The Impact of Advertising on Consumer Price Sensitivity in Experience Goods Markets

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February 2004
Revised March 2006

Acknowledgements: This research was supported by NSF grants SBR-9812067 and SBR-9511280.

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Abstract

In this paper we use Nielsen scanner panel data on four categories of consumer goods to examine how TV advertising and other marketing activities affect the demand curve facing a brand. Advertising can affect consumer demand in many different ways. Becker and Murphy (1993) have argued that the "presumptive case" should be that advertising works by raising <u>marginal</u> consumers' willingness to pay for a brand. This has the effect of flattening the demand curve, thus increasing the equilibrium price elasticity of demand and the lowering the equilibrium price. Thus, "advertising is profitable not because it lowers the elasticity of demand for the advertised good, but because it raises the level of demand." Our empirical results support the Becker-Murphy conjecture for 17 of the 18 brands we examine.

There have been many prior studies of how advertising affects two equilibrium quantities: the price elasticity of demand and/or the price level. Our work is differentiated from previous work primarily by our focus on how advertising shifts demand curves <u>as a whole</u>. As Becker and Murphy pointed out, a focus on equilibrium prices or elasticities alone can be quite misleading. Indeed, in many instances, the observation that advertising causes prices to fall and/or demand elasticities to increase, has misled authors into concluding that consumer "price sensitivity" must have increased, meaning the number of consumers' willing to pay any particular price for a brand was reduced – perhaps because advertising makes consumers more aware of substitutes. But, in fact, a decrease in the equilibrium price is perfectly consistent with a scenario where advertising actually raises each individual consumer's willingness to pay for a brand.

Thus, we argue that to understand how advertising actually works one needs to estimate how it shifts the whole distribution of willingness to pay in the population. This means estimating how it shifts the shape of the demand curve as a whole, which in turn means estimating a complete demand system for all brands in a category – as we do here.

We estimate demand systems for toothpaste, toothbrushes, detergent and ketchup. Across these categories, we find one important exception to conjecture that advertising should primarily increase the willingness to pay of marginal consumers. The exception is the case of Heinz ketchup. Heinz advertising has a greater positive effect on the WTP of infra-marginal consumers. This is not surprising, because Heinz advertising focuses on differentiating the brand on the "thickness" dimension. This is a horizontal dimension that may be highly valued by some consumers and not others. The consumers who most value this dimension have the highest WTP for Heinz, and, by focusing on this dimension; Heinz advertising raises the WTP of these infra-marginal consumers further. In such a case, advertising is profitable because it reduces the market share loss that the brand would suffer from any given price increase. In contrast, in the other categories we examine, advertising tends to focus more on vertical attributes.

Key Words: Advertising, Consumer Price Sensitivity, Brand Choice

1. Introduction

The question: "How does non-price advertising affect consumer price sensitivity in experience goods markets?" has received considerable attention in both marketing and economics. In the theoretical literature there are two dominant views of the role of advertising, which we will refer to as the "information" and the "market power" views.

In the information view (see Stigler (1961), Nelson (1970, 1974), Grossman and Shapiro (1984)), non-price advertising provides information about the existence of a brand or about its quality.[1] This leads to increased consumer awareness of attributes of available brands, reduced search costs and expanded consideration sets, which, in turn, results in more elastic demand. In this view, advertising can increase consumer welfare by reducing markups of price over marginal cost and generating better matches between consumer tastes and attributes of chosen brands.

The market power view of advertising is that it creates or augments the perceived degree of differentiation among brands. This will increase brand "loyalty" which, in turn, will reduce demand elasticities, increase markups of price over marginal cost, increase barriers to entry and reduce consumer welfare (see, e.g., Bain, 1956; Comanor and Wilson, 1979). However, it is controversial whether advertising actually creates barriers to entry, because this depends on how effectively new brands can use advertising to induce trial by consumers who are loyal to other brands (see Schmalensee, 1983, 1986; Shapiro, 1982; Shum, 2002).

In this paper, we use Nielsen supermarket scanner data on four product categories to examine how advertising, use experience, price and promotional activity interact in the determination of consumer demand. We examine one to three years of weekly household level purchase information for the toothbrush, toothpaste, detergent and ketchup categories.

A key point is that advertising may affect the price elasticity of demand for a brand in two fundamentally different ways. First, advertising may affect the parameters of the demand functions of individual consumers in such a way as to make individual consumers more or less

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[1] Nelson (1970) argued that most advertising contains no solid content that can be interpreted as signaling quality directly. He therefore argued that firms' advertising expenditures could best be rationalized if the volume of advertising, rather than its content, signals brand quality in experience goods markets. This view has been challenged by Erdem and Keane (1996), Anand and Shachar (2000) and Ackerberg (2001). They argue there is compelling evidence that advertising does contain substantial information content. Abernethey and Franke (1996) have systematically analyzed TV ads, and concluded that more than 84% contain at least one information cue. Thus, it is an empirical question whether advertising signals quality primarily through content or volume.

price sensitive. Second, advertising may affect the composition of the set of consumers who buy a brand. If advertising draws more price sensitive consumers into the set that are willing to pay for a particular brand, this will increase the price elasticity of demand facing the brand.

