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A Dynamic Model of Brand Choice When Price and Advertising Signal Product Quality

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In this paper, we develop a structural model of household behavior in an environment where there is uncertainty about brand attributes and both prices and advertising signal brand quality. Four quality signaling mechanisms are at work: (1) price signals quality, (2) advertising frequency signals quality, (3) advertising content provides direct (but noisy) information about quality, and (4) use experience provides direct (but noisy) information about quality. We estimate our proposed model using scanner panel data on ketchup. If price is important as a signal of brand quality, then frequent price promotion may have the unintended consequence of reducing brand equity. We use our estimated model to measure the importance of such effects. Our results imply that price is an important quality-signaling mechanism and that frequent price cuts can have significant adverse effects on brand equity. The role of advertising frequency in signaling quality is also significant, but it is less quantitatively important than price.

Key words: consumer choice under uncertainty; Bayesian learning; signaling; advertising and price as signals of quality; brand equity; pricing policy; dynamic choice
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1. Introduction

Consumers may learn about experience goods through several channels. We estimate a dynamic brand choice model in which consumers learn about brand quality through four kinds of signals: use experience, advertising content, advertising intensity,[1] and price. The relative importance of these mechanisms influences how demand responds to changes in price and advertising intensity. Thus, our work is of interest to both marketing and industrial organization.[2]

Prior work has modeled a subset of the signaling mechanisms that we consider here. For instance, in Erdem and Keane (1996) and Anand and Shachar (2002), advertising content and use experience provide noisy signals about brand attributes. In Ackerberg (2003), advertising intensity and use experience signal product quality. But, to our knowledge, prior empirical work has not incorporated price as a signal of quality in brand choice models. Nor has it allowed for the possibility that advertising may signal quality through *both* its content and its quantity.

In the theoretical literature, Milgrom and Roberts (1986) developed a model in which price and advertising expenditure signal quality of an experience

[1] Throughout this paper, we use the terms "advertising intensity," "advertising quantity," and "advertising frequency" interchangeably with advertising expenditure. This is legitimate under the assumption that a brand's expenditure on advertising determines the frequency with which its ads reach consumers.

[2] Indeed, the recognition that dynamics in consumer demand have important implications for market equilibrium has recently led to a burst of interest by industrial organization economists in estimation of dynamic demand models (see, e.g., Ching 2002, Crawford and Shum 2005, Ackerberg 2003, Hendel and Nevo 2006). Marketers have been interested in the estimation of dynamic demand models using scanner data for many years (see Keane 1997 for a review). More recent work includes Erdem et al. (2003) and Mehta et al. (2003).

good.[3] In their model, high-quality producers get more repeat sales. Thus, their long-run marginal revenue from advertising (which generates *initial* sales) is greater. In Kihlstrom and Riordan (1984), advertising expenditure signals quality by conveying information about a firm's sunk costs. In their model, high quality raises fixed but not marginal cost. Thus, by spending on advertising, a firm signals to consumers the belief that it can recover its sunk costs, because its higher product quality will enable it to charge a higher price than low-quality firms (that have the same marginal production cost).[4]

These papers were motivated by Nelson (1988), who argued that most advertising contains no solid content. But he argued that firms' advertising expenditures could be rationalized if the volume of advertising (rather than its content) served as a quality signal. This view has been challenged by Erdem and Keane (1996), Anand and Shachar (2002), and Erdem and Sun (2002), who argue that advertising does convey information.[5] Resnick and Stern (1977) and Abernethey and Franke (1996) analyzed TV ads and concluded that most do contain information content. Thus, whether advertising signals quality primarily through content or volume is an empirical question.

Consumers may also use the price–quality relationship that exists in a market to infer quality from price.[6] Research has shown that this relationship is category specific. For instance, Lichtenstein and Burton (1989) find that objective and perceived quality–price relationships are stronger for nondurables. Caves and Greene (1996) find that there is a strong positive relationship between price and objective quality for frequently purchased convenience goods. Rao and Monroe (1989) argue that a strong positive relationship exists for lower-priced, frequently purchased product categories but that the relationship is not well documented for other categories.

In this paper, we extend the Bayesian learning model of Erdem and Keane (1996) to incorporate both price and advertising frequency as signals of product quality (in addition to use experience and advertising content). Our structural modeling approach will enable us to evaluate the effects of advertising and price promotions in both the short run and the long run.

A key issue in marketing is whether frequent price promotions or "deals" reduce brand equity (Aaker 1991), i.e., reduce the perceived quality of a brand, reducing consumer willingness to pay in the long-run. Using a reduced-form model, Jedidi et al. (1999) concluded that advertising increases "brand equity," whereas promotions reduce it. Because our model incorporates both price and advertising as quality signals, we will be able to investigate these questions explicitly.

Of course, price fluctuations due to promotions are a salient feature of most frequently purchased consumer goods markets. Consumers in our model use the history of prices to infer the mean price of a brand. It is this mean price that signals brand quality. Thus, if a brand cuts its price in week t, consumers solve a signal extraction problem to determine the extent to which this represents a transitory fluctuation around the mean versus a more permanent decline in the brand's mean price. To the extent that consumers revise downward their estimate of the brand's mean price, they will also revise downward their estimate of its quality, reducing brand equity.

Recently, Erdem et al. (2003) and Hendel and Nevo (2006) have developed dynamic demand models for frequently purchased storable consumer goods. In these inventory models, consumers attempt to time purchases to occur in periods when prices are relatively low. Thus, both inventory and learning models contain a mechanism whereby, if a brand shifts to a strategy of more frequent "deals," consumer demand for the brand at any given price will fall.

Consistent with these predictions, a substantial literature in marketing, originating with Winer (1986), shows that the fit of reduced form demand models is improved if they include not just a brand's current price, but also some measure of its "reference price," typically operationalized as an average of lagged prices. Because learning models where price signals quality and inventory models provide alternative rationalizations for reference prices, an important avenue for future research is to distinguish demand effects of frequent promotions operating through

[3] Price's role as a signal of quality has also been discussed by Farell (1980), Gerstner (1985), and Spence (1974).

[4] Price and advertising will function as credible signals only if sellers do not find it profitable to "cheat" by conveying false market signals, for example, charging higher prices for lower quality. Two reasons why sellers might refrain from cheating are desire for repeat sales and presence of informed consumers (Tirole 1991).

[5] Anand and Shachar (2002) find that increased exposure to ads reduces some consumers' demand for certain brands. The implication is that consumers learn from the ad content that the brand is not a good match with their tastes. If advertising signals quality only through its quantity, then increased exposure would never reduce demand.

[6] Wathieu and Bertini (2007) find experimental evidence that consumers use observed price to update their willingness to pay for a product (e.g., a higher than expected price may increase its perceived quality or usefulness).

changes in expected future prices versus perceived quality.[7, 8]

We estimate our model on scanner data for ketchup. It may seem unglamorous, but this category is well suited to the analysis. One dominant brand (Heinz) is generally perceived as being high quality. It is also higher priced and has substantially higher advertising expenditure than its name-brand competitors, Hunt's and Del Monte. In fact, the lowest-priced name brand (Del Monte) does not engage in any TV advertising. Thus, there is scope for consumers to use price and ad expenditures as signals of quality in this market.

Our model sheds light on the importance of different information sources in influencing perceived quality. For instance, we predict that a 10% permanent price cut for Heinz would increase its sales by 26%. However, if the price cut could be implemented without reducing perceived quality (and, hence, brand equity), the increase in sales would be considerably greater (32%).

2. The Model

2.1. Overview

We model household behavior in an environment where households are uncertain about quality levels of brands and may be risk averse with respect to quality variation. Households may use prices, use experience, ad frequency, and ad content as signals of quality. They use the frequency with which they see TV ads for a brand as a signal of its level of ad expenditures[9] and weekly prices as signals of a brand's mean price. They update their expectations of brand quality in a Bayesian manner as they see additional signals.

