been some work done that explores regular price algorithms (see, for example, Nakamura and Steinsson (2008)), but these past algorithms do not perform well for my data. Instead, I employ a different algorithm which seems to perform better, though in a somewhat ad hoc way. Specifically, the algorithm does the following for any given UPC’s price series:

1. Given a threshold for price increases or decreases, define observed prices to be either regular or promoted.

2. If the current price is not the regular price but is within some tolerance window of the previous regular price, set the current regular price to the previous regular price, iterating forward through the series. Then, do the same, but in reverse, comparing current regular prices to the following regular prices.

Recall that my relevant sizes are single-serving yogurts smaller than 10 ounces. All price imputations use only prices of these UPCs of yogurts.

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3. Find “valleys” of promoted prices, which are a series of promoted prices surrounded by regular prices on both sides. If all prices in the valley are smaller or equal to the maximum over regular prices at either end of the valley, and if at least one observed price is smaller than some threshold, set all regular prices in this valley to be the last regular price.

4. Some valleys may end with promoted prices that are bigger than the last observed regular price. In these cases, say that the regular price is “adjusting,” and set all adjusting regular prices to the current price.

5. Re-run step 2.

6. If there is a time window between regular prices in which prices are monotonically weakly increasing or decreasing, set these periods’ regular prices to the observed prices.


8. If the regular price decreased by a little at some point, there may be a subsequent “valley” of regular prices created by accident. Check if this “valley” would fit any of the above promotion criteria, and if so, set the regular price in this valley to the last regular price.

9. If there are gaps in the regular price series and there are promotions in these gaps, run forward the regular prices.


With these observed and imputed prices in hand, I generate store-week-brand prices by the ACV-weighted mean over both types of prices per ounce for all UPCs within a brand. In order to keep the estimation tractable, I group UPCs under the following brands: Chobani, Dannon, Fage, Stonyfield, Yoplait (the five largest national brands of yogurt in the RMS), Store (the six of which comprise 88% of the market for yogurt), and Other.

Non-purchased brand prices from trips to stores not in the RMS are more problematic, because so few Homescan panelists visit any particular store in a given week. Additionally, the Homescan does not contain information on which specific store location is visited within a three digit zip code by a given panelist. In order to deal with this, I use weighted average brand prices (as defined above) at RMS stores in the same three digit zip code. In particular, for occasions when a household purchases yogurt, I weight each relevant RMS store using a normal kernel centered on the observed purchase price for the purchased brand\textsuperscript{8}. If the

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\textsuperscript{8}I arbitrarily set the kernel width to $0.01 per ounce.
household is observed to make a shopping trip but does not purchase yogurt, I weight the relevant RMS stores using the sum of all weights from occasions when the household did make a purchase.

A problem that becomes clear here is that Chobani’s launch may not be uniform across stores within a Zip-3, so using this average may incorrectly assume that Chobani is available when it is not, or that it is not available when it is. I do not have a solution for this problem using this data. But, so long as the non-uniformity of launch is exogenous to which stores are in the RMS, then the problem is contained to one of measurement error.
B Bayesian MCMC Estimation Details

B.1 Likelihood

Let $d_{ht} \in J \cup \emptyset$ be household $h$’s purchase decision at time $t$. Let $s_{ht}$ be household $h$’s current state, where $s_{ht} = \max_{s<t} d_{hs}$, $d_{hs} \neq 0$. Let $\Theta$ be all parameters in the model and $D$ be the data. Let there be one brand in $J_L$, and index this brand by 0. Let $\theta_h$ have a prior distribution which consists of a mixture of $K$ normal distributions, indexed by $k$. $\text{ind}_h \in K$ denotes which normal distribution household $h$’s prior is. The likelihood is given by

$$L(\Theta|D) \propto \prod_{h \in H} \left[ \prod_{t \in T} f(d_{ht}|s_{ht}, p_{ht}, Q_{ht}, \bar{Q}_{hot}, \sigma_{hot}^2, \theta_h) f(Q_{hot}|Q_{hot-1}, \sigma_{hot}^2, \sigma_{h,l}^2, d_{htj-1}) \right]$$

$$f(\theta_h|\{\bar{\theta}_k, \Sigma_k\}, \text{ind}_h) f(\text{hyperparameters}|\text{prior})$$