We do not attempt to model producer behavior. Rather, we specify functional relationships among price, advertising frequency, and quality that we assume hold in equilibrium. We estimate the parameters of these functional relationships jointly with the parameters of our structural model of household behavior. Households are assumed to know these equilibrium relationships and to use them to help infer brand quality.[10]

We estimate a pure brand choice model, ignoring the issues of quantity choice and inventories that are the focus of Erdem et al. (2003) and Hendel and Nevo (2006). Those papers ignore consumer learning. Thus, each approach leaves out a potentially important aspect of consumer behavior. A unification of these two approaches is left for future research.

2.2. Utility Function

We assume that consumers have utility functions of the form:

$$U_{ijt} = \alpha_i P_{ijt} + w_i Q_{Eijt} + w_i r_i Q_{Eijt}^2 + e_{ijt}, \tag{1}$$

where P_{ijt} is the price of brand $j = 1, \ldots, J$ faced by household i at time t, and Q_{Eijt} is household i's *experienced* quality of brand j at time t. The price coefficient α_i is the negative of i's marginal utility of consumption of the outside good. It is assumed constant over the small range of outside good consumption levels generated by the household's brand choice decisions. The parameter w_i is household i's utility weight on quality, and r_i captures i's risk aversion toward variation in quality. Finally, e_{ijt} is a taste shock known to the household but not by the econometrician.

Variability of *experienced* quality Q_{Eijt} around a brand's true quality Q_j occurs for several reasons. One is variability of product quality across units. But, in categories covered by scanner data, a more plausible explanation is that a user's experience of a brand is context dependent. Thus, we assume that each use experience provides a noisy but unbiased signal of quality, according to $Q_{Eijt} = Q_j + \xi_{ijt}$ where $\xi_{ijt} \sim N(0, \sigma_\xi^2)$. We refer to σ_ξ^2 as the "experience variability."

Household i has an information set I_{it} containing all brand quality signals it has received up through time t. Given this information, it forms an expectation of Q_{Eijt}. Let $Q_{ijt} \equiv \mathrm{E}[Q_j \mid I_{it}]$ denote household i's expectation of brand j's true quality level at time t. We describe the contents of I_{it} and how expectations are formed below. For now, we just note that all signals are assumed unbiased. Hence, $\mathrm{E}[Q_{Eijt} \mid I_{it}] = \mathrm{E}[Q_j \mid I_{it}] = Q_{ijt}$, and we may write $Q_{Eijt} = Q_{ijt} + (Q_j - Q_{ijt}) + \xi_{ijt}$.

Hence, the expected utility to household i from buying and consuming brand j at time t is

$$\mathrm{E}[U_{ijt} \mid I_{it}] = \alpha_i P_{ijt} + w_i Q_{ijt} + w_i r_i Q_{ijt}^2 + w_i r_i E[(Q_j - Q_{ijt})^2 \mid I_{it}] + w_i r_i \sigma_\xi^2 + e_{ijt}. \tag{2}$$

In (2) there are two sources of *expected* variability of experienced quality Q_{Eijt} about true quality. First is

[7] Another type of evidence for inventory models is that duration to next purchase is longer after a deal purchase. But this could also be rationalized by a learning model with an outside good, if deals reduce quality perceptions.

[8] Current computational technology makes it infeasible to incorporate both learning and inventories in one model.

[9] In most mass-marketed, frequently purchased categories, brands are nationally advertised on TV. Airtime is priced based on ratings. Thus, we assume that the frequency with which a person sees ads for a brand is proportional to ad expenditure.

[10] Such a quasi-structural approach was used in different contexts by Ching (2002), Erdem et al. (2003), and Hendel and Nevo (2006), who estimate that price policy functions jointly with various structural models of consumer behavior.

experience variability, σ_ξ^2. Second is $E[(Q_j - Q_{ijt})^2 \mid I_{it}]$, the variability of true quality around perceived quality. A household understands that it has incomplete information and that true quality will tend to depart somewhat from expected quality. If a household has little information about a brand, this "risk term" is large. Thus, *ceteris paribus*, risk-averse households will tend to avoid an unfamiliar brand in favor of a familiar one, even if both have the same expected quality.

Note that Equation (1) is the same type of utility function used by Erdem and Keane (1996). However, unlike Erdem and Keane, we let α_i, w_i, and r_i be heterogeneous across consumers. We adopt a discrete mass point (latent class) approach, as in Heckman and Singer (1982).[11] We thus estimate a vector (α_k, w_k, r_k) for each segment of consumers $k = 1, \ldots, K$, as well as the population type proportions for each segment, which we denote by π_k for $k = 1, \ldots, K$.

Finally, we specify that the expected utility from no purchase, $\mathrm{E}[U_{i0t} \mid I_{it}]$, is given by

$$\mathrm{E}[U_{i0t} \mid I_{it}] = \Phi_0 + \Phi_1 \cdot t + e_{i0t}.$$

The time trend in this equation captures changes in the value of the outside option over time.

2.3. The Price Process and the Price–Quality Relationship

In using prices to infer quality, consumers assume that the stochastic process for prices is

$$\ln P_{ijt} = P_j^M + \omega_{ijt}, \quad \omega_{ijt} \sim N(0, \sigma_\omega^2), \tag{3}$$

where P_{ijt} is the price of brand j faced by household i at time t, P_j^M is the mean of the log price of brand j, and ω_{ijt} is a stochastic term that is i.i.d. over time.[12] Consumers believe that, in the market equilibrium, the mean price P_j^M is related to brand quality according to the relation:

$$P_j^M = P_0 + \phi Q_j + \eta_j, \tag{4}$$

where Q_j is a latent quality index for brand j, ϕ is a parameter, and η_j is the deviation of brand j from the "typical" price-quality relationship (e.g., its price being high or low relative to its quality).

Households perceive that the η_j are distributed in the population of firms according to $\eta_j \sim N(0, \sigma_\eta^2)$. Combining Equations (3) and (4) we have

$$\ln P_{ijt} = P_0 + \phi Q_j + \eta_j + \omega_{ijt}. \tag{5}$$

We will estimate P_0, ϕ, σ_ω, σ_η, and a set of η_j. Obviously we cannot estimate both P_0 and a value of η_j for each brand, so we restrict $\eta_J = \sum_{j=1,\,J-1} \eta_j$ so that the η_j are mean zero across brands.

2.4. Consumer Learning About Quality: The Case of Price as the Only Signal

To illustrate how households learn about quality in our model, it is helpful to consider a hypothetical case where price is the only signal. At $t = 0$, prior to any experience in the market, a household has priors about the mean prices and quality levels of brands. The prior for quality is

$$Q_j \sim N(Q_0, \sigma_{Q_0}^2) \quad \text{for } j = 1, \ldots, J, \tag{6}$$

and combining (4) and (6), the prior for mean log price is

$$P_j^M \sim N(P_0 + \phi Q_0, \phi^2 \sigma_{Q_0}^2 + \sigma_\eta^2) \quad \text{for } j = 1, \ldots, J. \tag{7}$$

In (6) the household's prior is that all brands have a quality level of Q_0 but that the true quality of brand j has variance $\sigma_{Q_0}^2$ around that mean. The prior perceived standard deviation σ_{Q_0} is a parameter to be estimated in our model. The prior mean Q_0 is restricted to equal the mean of the brand-specific quality levels Q_j for $j = 1, \ldots, J$, and it is the latter that are estimated.

In (7) the household's prior is that all brands have a mean log price equal to the mean log price in the category, $P_0 + \phi Q_0$, but that the true mean log price for brand j has a variance of $\phi^2 \sigma_{Q_0}^2 + \sigma_\eta^2$ around that mean. Note that a brand may have an above-average price because it is high quality (the $\phi^2 \sigma_{Q_0}^2$ component) or because it is priced high given quality (the σ_η^2 component).

Let P_{ijt}^M and Q_{ijt} denote household i's prior means for mean log price and quality of brand j conditional on information at t. At $t = 0$, these are simply $P_{ij0}^M = P_0 + \phi Q_0$ and $Q_{ij0} = Q_0$. When a price is observed for brand j at $t = 1$, the household updates its priors about mean log price and quality of brand j using standard Bayesian updating rules (see, e.g., DeGroot 1970):

$$P_{ij1}^M = P_{ij0}^M + [\ln P_{ij1} - P_{ij0}^M] \cdot K_{1ij}^P, \tag{8}$$

$$Q_{ij1} = Q_{ij0} + [\ln P_{ij1} - P_{ij0}^M] \cdot K_{1ij}^{PQ}, \tag{9}$$

[11] We must solve a household's dynamic optimization problem conditional on its being each of the K types in order to form the likelihood function of our model. Thus, it is infeasible to have a continuous heterogeneity distribution.

[12] Erdem et al. (2003) and Hong et al. (2002) note that prices of frequently purchased consumer goods exhibit complex serial correlation patterns. Because expected future prices do not affect consumer demand in our model (there are no inventories), the behavior predicted by our model should be fairly insensitive to ignoring serial correlation.

where K_{1ij}^{P} and K_{1ij}^{PQ} are the Kalman gain coefficients, which at $t=1$ are

$$K_{1ij}^{P} = (\phi^2\sigma_{Q_0}^2 + \sigma_\eta^2)/(\phi^2\sigma_{Q_0}^2 + \sigma_\eta^2 + \sigma_\omega^2), \tag{10}$$

$$K_{1ij}^{PQ} = \phi\sigma_{Q_0}^2/(\phi^2\sigma_{Q_0}^2 + \sigma_\eta^2 + \sigma_\omega^2). \tag{11}$$

K_{1ij}^{PQ} captures how the household revises its perceived quality of brand j in response to the price surprise. The numerator in (11) is ϕ times the part of price variability that arises because j may be above or below average quality. Given a positive price surprise (i.e., $\ln P_{ij1} > P_{ij0}^{M}$) the household will revise upward its perception of the quality of brand j provided that $\phi > 0$ (i.e., price is related to quality) and that $\sigma_{Q_0}^2 > 0$ (i.e., the household is uncertain about the quality of brand j).[13]

Prior uncertainty about quality σ_{Q_0} is a parameter to be estimated in our model. Intuitively, σ_{Q_0} is identified from how brand choice behavior of households with substantial prior experience *differs* from that of households with little prior experience. If we estimate $\sigma_{Q_0}=0$, our model reduces to a static model in which no learning occurs.

As households acquire information, priors become tighter. Let $\sigma_{Pijt}^2 = \mathrm{Var}(P_{ijt}^{M} - P_j^{M})$ and $\sigma_{Qijt}^2 = \mathrm{Var}(Q_{ijt} - Q_j)$ denote the household's perceived variability of price and quality for brand j conditional on information received up through time t. At $t=0$, these perception variances are $\sigma_{Pij0}^2 = \phi^2\sigma_{Q_0}^2 + \sigma_\eta^2$ and $\sigma_{Qij0}^2 = \sigma_{Q_0}^2$. Given the price for brand j at $t=1$, the household updates these prior variances using standard Bayesian updating rules (see, e.g., DeGroot 1970), to obtain

$$\sigma_{Pij1}^2 = [1/\sigma_{Pij0}^2 + 1/\sigma_\omega^2]^{-1}, \tag{12}$$

$$\sigma_{Qij1}^2 = [1/\sigma_{Qij0}^2 + \phi^2/(\sigma_\eta^2 + \sigma_\omega^2)]^{-1}. \tag{13}$$

According to (12), if σ_ω^2 is large then one price signal is not very informative about mean price, so it causes little reduction in perceived variance. Similarly, (13) says that if $\sigma_\omega^2 + \sigma_\eta^2$ is large or ϕ is small then a single price realization is not very informative about brand quality.

In period $t=2$, updating is done the same way, using (8)–(9) as the new prior means and (12)–(13) as the new prior variances. At $t \geq 2$, the Kalman gain coefficients for brand j are

$$K_{tij}^{P} = \sigma_{Pij,t-1}^2/(\sigma_{Pij,t-1}^2 + \sigma_\omega^2) \quad \text{and}$$
$$K_{tij}^{PQ} = \phi\sigma_{Qij,t-1}^2/(\phi^2\sigma_{Qij,t-1}^2 + \sigma_\eta^2 + \sigma_\omega^2).$$

[13] The denominator of (11) also contains σ_η^2 and σ_ω^2. If these are large relative to $\phi^2\sigma_{Q_0}^2$, then most price variability is idiosyncratic and conveys little information about quality.

2.5. Introducing Advertising Frequency as a Signal of Quality

Now we incorporate advertising frequency as a signal of quality. Let A_{ijt} denote the (normalized) number of TV ads seen by household i for brand j during week t. The normalization adjusts for how often a household watches TV and is implemented as follows: First, find the mean number of ketchup ads (for all brands) a household sees per week during the entire sample period. Second, scale this variable so it has a mean of one. Third, use this value to normalize A_{ijt}.

A_{ijt} is highly nonnormal due to concentration of mass at zero ads. But we cannot allow nonnormal errors because it is very difficult to implement Bayesian updating rules with multiple signals if some are nonnormal. Thus, we use a Box-Cox transform to bring the ad exposure distribution closer to normality. The Box-Cox likelihood is not well behaved when the dependent variable is zero, so we use $1+A_{ijt}$ rather than A_{ijt}. Thus, the assumed process for ad exposures is

$$[(1+A_{ijt})^\beta - 1]/\beta = A_j^M + \theta_{ijt} \quad \text{with } \theta_{ijt} \sim N(0, \sigma_\theta^2), \tag{14}$$

where β is the Box-Cox parameter, A_j^M is mean transformed weekly ad exposures for brand j, and θ_{ijt} is a stochastic term that is i.i.d. over time.[14] θ_{ijt} captures idiosyncratic reasons a household might see more (or fewer) ads than usual for brand j during week t (e.g., true ad intensity of a brand varies by week, and, by chance, a household may or may not be watching TV when ads appear).

Households believe that A_j^M is related to brand quality according to the relation

$$A_j^M = A_0 + \delta Q_j + \mu_j. \tag{15}$$

Here, Q_j is the quality of brand j, which also appeared in (4), δ is a parameter, and μ_j represents the departure of brand j from the "typical" ad frequency–quality relationship (i.e., some brands may advertise relatively heavily given their quality). Households perceive that the μ_j are distributed in the population of firms according to $\mu_j \sim N(0, \sigma_\mu^2)$. Combining (14) and (15), we have

$$[(1+A_{ijt})^\beta - 1]/\beta = A_0 + \delta Q_j + \mu_j + \theta_{ijt}. \tag{16}$$

We will estimate A_0, β, δ, σ_θ, σ_μ, and a set of μ_j. Obviously, we cannot estimate both A_0 and a μ_j for

[14] The right side of (14) must be greater than $-1/\beta$ for $(1+A_{ijt})^\beta > 0$, which is necessary for the implied value of A_{ijt} to be well defined (given $0<\beta<1$). Thus, taken literally, (14) rules out normal errors. This is an oft-noted problem with Box-Cox transformations. Given our estimates, a value of the right side less than $-1/\beta$ is an extreme outlier.

each brand j, so we restrict $\mu_J = \sum_{j=1,\,J-1} \mu_j$ so the μ_j are mean zero across brands.

At $t=0$, prior to seeing any ads, households' prior is that each brand j's (transformed) advertising rate is the same as the mean rate in the category, $A_0 + \delta Q_0$, but that the true rate for brand j is distributed around that mean according to

$$A_j^M \sim N(A_0 + \delta Q_0, \delta^2 \sigma_{Q_0}^2 + \sigma_\mu^2). \tag{17}$$

Note that a brand may have an above-average advertising rate due to either high quality or the deviation (μ_j) from the "typical" ad frequency–quality relationship.