$$f(d_{ht}|s_{ht}, p_{ht}, Q_{ht}, \bar{Q}_{hot}, \sigma_{hot}^2, \theta_h) = \frac{\exp(\bar{U}_{htj,t})}{\sum_{k \in J \cup \emptyset} \exp(\bar{U}_{htk})}$$

$$\bar{U}_{htj} = E[- \exp(-r_h Q_{htj})|Q_{ht}, \bar{Q}_{hot}, \sigma_{hot}^2, \theta_h] + \beta_{h,p} p_{htj} + \gamma_h \mathbb{1}\{s_{ht} = j\}$$

$$Q_{hot}|Q_{hot-1}, \sigma_{hot}^2, \sigma_{h,l}^2, d_{htj-1} \sim \mathcal{N}(\bar{Q}_{hot}, \nu_{hot}^2)$$

$$\nu_{hot}^2 = 1\{d_{htj-1} = 0\} \frac{\sigma_{hot}^4}{\sigma_{h,l}^2}$$

$$\sigma_{hot}^2 = (\sigma_{hot-1}^2 + 1\{d_{htj-1} = 0\} \sigma_{h,l}^{-2})^{-1}$$

$$\bar{Q}_{hot} = \frac{\sigma_{hot}^2}{\sigma_{h,l}^2} \bar{Q}_{hot-1} + 1\{d_{htj-1} = 0\} \frac{\sigma_{hot}^2}{\sigma_{h,l}^2} Q_{htj}$$

$$\theta_h|\{\bar{\theta}_k, \Sigma_k\}, \text{ind}_h \sim \mathcal{N}(\bar{\theta}_{\text{ind}_h}, \Sigma_{\text{ind}_h})$$

B.2 Metropolis Hastings Draws

Though the majority of this estimation is directly out of Rossi et al. (2004), the Metropolis Hastings draws for households’ match value belief means and households’ parameters require some elaboration. In particular, I use random walk Metropolis Hastings algorithms. My approach for drawing households’ match value belief means is similar to that found in Narayanan and Manchanda (2009); my random walk increments are drawn from a normal distribution with variance given by $c_Q^2 # \text{ signals received}$, where I choose $c_Q = 2$ for roughly optimal numerical efficiency. To draw households’ parameter vectors, I use a variance-covariance matrix equal to $c_\theta^2 \Sigma_{\text{ind}_h}$, setting $c_\theta = 2.93$ for, again, roughly optimal numerical efficiency.
B.3 Priors

I set $\text{ind}_h \sim \text{Multinomial}(\pi)$, $\pi \sim \text{Dirichlet}(a)$, $\Sigma_k \sim \text{IW}(\nu, \nu I)$, and $\mu_k | \Sigma_k \sim N(\bar{\mu}, a_{\mu}^{-1} \Sigma_k)$, with $a = \{5.0, 5.0, \ldots, 5.0\}$, $\bar{\mu} = \{0.0, 0.0, \ldots, 0.0\}$, $a_{\mu}^{-1} = \frac{1}{16}$, and $\nu = \text{dim}(\theta_h) + 3$. 
Appendix: Sufficiency of the Number of Purchases

Recall that household $h$'s utility for $j$ at $t$ can be expressed as

$$E[U_{hjt}] = -e^{-r_h Q_{hjt} + r_h^2 Q_{hjt}^2 / 2} + \beta_h p_{jt} + \gamma_h \mathbb{1}\{s_{ht} = j\} + \epsilon_{hjt} = E[\bar{U}_{hjt}] + \epsilon_{hjt},$$

and for the outside option 0 at $t$ as

$$U_{h0t} = U_{h0} + \epsilon_{h0t}.$$

Consider only the case where there is only one product $j = 1$ along with the outside option. From here on, I suppress the subscript $h$.