Let A_{ijt}^M denote household i's prior mean for (transformed) advertising frequency of brand j conditional on information at t. At $t=0$, this is simply $A_{ij0}^M = A_0 + \delta Q_0$. The formulas for how the household updates its perceptions of A_{ijt}^M and Q_{ijt} based on observing a certain (normalized) number of ads A_{ijt} are exactly analogous to Equations (8)–(13), so we give them in Technical Appendix A. The Technical Appendices can be found at http://mktsci.pubs.informs.org.

2.6. Introducing Use Experience and Advertising Content Signals

Use experience and ad content also provide noisy signals about product quality. Define d_{ijt} as an indicator equal to 1 if brand j is purchased at time t and 0 otherwise. As we noted in §2.2, use experience provides a direct but noisy information signal Q_{Eijt} according to

$$Q_{Eijt} = Q_j + \xi_{ijt} \quad \text{with } \xi_{ijt} \sim N(0, \sigma_\xi^2). \tag{18}$$

Advertising exposure provides a direct but noisy information signal AD_{ijt} according to

$$AD_{ijt} = Q_j + \tau_{ijt} \quad \text{with } \tau_{ijt} \sim N(0, \sigma_\tau^2).^{15} \tag{19}$$

The updating of expectations with use experience and ad content signals is described in detail in Erdem and Keane (1996), so we will not repeat that here.

2.7. The Household's Dynamic Optimization Problem and the Likelihood Function

In our model, a household's time t purchase decision affects not only its time t utility, but also its state $I_{i,\,t+1}$ at the start of period $t+1$. Hence, if a household has little information about a brand, it may be optimal to try it when it is on sale, because it may be better than the household's "preferred" brand (i.e., that with highest expected utility given current information). The mathematical representation of this optimization problem is given in Technical Appendix B.

[15] Note that we assume that ad signals are one-dimensional. We abstract from the issue, analyzed in Bass et al. (2007), that firms can have a portfolio of ads that serve different purposes or emphasize different aspects of the product.

The details of how we construct and simulate the likelihood function are given in Technical Appendix C. Here, it is important to note that the first observation period does not coincide with the start of a household's choice process, creating an initial conditions problem. Because our data contain ad viewing data only for the last 51 weeks, we use the first 102 weeks to estimate each household's initial conditions and the last 51 to estimate the model. Assume that household i's prior variance on the quality level of brand j at the start of our estimation period is given by

$$\ln \sigma_{Q_{ij0}} = k_0 - k_1 \sum_{\tau=-101}^{0} d_{ij\tau}, \tag{20}$$

where k_0 and k_1 are parameters. Equation (20) says that initial uncertainty about brand j is less if a household bought j more during the proceeding 102 weeks, reducing its prior variance on j from $\sigma_{Q_0}^2$ to $\sigma_{Q_{ij0}}^2$. Technical Appendix C explains how we integrate out the initial conditions.

2.8. Identification

A detailed discussion of identification is provided in Technical Appendix D. The usual utility scale normalization in discrete choice models is imposed by setting $Q_1 = 1$, so Heinz quality is 1, and other brands are measured relative to Heinz. We note that a location normalization like $\Phi_0 = 0$ is needed in a static model (where all consumers have complete information about quality) but is not needed in a dynamic model. Not surprisingly, the parameters r, σ_ξ, and σ_{Q_0} that measure risk aversion and experience variability are not identified in a static model, but only from dynamics, i.e., how brand choice probabilities evolve as a household receives signals. For example, if $r < 0$, willingness to pay for a brand is increasing in prior experience, holding perceived quality fixed.

3. Data

We estimate the model on Nielsen scanner data for ketchup. For a panel of more than 3,000 households in Sioux Falls, SD, and Springfield, MO, the data record all store visits for 153 weeks in 1986–1988. Both the brand purchased and price paid are recorded. TV ad exposures are recorded for approximately 60% of households in the last 51 weeks. This is the calibration period.

We analyze the three leading brands, Heinz, Hunt's, and Del Monte, which together have an 85% market share, and ignore purchase occasions when households bought other brands. We focus on regular ketchup users by excluding households that made fewer than four purchases during the 51 weeks.

Table 1 Descriptive Statistics

Brand name	Market share (%)	Mean offered price[1] ($)	Mean accepted price[1] ($)	Mean weekly advertising frequency[2]	Mean number of advertising exposures[3]
Heinz	66.15	1.349	1.302	0.180	2.12
Hunt's	17.26	1.197	1.141	0.096	1.57
Del Monte	16.58	1.184	1.104	0	0

[1]Prices are normalized at 32 oz. per bottle.
[2]The percentage of households who see at least one ad for the brand in a typical week.
[3]The mean number of ads seen in a given week, conditional on ad exposure.

We randomly select 250 households for calibration and 100 for validation. Because the sample covers 51 weeks, the calibration and holdout samples have 12,750 and 5,100 observations, respectively. In the calibration sample, the mean number of ketchup purchases is 8.93. Sample means of age, family size, and household income are 46, 3.6, and $24,375, respectively.

As noted earlier, our model abstracts from quantity choice. Thus, we always use 32-oz. prices, for both the purchased brand and alternative brands, regardless of the size a household actually bought (i.e., we assume that households compare 32-oz. prices when choosing among brands), because 32 oz. is clearly the dominant size for ketchup. Table 1 reports descriptive statistics for the calibration sample. Note that Heinz has the highest mean price and highest ad frequency. Figure 1 shows the frequency distribution of prices for Heinz 32 oz.[16] There is substantial mass (i.e., 2% or more) at 15 price points.[17] So our assumption of a continuous distribution seems reasonable.

Ketchup is well suited to our purposes for two reasons. First, the literature on the price–quality relationship suggests that it is stronger in frequently purchased product categories (Rao and Monroe 1989). Second, the brand with the high-quality positioning, which gets the highest ranking in *Consumer Reports* (1983), namely Heinz, also has the highest mean price and advertising intensity. Thus, there is scope for consumers to use price and ad frequency as quality signals. In contrast, Erdem et al. (2008) find that ad frequency and price are not consistently positively correlated in other categories where scanner data are available.

Furthermore, Erdem and Keane (1996) found that a learning model provides a good fit to dynamics of consumer choice behavior, including responses to ad and experience signals, in another frequently purchased consumer goods category: detergent. As we show below, such markets can be characterized by a situation where even experienced consumers are familiar with one or a few brands, while uncertainty about other options remains unresolved. The learning model with risk aversion is able to explain brand loyalty for familiar brands via this mechanism.

4. Empirical Results

4.1. Model Fit and Model Selection

Our model allows for heterogeneity in the price coefficient (α_k), utility weight on quality (w_k), and risk coefficient (r_k), so we must first choose the number of types K. We estimated models with 1, 2, and 3 types, and we report measures of fit in Table 2. Increasing K from one to two improves Akaike's information criterion (AIC) and Bayesian information criterion (BIC) by 95 and 80 points, respectively, and the holdout sample log-likelihood by 41 points. However, when we increase the number of types from two to three, the information criteria are ambiguous (AIC improves slightly whereas BIC deteriorates), and the holdout log-likelihood barely improves.[18] Table 3 reports brand-switching matrices for each model. The homogeneous model understates persistence in choices, but the two- and three-type models both provide an excellent fit to the switching matrix. Table 4 compares choice frequencies for the data versus the model, and these also suggest that the two-type model fits the data well. Based on these results, we decided to use the two-type model for further analysis.

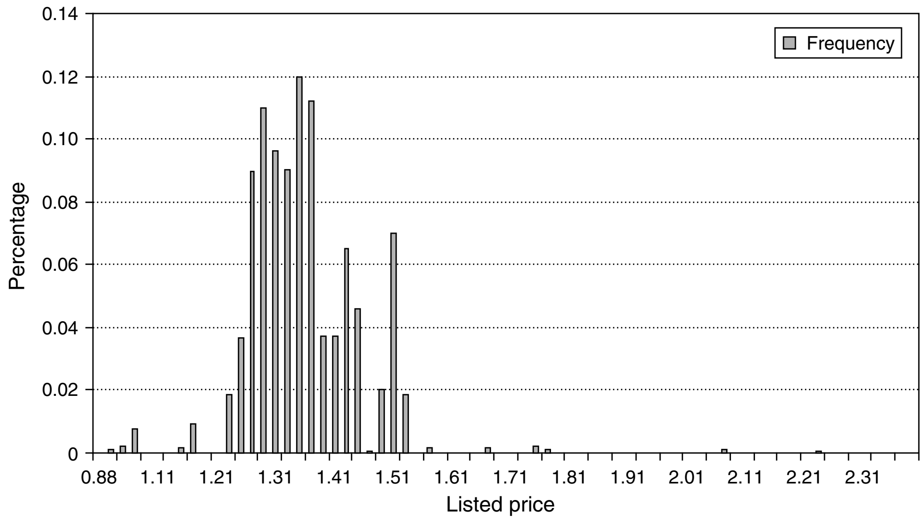
Table 3 reveals an interesting result: we capture persistence in brand choice without needing heterogeneity in intrinsic brand preferences (i.e., heterogeneous brand intercepts). Our heterogeneity is at a more fundamental level: taste for quality, risk aversion, tastes for the outside good. Our model generates persistence in brand choices through these factors and also learning, which causes perceptions of brands to diverge over time as households see different signals.

[16] Constructing prices for brands a household did not purchase is complicated, because these are not necessarily reported in the Nielsen data. We use the imputation procedure described in Erdem et al. (1999).

[17] Note that Figure 1 describes the distribution of offer prices for Heinz 32 oz. across all the observations in the data. This includes both variation within stores over time and variation across stores. We assume that store choice is exogenous (i.e., consumers don't choose which store to visit based on ketchup prices), so store switching generates exogenous variation in prices. The mean and median percentages of weeks that households visit a store are 80% and 86%, respectively (though we assume that they consider the ketchup category—and see prices—in every week).

[18] Table 2 also shows that the two-type myopic model has a log-likelihood 63 points worse than the two-type model with forward-looking consumers. Thus, the forward-looking aspect of the model (i.e., trial purchases) is important.

Figure 1 Frequency Distribution of Listed Prices for Heinz 32 oz.



4.2. Parameter Estimates

We report parameter estimates for our preferred (two-type) model in Table 5. The price coefficient, utility weight on quality, and risk parameter all have expected signs, with the latter implying that consumers are risk averse with respect to quality variation. Households in segment 2, which is the larger segment (62%) are more price sensitive, place slightly less weight on quality, and are less risk averse with respect to quality variation than households in segment 1.

The estimates of $k(0)$ and $k(1)$ imply that the average, across households and brands, of the "initial" perception error variance (after the 102-week initialization period) is $\sigma^2_{Q_{ij0}} = 0.146$, suggesting that there is quality uncertainty. Regarding true quality, our estimates imply that Heinz is the highest quality, while Hunt's and Del Monte are very similar. As expected, the estimates imply that use experience provides more accurate signals of quality than ad exposures.

Our estimates of the slopes in the price–quality and ad frequency–quality relationships are positive ($\phi = 0.398$, $\delta = 0.284$), suggesting that there is scope to use price and ad frequency as signals of quality in this market. Households perceive more noise in the ad frequency–quality than in the price–quality relationship ($\sigma_\mu = 0.532$ versus $\sigma_\eta = 0.281$), and ad frequency varies over time more than prices. These factors make price much more effective as a signal of quality than ad frequency.

As we note in Technical Appendix D, different choice behavior of households with complete versus limited quality information is crucial for identifying r and σ_{Q_0}. Table 6 reports simulated choice frequencies of households who know brand quality exactly versus ones who have not received any quality signals. As expected, uncertainty lowers the market share of Heinz (the highest Q brand) and increases frequency of no purchase (because uncertainty lowers expected utility of all brands).

Table 2 Model Selection

	Myopic model with learning (two types)	Dynamic models		
		One type	Two types	Three types
In-sample (Sioux Falls):				
−LL	11,854.0	11,890.2	11,791.1	11,779.0
AIC	11,882.0	11,914.2	11,819.1	**11,811.0**
BIC	11,986.3	12,003.6	**11,923.4**	11,930.3
Out-of-sample (Springfield):				
−LL	4,960.1	4,872.7	4,832.0	**4,829.2**

Notes. The best-fitting model is indicated in boldface type. Calibration sample: Number of observations = 12,750, number of households = 250, number of periods = 51. Holdout sample: Number of observations = 5,100, number of households = 100, number of periods = 51. AIC = −Log-likelihood + number of parameters. BIC = −Log-likelihood + 0.5∗number of parameters ∗ ln(number of observations). There are 28, 24, 28, and 32 parameters in the four estimated models.

4.3. The Roles of Consumer Heterogeneity and Learning in Generating Persistence

Tables 3 and 4 shed light on the extent that persistence in choice behavior is generated by consumer heterogeneity. Note that type-1 households prefer Heinz (relatively speaking) more than type-2 households. Still, comparing Tables 3 and 4, we see that unconditional choice frequencies for both segments are well below the diagonal elements in the switching matrix. For example, the unconditional probability of buying Hunt's is 14% in segment 1 and 19% in segment 2, but the Hunt's-to-Hunt's transition rate is

Table 3 Brand-Switching Matrices

Sample	Myopic model with two types	One-type model	Two-type model	Three-type model
0.901 0.072 0.027	0.891 0.073 0.036	0.891 0.061 0.048	0.907 0.068 0.025	0.908 0.061 0.031
0.302 0.530 0.168	0.295 0.535 0.170	0.321 0.482 0.197	0.294 0.548 0.192	0.302 0.527 0.171
0.337 0.260 0.403	0.351 0.273 0.376	0.354 0.293 0.353	0.314 0.285 0.401	0.347 0.253 0.400
			Segment 1 (38.4%)	Segment 1 (28.0%)
			0.918 0.063 0.019	0.919 0.059 0.020
			0.289 0.554 0.157	0.285 0.550 0.150
			0.306 0.277 0.417	0.309 0.280 0.423
			Segment 2 (61.6%)	Segment 2 (42.0%)
			0.900 0.071 0.029	0.897 0.067 0.026
			0.241 0.533 0.213	0.250 0.504 0.222
			0.319 0.290 0.391	0.322 0.286 0.379
				Segment 3 (30.0%)
				0.906 0.054 0.048
				0.391 0.548 0.119
				0.417 0.182 0.408

55% in the full model. Thus, a priori consumer heterogeneity explains little of the persistence in brand choice generated by the model. As we will see below, most persistence is generated by the various learning mechanisms.

4.4. The Roles of the Different Information Channels

The key feature that distinguishes our model from prior work on learning is that we model four key channels through which consumers may learn about quality. How important is each channel? One way to address this question is to ask what happens to model fit, and predicted behavior, if we drop channels. So, in panel A of Table 7 we report measures of fit for various nested models that drop particular channels. Fit deteriorates most when we drop use experience as a signal of quality (206 likelihood points), followed by price (159 points), and then by ad frequency (148 points). The smallest deterioration occurs when we drop ad content as a signal of quality (114 points).

It is also interesting to drop *both* ad signaling mechanisms (i.e., frequency and content) at the same time. The deterioration in the likelihood when we do this (158 points) is almost identical to when we drop price as a signal of quality (159 points). Thus, in this mature market, price and ad signaling appear to be of roughly equal importance. Also note that the drop in the likelihood when we drop both roles of advertising is only 10 points greater than when we drop ad frequency signaling alone. Thus, one is tempted to say that ad frequency is the primary mechanism through which ads signal quality. However, this conclusion cannot be supported, because the effect of dropping the two ad signaling mechanisms is clearly nonadditive.