Suppose that the household's prior for $j = 1$ has a mean of $\bar{Q}_{10} \sim \mathcal{N}(Q_1, \sigma_0^2)$ with variance $\sigma_0^2$ and that the household receives a signal $\bar{Q}_{11}$ the first time the household purchases the product, $\bar{Q}_{12}$ the second time, and so on. Because of the assumptions on households’ learning process,

$$\bar{Q}_{1t} = \sum_{s=0}^{n_{1t}} \bar{Q}_{1s},$$

where $n_{1t}$ is the number of times the household purchased $j = 1$. Moreover, $\sigma_{1t}^2 = \frac{\sigma_0^2}{n_{1t} + 1}$ and $s_{ht} = j$ if and only if $n_{1t} \geq 1$. Therefore, conditional on $\theta = \{r, \beta, \gamma, U_0\}, \{\bar{Q}_{10}, \bar{Q}_{11}, \ldots\}$, and $p_{1t}$,

$$Pr\{E[U_{1t}] > U_{0t}|n_{1t} = s\} = \frac{\exp(E[\bar{U}_{1ts}])}{\exp(E[\bar{U}_{1ts}] + \exp(U_0))},$$

where

$$E[\bar{U}_{1ts}] = -e^{-r_{1s} \bar{Q}_{1s} + \bar{Q}_{1s}^2 / 2} + \beta p_{1t} + \gamma \mathbb{1}\{s > 0\}.$$

In other words, neither the order nor the timing of past purchases of $j = 1$ change mean (expected) utilities if the number of past purchases $n_{1t}$, the sequence of received signals $\{\bar{Q}_{10}, \bar{Q}_{11}, \ldots\}$, the price $p_{1t}$, and $\theta$ are fixed.
D Appendix: Integrating out $\epsilon$

The integral of interest is

$$\Pi (\{ p_r \}; \Theta) \equiv \sum_{t=1}^{T} \delta^t \int \pi_t(\{ p_r \}, \epsilon, \hat{Q}; \theta_h) f_\epsilon(\epsilon) f_Q(\hat{Q}|\theta_h) f_{\theta_h}(\theta_h)d\epsilon d\hat{Q} d\theta_h,$$

where $T$ is some maximum number of periods and $\delta$ is the firm’s discount factor.

More explicitly,

$$f_\epsilon(\epsilon) d\epsilon \equiv f_\epsilon(\epsilon_{01}) f_\epsilon(\epsilon_{11}) \ldots f_\epsilon(\epsilon_{0T}) f_\epsilon(\epsilon_{1T}) d\epsilon_{01} d\epsilon_{10} \ldots d\epsilon_{0T} d\epsilon_{1T};$$

$$f_Q(\hat{Q}|\theta_h) d\hat{Q} \equiv \phi \left( \frac{\hat{Q}_{10} - Q_1}{\sigma_L} \right) \ldots \phi \left( \frac{\hat{Q}_{1S} - Q_1}{\sigma_L} \right) d\hat{Q}_{10} \ldots d\hat{Q}_{1S},$$

where $f_\epsilon(\cdot)$ is the Type 1 Extreme Value density, $\phi(\cdot)$ is the standard normal density, and $S$ is the maximum number of signals receivable (in this case, $S = T$, since the maximum number of receivable signals is one per period).

Using these,

$$\int \pi_t(\{ p_r \}, \epsilon, \hat{Q}; \theta_h) f_\epsilon(\epsilon) d\epsilon =$$

$$= \int \pi_t(\{ p_r \}, \epsilon, \hat{Q}; \theta_h) f_\epsilon(\epsilon_{01}) f_\epsilon(\epsilon_{11}) \ldots f_\epsilon(\epsilon_{0T}) f_\epsilon(\epsilon_{1T}) d\epsilon_{01} d\epsilon_{10} \ldots d\epsilon_{0T} d\epsilon_{1T}$$

$$= E_{\epsilon_{01}, \epsilon_{11}, \ldots, \epsilon_{0T}, \epsilon_{1T}}[\pi_t(\{ p_r \}, \epsilon, \hat{Q}; \theta_h)]$$

$$= \sum_{s=0}^{t-1} E_{\epsilon_{01}, \epsilon_{11}, \ldots, \epsilon_{0T}, \epsilon_{1T}}[\pi_t(\{ p_r \}, \epsilon_{0t}, \epsilon_{1t}, \hat{Q}; \theta_h)|n_{1t} = s] Pr\{ n_{1t} = s \}$$

$$= \sum_{s=0}^{t-1} E_{\epsilon_{0t}, \epsilon_{1t}}[\pi_t(\{ p_r \}, \epsilon_{0t}, \epsilon_{1t}, \hat{Q}; \theta_h)|n_{1t} = s] Pr\{ n_{1t} = s \}$$

where (III) is by the definition of $d\epsilon$, (II) is by the definition of an expectation and because future idiosyncratic utilities do not affect decisions at $t$, (I) is by the law of iterated expectations, and (III) is because $n_{1t}$ is a sufficient statistic for $\epsilon_{01}, \epsilon_{11}, \ldots, \epsilon_{0t-1}, \epsilon_{1t-1}$ (see Appendix D). As a result, the integral of $t$-period profits over idiosyncratic utilities prior to $t$ can be reduced to a sum of purchase probabilities at $t$ over all possible purchase histories prior to $t$.