Panel B of Table 7 provides information on how each signaling mechanism contributes to persistence in brand choice. When we eliminate price, ad frequency or ad content signaling, the deterioration in persistence is modest. But dropping use experience as a quality signal leads to a substantial drop in persistence (e.g., the Hunt's-to-Hunt's transition rate drops from 54.8% to only 26.0%). Clearly, experience signals are the main factor generating persistence in the model.

Expanding on this issue, Figure 2 shows how quality uncertainty is resolved slowly in our model. Comparing the distribution of perception error variance

Table 4 Comparison of Simulated and Sample Frequencies

		Model prediction (%)		
	Data (%)	One type	Two types	Three types
Heinz	11.61 (66.15)	10.73 (64.48)	11.68 (66.78)	11.98 (67.71)
Hunt's	3.03 (17.26)	3.09 (18.57)	2.94 (16.81)	3.16 (17.70)
Del Monte	2.91 (16.58)	2.82 (16.95)	2.87 (16.41)	2.71 (15.18)
No purchase	82.45	83.36	82.51	82.15
Segment 1			38.4	28.0
Heinz			13.22 (71.77)	14.35 (75.57)
Hunt's			2.61 (14.17)	2.50 (13.16)
Del Monte			2.59 (14.06)	2.14 (11.27)
No purchase			81.60	81.01
Segment 2			61.6	42.0
Heinz			10.73 (63.76)	12.61 (68.76)
Hunt's			3.15 (18.60)	3.02 (16.47)
Del Monte			3.04 (18.00)	2.71 (14.78)
No purchase			83.08	81.66
Segment 3				30.0
Heinz				8.89 (55.19)
Hunt's				3.97 (24.67)
Del Monte				3.24 (20.14)
No purchase				83.90

Notes. Probabilities conditional on purchase are in parentheses. In the two-segment model, the segment proportions are 38.4% and 61.6%. In the three-segment model, the segment proportions are 28.0%, 42.0%, and 30.0%.

Table 5 Structural Model Estimation Results

	Segment 1		Segment 2	
	Estimate	Std. error	Estimate	Std. error
Parameters that differ by consumer segment				
Price coefficient (α)	−0.111	0.06	−0.307	0.06
Utility weight (w)	1.992	0.33	1.606	0.41
Risk coefficient (r)	−0.363	0.09	−0.247	0.10
Segment membership probability (π)	0.384	0.10	0.616	—

Homogenous parameters	Estimate	Std. error
$k(0)$	−0.661	0.29
$k(1)$	0.066	0.02
Quality levels:		
Q_{Heinz}	0.501	—
$Q_{\text{Hunt's}}$	0.393	0.12
$Q_{\text{Del Monte}}$	0.368	0.08
Use experience signal variability (σ_ξ)	0.292	0.12
Advertising message variability (σ_τ)	0.612	0.19
Price signaling quality equation:		
Intercept (P_0)	−0.031	0.01
Slope (ϕ)	0.398	0.12
Brand-specific constants:		
η_{Heinz}	0.053	0.02
$\eta_{\text{Hunt's}}$	−0.025	0.01
Standard deviation of η cross brands (σ_η)	0.281	0.09
Price variability (σ_w)	0.401	0.13
Advertising signaling quality equation:		
Intercept (A_0)	−0.194	0.27
Slope (δ)	0.284	0.10
Brand-specific constants:		
μ_{Heinz}	0.085	0.023
$\mu_{\text{Hunt's}}$	−0.005	0.003
Standard deviation of μ cross brands (σ_μ)	0.532	0.19
Box-Cox parameter (β)	0.621	0.20
Advertising (frequency) variability (σ_θ)	0.532	0.15
Utility from no purchase option:		
Intercept (Φ_0)	0.983	0.10
Time trend (Φ_1)	0.001	0.13

for Del Monte at weeks 17 and 51, we see the mean drops only from 0.1672 to 0.1572. This is because switching from other brands to Del Monte is rare (see Table 7B), so consumers initially unfamiliar with the brand rarely get accurate experience signals. Other signals (price, ad frequency, ad content) do arrive, but they are much less accurate. This clarifies how the learning model generates persistence in choices, because risk-averse consumers are reluctant to buy unfamiliar brands.

Another way to state the message of Figure 2 is that even consumers who are very "experienced" in the category tend to be familiar with just one (or a few) brands that they buy frequently—leaving them unfamiliar with alternatives. This is exactly the mechanism through which learning models generate brand equity for the preferred familiar brand via the risk term.

Table 6 Comparison of Choice Probabilities for Households with Different Degrees of Knowledge About Quality

Perception error variance	Average purchase probabilities (%)			
	Heinz	Hunt's	Del Monte	No purchase
$\sigma^2_{\theta_0} = 0.146$	11.68	2.94	2.87	82.51
$\sigma^2_{\theta_0} = 0$	13.62	2.58	2.52	81.28

Notes. 0.146 is the average initial perception error variance across consumers and brands. The estimate of $k(0)$ implies that the prior standard deviation before any learning takes place is $\exp(-0.661) = 0.5163$, giving a prior variance of 0.267. Use experience in our 102-week initialization period reduces this, on average, to 0.146.

5. Policy Experiments—Transitory and Permanent Price Cuts

A key issue in marketing is whether frequent price promotion dilutes brand equity. In our model, a brand's *mean* offer price is a signal of its quality. Frequent price promotion reduces perceived mean price, thus reducing perceived quality. It also raises the variance of prices, making price less accurate as a signal of quality and increasing the perceived quality risk associated with a brand. Both factors reduce willingness to pay for a brand.

Here, we conduct experiments to shed light on these issues. First, in Table 8, we simulate a temporary 10% Heinz price cut lasting one week.[19] In that week, Heinz sales increase 33%.[20] Total category sales increase 18%, and Hunt's and Del Monte sales fall by approximately 13%. Thus, 80% of Heinz' short-run sales increase is due to category expansion, with 20% due to brand switching.

In weeks 2–10, Heinz prices return to their baseline levels. Its sales fall relative to the baseline, while sales of competitors rise. Our model has no inventory mechanism to generate this "postpromotion dip." Rather, Heinz's price promotion causes consumers to revise down their perception of its mean price. This, in turn, reduces their perceived quality for Heinz, *reducing* its sales for several weeks postpromotion.[21] On the other hand, increased Heinz sales in week 1 lower its perceived risk in week 2 (among those who switched to Heinz in week 1). And, because Heinz is relatively high quality, the extra consumers buying it in week 1 tend to perceive it as higher quality

[19] The simulation is conducted in week 17, but results were very similar using week 40. This is precisely because of the rather slow evolution of the distribution of perception error variance discussed in §4.4 and Figure 2.

[20] This implies a short-run price elasticity of demand of approximately −3.3, which is in line with previous estimates for ketchup (see Keane 1997; Erdem et al. 2003, 2008).

[21] Eventually, as other quality signals arrive over time, consumers' perception of Heinz quality moves back into line with their baseline perceptions. By week 10, Heinz sales return to their baseline level.

Table 7 **Comparing the Importance of the Information Channels**

	No price signaling quality	No ad frequency signaling	No ad content signaling	No ad frequency or content signaling	No use experience signaling	Price as only signal of quality	Full model
				A. Model fit			
In-sample (Sioux Falls):							
−LL	11,950.5	11,939.1	11,904.7	11,949.5	11,996.8	12,051.2	11,791.1
AIC	11,973.5	11,960.1	11,931.7	11,969.5	12,023.8	12,070.2	11,819.1
BIC	12,063.9	12,038.4	12,032.3	12,044.0	12,124.4	12,144.0	11,923.4
Out-of-sample (Springfield):							
−LL	4,902.0	4,881.8	4,879.9	4,894.7	4,922.8	4,940.1	4,832.0
				B. Brand-switching matrices			
	0.857 0.074 0.069	0.864 0.081 0.055	0.883 0.062 0.055	0.848 0.107 0.045	0.720 0.214 0.066	0.601 0.295 0.104	0.907 0.068 0.025
	0.280 0.462 0.258	0.318 0.453 0.229	0.320 0.481 0.199	0.299 0.446 0.255	0.444 0.260 0.296	0.427 0.192 0.381	0.294 0.548 0.192
	0.349 0.289 0.362	0.359 0.302 0.339	0.368 0.288 0.344	0.365 0.300 0.335	0.383 0.378 0.239	0.441 0.378 0.181	0.314 0.285 0.401

by week 2. Both factors *increase* Heinz sales in week 2 onward. Our simulations imply that the perceived-quality-reducing effect of a price cut dominates the reduced risk and positive use experience effects, so a postpromotion dip does emerge.