Finally, remembering that $\pi_t(\{ p_r \}, \{ \epsilon_{0t}, \epsilon_{1t} \}, \hat{Q}; \theta_h)|n_{1t} = s) = 1\{ U_{jt} > U_0 \}(p_t - c)$,

$$E_{\epsilon_{0t}, \epsilon_{1t}}[\pi_t(\{ p_r \}, \{ \epsilon_{0t}, \epsilon_{1t} \}, \hat{Q}; \theta_h)|n_{1t} = s] = Pr\{ E[U_{1t}] > U_{0t}|n_{1t} = s \}(p_t - c)$$

$$= \frac{exp(E[\hat{U}_{1ta}])}{exp(E[\hat{U}_{1ta}]) + exp(U_0)} (p_t - c).$$

34
Equivalence to Signals Fixed in Time

Suppose instead that the firm integrates over \( \hat{Q} \equiv \{ \hat{Q}_{h1} \}_{t=0}^{T} \), i.e. that instead of integrating over signal draws which are received in a fixed order, the firm integrates over signal draws which are fixed in time. Aggregate profits are given by

\[
\hat{\Pi}(\{p_r\}; \Theta) = \sum_{t=1}^{T} \delta^t \int \pi_t(\{p_r\}, \epsilon, \hat{Q}; \theta_h) f_{\epsilon}(\epsilon) f_{\hat{Q}}(\hat{Q}|\theta_h) f_{\theta_h}(\theta_h) d\epsilon d\hat{Q} d\theta_h \\
= \sum_{t=1}^{T} \delta^t \mathbb{E}_{\epsilon, \hat{Q}, \theta}[\pi_t(\{p_r\}, \epsilon, \hat{Q}; \theta_h)]
\]

where, given \( \hat{Q} \), which signals are received depend on when the new brand is purchased. Otherwise, profits are the same as before.

In order to show that this aggregation is equivalent to \( \Pi(\{p_r\}; \Theta) \), I only need to show that \( \mathbb{E}_{\epsilon, \hat{Q}, \theta}[\pi_t(\{p_r\}, \epsilon, \hat{Q}; \theta_h)] = \mathbb{E}_{\epsilon, \hat{Q}, \theta}[\pi_t(\{p_r\}, \epsilon, \hat{Q}; \theta_h)] \). Let \( h_t \) be the history of purchases upon entering period \( t \), where \( h_t = \{ k_{1}, \ldots, k_{t-1} \} \), the purchase decisions at each time period prior to \( t \). By the law of total probability,

\[
\mathbb{E}_{\epsilon, \hat{Q}, \theta}[\pi_t(\{p_r\}, \epsilon, \hat{Q}; \theta_h)] = \sum_{h_t} \mathbb{E}_{\epsilon, \hat{Q}, \theta}[\pi_t(\{p_r\}, \epsilon, \hat{Q}; \theta_h)|h_t] Pr_{\epsilon, \hat{Q}, \theta}\{h_t\}.
\]

Again, by the law of total probability, \( Pr_{\epsilon, \hat{Q}, \theta}\{h_t\} = \sum_{h_{t-1}} Pr_{\epsilon, \hat{Q}, \theta}\{h_t|h_{t-1}\} Pr_{\epsilon, \hat{Q}, \theta}\{h_{t-1}\} \).

Since

\[
Pr_{\epsilon, \hat{Q}, \theta}\{h_t|h_{t-1}\} = \mathbb{E}_{\epsilon, \hat{Q}, \theta}[\mathbb{1}\{U_{t-1} > U_{t-2}\}|h_{t-1}],
\]

and

\[
\mathbb{E}_{\epsilon, \hat{Q}, \theta}[\pi_t(\cdot)|h_t] = (p_t - c) \mathbb{E}_{\epsilon, \hat{Q}, \theta}[\mathbb{1}\{U_t > U_{t-1}\}|h_t],
\]

As long as

\[
\mathbb{E}_{\epsilon, \hat{Q}, \theta}[\mathbb{1}\{U_t > U_{0t}\}|h_t] = \mathbb{E}_{\epsilon, \hat{Q}, \theta}[\mathbb{1}\{U_t > U_{0t}\}|h_t],
\]

proving aggregate profit equivalence follows by induction\(^9\).