Table 9 elucidates the three different effects of a price cut on perceived quality. In this table, households are divided into seven (exhaustive) groups: (i) those who bought Heinz in period 1 under both the baseline and the promotion, (ii) those who bought Hunt's under the baseline but switched to Heinz under the promotion, etc. Of the 1,230 households who buy Heinz in period 1 in both cases, the number who buy Heinz in period 2 drops from 164 in the baseline to 156 under the promotion. For these households, the only change is that the promotion lowered their perceived quality for Heinz, illustrating the first mechanism. On the other hand, there are three groups of consumers who switch to Heinz due to the promotion in period 1. For each of these groups, Heinz sales are *higher* in period 2 under the promotion than the baseline, due to the second and third mechanisms.

Figure 2 **Distribution of Perceived Quality Variance (Del Monte)**

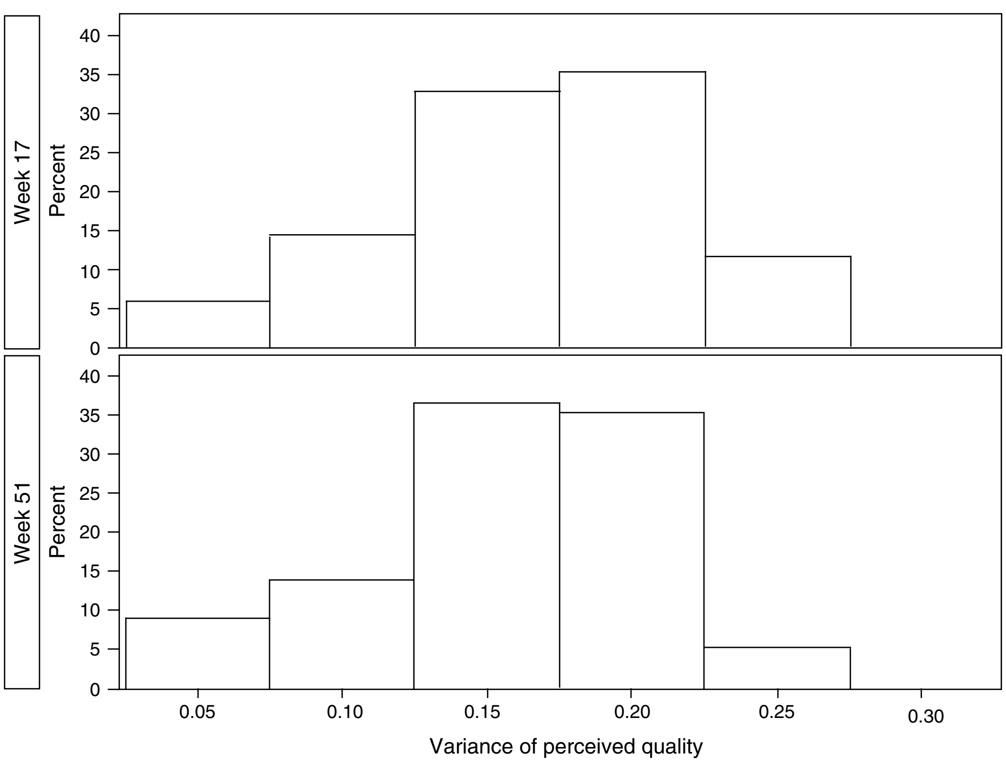


Table 8 Effects of Temporary 10% Heinz Price Decrease in Week 17

	Change of average purchase probabilities			
Week	Heinz	Hunt's	Del Monte	Total
17	32.91	−12.90	−12.70	17.65
18	−3.50	2.35	1.99	−1.61
19	−2.23	1.21	0.94	−1.17
20	−1.33	0.85	0.32	−0.79
21	−0.80	0.42	0.13	−0.44
22	−0.54	0.28	0.03	−0.32
23	−0.30	0.10	0.02	−0.19
24	−0.15	0.04	0.01	−0.09
25	−0.04	0.01	0.00	−0.02
26	−0.01	0.00	0.00	−0.01
Cumulative over 10 weeks	2.33	−0.85	−0.95	1.29
Cumulative, assuming no change after week 17	3.19	−1.35	−1.28	1.75

Notes. The table reports the percentage change of average probabilities for each brand by week, following a temporary 10% price cut for Heinz in week 17, compared to a baseline simulation under the present pricing policy. The average probabilities are calculated using a sample of 10,000 hypothetical consumer histories simulated from the model. "Week 1" of the simulation is actually week 17 in the data. We choose week 17 as the base period for the simulation because all brands were selling at roughly their average prices during that week (i.e., there were no sales in the baseline).

The first mechanism dominates, giving a postpromotion dip in Heinz sales.

Now, returning to Table 8, note that, over the whole 10-week period, Heinz sales increase 2.33%. If sales in weeks 2–10 had not fallen, the increase would have been 3.19%. Thus, 2.33/3.19 = 73% of increased period-1 Heinz sales induced by the promotion are "incremental," whereas 27% represent cannibalization of future sales (due to reduced perceived quality).

It is interesting to contrast this with what Erdem et al. (2003) obtain by fitting an inventory model to ketchup data. Their simulation (see their Table 10) implies that 20% of the temporary sales increase induced by a Heinz price promotion represents cannibalization of future sales. Thus, the inventory model implies a slightly weaker postpromotion dip than does our signaling model (−20% versus −27%). Also, in the inventory model, sales of all brands fall in period 2, not just Heinz. The other key difference is that our model implies cross-price elasticities of demand of approximately 1.3, whereas the inventory model generates cross-elasticities of only approximately 0.4.

In Table 10, we simulate a temporary 10% price cut by Del Monte, the low-priced brand. In the week of the promotion Del Monte sales increase 41%, implying, as expected, a larger price elasticity of demand for the economy brand than for the premium brand, Heinz (−3.3 versus −4.1). Note that Hunt's and Heinz sales fall 5% and 2%, respectively. So, the cross-price elasticity for Heinz with respect to Del Monte is only 0.2%, whereas that in the opposite direction (see Table 8) is 1.3—consistent with Blattberg and Wisniewski's (1989) "asymmetric switching effect."

Next, we consider fundamental changes in pricing and advertising *policy*. Such changes generally alter consumers' purchase decision rules (see Keane 1997). But our structural model predicts how consumers tailor their decision rules to a new environment (see Marschak 1952).

We report our policy simulations in Table 11. In panel A, Heinz's mean offer price is permanently cut by 10%. This generates a 26% increase in Heinz sales, implying an elasticity of demand with respect to permanent price changes of approximately 2.6.[22] Of course, the permanent price cut reduces perceived Heinz quality. To what extent does this detract from Heinz sales? Panel A also reports the same experiment, but holding perceived Heinz quality fixed at baseline levels. Then, sales increase 32%. Thus, reduced quality perceptions counteract 6 points (approximately one-fifth) of the increase in Heinz sales that would have occurred if price could have been cut without altering quality perceptions. This suggests that price plays an important role in signaling quality.[23]

In Table 11, panel B, we decrease Heinz's price variability by 20% while holding its mean price fixed.[24] This makes price a more accurate quality signal, enhancing perceived quality for Heinz, while also reducing perceived risk. But these factors are dominated by the direct effect of less-frequent price promotion, so Heinz total sales over the sample period fall by 7.9%.