Conditional on \( h_t \), only the signals during periods when the consumer purchased affect profits at \( t \). Enumerate these signals as \( \hat{Q}_{1t}, \ldots, \hat{Q}_{1t} \). We can rewrite

\[
\mathbb{E}_{\epsilon, \hat{Q}, \theta}[\mathbb{1}\{U_t > U_{0t}\}|h_t] = \mathbb{E}_{\epsilon, \hat{Q}_{1t}, \hat{Q}_{1t}, \ldots, \hat{Q}_{1t}}[\mathbb{1}\{U_t > U_{0t}\}|h_t].
\]

\(^9\)Trivially, \( h_1 \) takes only one value, since no consumer can purchase the new brand prior to launch.
Similarly, we can rewrite

\[ E_{\epsilon, \tilde{Q}, \theta}[\mathbb{1}\{U_{1t} > U_{0t}\}|h_t] = E_{\epsilon, \tilde{Q}_{10}, \tilde{Q}_{11}, \ldots, \tilde{Q}_{1n_t}, \theta}[\mathbb{1}\{U_{1t} > U_{0t}\}|h_t]. \]

Since the joint distribution of \( \epsilon, \tilde{Q}_{10}, \tilde{Q}_{11}, \ldots, \tilde{Q}_{1n_t}, \theta \) is the same as the joint distribution of \( \epsilon, \hat{Q}_{10}, \hat{Q}_{11}, \ldots, \hat{Q}_{1n_t}, \theta \), and since utilities and beliefs have the same functional form, these two expectations are mathematically equivalent.
F Appendix: Objective Function Evaluation

Let $s_t$ be the total share of consumers who buy the new brand at $t$. The algorithm for calculating $s_t$, $\pi_t$, and the relevant gradients (for maximization) in each $t$ follows.

1. Set $t = 0$ with $v_0 = \{1\}$. Here, $v_{ts}$ is the fraction of consumers at $t$ who have already purchased the new brand $s$ times. At $t = 0$, nobody has purchased the new brand beforehand and their priors are all one signal which is why $v_{01} = 1$.

2. Set $w_t^1 = \{0, v_{t1}Pr_{t1}, \ldots, v_{tt+1}Pr_{tt+1}\}$ and $w_t^0 = \{v_{t1}(1-Pr_{t1}), \ldots, v_{tt+1}(1-Pr_{tt+1}), 0\}$.

3. $s_t = \sum_s w_t^{1s}$, i.e. the share of consumers who buy is the sum over the fraction of buyers for each type. $\pi_t = s_t(p_t - c)$.

4. Set $z_{1\tau}^\tau = \{0, \frac{\delta w_{1\tau}^1}{\delta p_t}, \ldots, \frac{\delta w_{1\tau+1}^1}{\delta p_t}\}$ for all $\tau \leq t$, and similarly for $z_{0\tau}^\tau$. Note that if $t = \tau$, $\frac{\delta (v_{ts}Pr_{ts})}{\delta p_t} = v_{ts} \frac{\delta Pr_{ts}}{\delta p_t}$ since the price at $t$ only changes the probability of buying the product and does not change any previous decisions (consumers aren’t forward looking). Also note that if $t \neq \tau$, $\frac{\delta (v_{ts}Pr_{ts})}{\delta p_t} = \frac{\delta v_{ts}}{\delta p_t} Pr_{ts}$, since past prices do not affect a consumer’s decision conditional on having $s$ signals.

5. $\frac{\delta s_t}{\delta p_t} = \sum_s z_{1ts}^t$, i.e. the sum over the partial derivatives of the fraction of buyers for each type with respect to the price at $\tau$. $\frac{\delta \pi_t}{\delta p_t} = \frac{\delta s_t}{\delta p_t} (p_t - c) + s_t \mathbb{1}\{t = \tau\}$.

6. Set $v_{t+1} = w_t^1 + w_t^0$ and $\frac{\delta v_{t+1}}{\delta p_t} = z_{1t}^1 + z_{0t}^0$.

7. Advance to $t = t + 1$ and go to 2.
References