In panel C of Table 11 we implement experiments to mimic a switch to an "everyday low pricing" (EDLP) strategy, i.e., joint reductions in mean and variance of price leaving total sales unchanged. With sales unchanged, it is reasonable that cost of goods sold is roughly fixed.[25] Then, increases in mean accepted

[22] Of the incremental sales, approximately 85% is due to category expansion, and 15% is due to brand switching.

[23] Indeed, we calculate that the average perceived quality of Heinz falls from 0.504 under the baseline to 0.457 with the permanent price reduction. This means that approximately 40% of its perceived quality advantage over Hunt's is dissipated.

[24] We do this as follows: (1) Find mean offer price for each brand. (2) Scale up the deviations of price realizations from that mean so as to achieve the desired increase in variance. (3) Determine how this transformation affects mean and variance of the log price. (4) Modify the log price equation accordingly so as to keep the mean price fixed in levels. (5) Simulate behavior given the new price data and the new price process.

[25] Of course, it is now well understood that reduced variability in prices, and hence in sales, lowers inventory along the supply chain, reducing inventory costs (see, e.g., Ohno 1988). Hence, costs may fall despite fixed average sales if price variability is reduced. Such supply chain considerations were presumably a key reason for EDLP adoption.

Table 9 The Competing Effects of a Price Promotion: Breakdown of the Effects of the Sale in Table 8

Choice in period 17			Choice in period 18: Baseline			Choice in period 18: Simulation		
Baseline	Simulation	Number of people	Heinz	Hunt's	Del Monte	Heinz	Hunt's	Del Monte
Heinz	Heinz	1,230	164	17	10	156	14	8
Hunt's	Heinz	43	8	3	0	10	1	0
Hunt's	Hunt's	287	7	10	5	3	5	2
Del Monte	Heinz	36	4	2	2	5	0	1
Del Monte	Del Monte	246	6	5	11	4	3	12
No purchase	Heinz	325	56	6	4	61	4	2
No purchase	No purchase	7,833	925	297	208	890	321	218
Total		10,000	1,170	340	240	1,129	348	245

Notes. We report the counts of consumers in each cell, based on a simulation of 10,000 hypothetical consumers. In period 17, the choice frequencies are Heinz 12.30%, Hunt's 3.30%, and Del Monte 2.80% under the baseline and Heinz 16.34%, Hunt's 2.87%, and Del Monte 2.46% under the simulation. Note that the changes in choice frequencies implied by these figures differ slightly from those in Table 8. This is because the figures in Table 8 are based on the choice probabilities implied by the model, averaged across 10,000 simulated consumers.

price translate into profits. Our simulations imply that Heinz could reduce mean price 2% while reducing price variability 48%, and this would increase revenues by 0.47%. If the initial price/cost margin were, say, 20%, this leads to a 2.5% increase in profits.

This experiment is suggestive that an EDLP policy can enhance brand equity, and it is interesting that such policies were widely adopted by many retailers shortly after our sample period. However, it should be stressed that our partial equilibrium model does not predict the impact of possible competitor reactions to such a change in Heinz pricing policy.

Finally, in Table 11, panel D, we simulate a 50% increase in ad intensity by Heinz. This enhances perceived quality for Heinz both because (i) high ad frequency signals quality, and (ii) households now receive more frequent ad content signals of Heinz's high-quality position. As a result, Heinz sales are predicted to rise by 17%. Of course, for a low-quality brand, effects (i) and (ii) would work against each other instead of being reinforcing.

Table 10 Effects of Temporary 10% Del Monte Price Decrease

	Change of average purchase probabilities			
Week	Heinz	Hunt's	Del Monte	Total
17	−2.21	−5.01	41.11	3.96
18	0.21	1.13	−3.53	−0.12
19	0.11	1.01	−2.21	−0.17
20	0.11	0.74	−1.94	−0.11
21	0.07	0.49	−1.18	−0.10
22	0.03	0.23	−0.59	−0.05
23	0.01	0.02	−0.19	−0.02
24	0	0.01	−0.03	−0.00
25	0	0	0.01	0.00
26	0	0	0	0
Cumulative over 10 weeks	−0.17	−0.19	3.18	0.34
Cumulative, assuming no change after week 17	−0.21	−0.53	4.15	0.39

6. Discussion and Conclusions

We have proposed and estimated a dynamic brand choice model in which consumers learn about brand quality through four distinct channels: (1) price signaling quality, (2) advertising frequency signaling quality, (3) use experience providing direct (but noisy) information about quality, and (4) advertising providing direct (but noisy) information about quality. The model was estimated on Nielsen scanner data for the ketchup category, and it appears to fit the data well.

Our estimates imply that mean offer price plays a very important role in signaling brand quality.[26] This implies that frequent price promotions, which reduce the perceived mean offer price of a brand, can feed back and adversely impact perceived quality. Simulations of the model imply that approximately one quarter of the increase in sales generated by a temporary price cut represents cannibalization of future sales due to the brand-equity-diluting effect of the promotion.

Interestingly, the postpromotion dip generated by the price/quality signaling mechanism in our model looks very similar to that generated by an inventory model (see Erdem et al. 2003). And both models are able to match the observed high level of persistence in

[26] Ranking signaling mechanisms by their order of importance, as measured by the deterioration in model fit when each mechanism is excluded, our results suggest that use experience is the most important signal of quality, followed by price, then ad frequency, and then ad content. However, all four mechanisms appear to be important, because dropping any one of them led to a significant deterioration in model fit.

Table 11 Effects of Permanent Changes in Heinz Pricing Policy on Sales

	Heinz	Hunt's	Del Monte	Total
A. Cut Heinz's price by 10% on a permanent basis				
Change of purchase probability	26.42	−8.37	−7.26	14.85
Change of purchase probability without changing perceived quality	32.23	−12.16	−11.90	27.04
B. Decrease Heinz's price variability by 20% while holding mean price fixed				
Change of purchase probability	−7.87	4.23	5.29	−4.05

Percentage cuts in mean offer price of Heinz (%)	Decrease in price variability (%)	Percentage change of average accepted price (%)
C. Combine cut in mean Heinz offer price with decrease in price variability to leave sales unchanged		
−2	48	+0.47
−4	81	+0.68

	Heinz	Hunt's	Del Monte	Total
D. Increase Heinz's advertising intensity by 50%				
Change of purchase probability	17.24	−6.74	−4.23	9.52

Note. The table reports the percentage changes in each of the indicated quantities for the period after the policy change, compared to a baseline simulation under the present pricing policy.

choice behavior, but using completely different mechanisms. Future work is needed to help distinguish between these two ways of interpreting the data.

Our findings also suggest that reductions in mean offer price combined with reductions in price variability, as in an EDLP policy, can potentially lead to increased profitability. But, because our partial equilibrium model does not incorporate competitor reaction to changes in pricing policy, this result is only suggestive and should be interpreted with caution.

Despite finding that price signaling quality plays an important role, we also found, not surprisingly, that use experience is by far the most accurate signal of quality. In our model consumers are risk averse and are reluctant to try unfamiliar brands. (Put another way, they will pay a premium for familiar brands.) And simulations of our model show that quality uncertainty is resolved slowly (see §4.4 and Figure 2). This is precisely because consumers are reluctant to try unfamiliar brands, and hence they rarely receive the highly accurate experience signals that would reduce uncertainty about them. Hence, even consumers who very are "experienced" in the category tend to be very familiar with just one (or few) brands that they buy frequently—leaving them rather unfamiliar with the alternatives. This is the mechanism through which our learning model generates (i) brand equity for the preferred familiar brand via the risk term and (ii) the observed high level of persistence in brand choice behavior.

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In the printed version of *Marketing Science*, Vol. 27, No. 6, Erdem et al. (2008) was mistakenly identified as a Research Note. It is a regular article and has been corrected here and in the online table of contents.