Becker and Murphy (1993) argue that this latter case, where advertising raises the demand elasticity, should be the "presumptive" case. Starting from an equilibrium with no advertising, a firm would, ideally, like to target its advertising at marginal consumers whose willingness to pay (WTP) is just below the initial equilibrium price. Increasing the WTP of marginal consumers flattens the demand curve in the vicinity of the initial equilibrium, leading to more elastic demand at that point. Despite the fact that the demand curve becomes more elastic, leading to a smaller markup, the firm's profits increase because the demand curve shifts up. As Becker and Murphy point out, "advertising is profitable not because it lowers the elasticity of demand for the advertised good, but because it raises the level of demand [at any given price]."[2]

In this example, how does advertising alter consumer price sensitivity? Most prior literature measures price sensitivity by demand elasticities, and, by that measure, price sensitivity has increased. Yet, individual consumer's WTP for the brand has, in all cases, either stayed constant or increased, and the number of consumers willing to pay any given price has increased. Thus, it is more appropriate to say that advertising has reduced consumer price sensitivity in this case. We adopt a terminology where advertising is said to increase consumer price sensitivity only if it reduces the number of consumers willing to pay any given price for the brand.

The Becker-Murphy example illustrates how the impact of advertising on the elasticity of demand at the brand level can be quite deceptive as a measure of how advertising impacts individual consumer price sensitivity. Unfortunately, much of the previous empirical literature has placed excessive emphasis on demand elasticities. In their review, Comanor and Wilson (1979, p. 458), in discussing empirical work that attempts to "test the effect of advertising on competition" (i.e., to distinguish the "information" vs. "market power" views), state that "the

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[2] Becker and Murphy (1993) also argue that the information approach to advertising is misleading, and that it may in general be more enlightening to view advertising as a complement that raises a consumer's WTP for the advertised good. The key point is that conventional welfare analysis using areas under demand curves remains valid in the latter case but not the former. The problem is that, if advertising conveys information about substitutes, then it may reduce WTP for a good without altering the utility a consumer receives from consuming the good. Our goal here is simply to provide evidence on <u>how</u> advertising affects the shape of the demand curve, not to attempt to distinguish between the information vs. perceived differentiation vs. complementarity stories for <u>why</u> advertising shifts the demand curve.

essential issue with which we are concerned is the impact of advertising on price elasticities of demand." Similar statements are commonly made. But, as Becker and Murphy point out, there is no necessary relationship between how advertising affects demand elasticities in equilibrium and how it affects the number of consumers who are willing to pay any given price for a brand.

The Becker-Murphy example also illustrates that accounting for consumer heterogeneity is critical in evaluating the impact of advertising on demand. The compositional effects of advertising cannot be measured unless we allow for a rich structure of observed and unobserved heterogeneity in consumer tastes, whereby some consumers may be affected differently by advertising than others. A main contribution of our work is that we allow for a much richer structure of heterogeneity than has prior work on the effect of advertising on consumer demand.

Specifically, in the conditional indirect utility function (given purchase of a brand) we allow for heterogeneity in brand intercepts, and in the advertising, prior use experience and price coefficients. Thus, we allow consumers to be differentially affected by price, advertising, and lagged purchases (i.e., they have differential degrees of brand "loyalty"). Furthermore, we allow for interactions between advertising and price, which lets advertising affect both the slope and level of demand curves in a flexible way. By allowing for unobserved heterogeneity in both the coefficient on advertising and the price-advertising interaction term, we accommodate the possibility that advertising may differentially affect the demand curves of different consumers. In order to accommodate unobserved heterogeneity in several utility function parameters, we estimate "mixed" or "heterogeneous" multinomial logit demand models (see, e.g., Elrod, 1988; Erdem, 1998; or Harris and Keane, 1999; for some applications of heterogeneous logit models).

To preview our results, we find that homogenous logit models mask the true relationships between advertising and price sensitivity. There is considerable consumer heterogeneity in the effect of advertising on demand in general and in the effect of advertising on price sensitivity in particular, and it is important to account for this heterogeneity in estimation. At the level of the demand curve facing a brand, we find that increased advertising increases the price elasticity of demand for 17 of the 18 brands we examine (spanning four categories). This finding is consistent with the Becker-Murphy view that this should be the "presumptive" case.

At the individual level, we find advertising generally increases consumers' WTP for a brand – in most cases more for marginal than infra-marginal consumers. This is again consistent with the Becker-Murphy argument that advertising is likely to be targeted at increasing WTP of marginal consumers (as preferences of infra-marginal types do not affect the equilibrium price).

The only exception to this general pattern is Heinz in the ketchup category. The price elasticity of demand facing Heinz decreases with additional advertising. This occurs for two reasons: First, Heinz advertising is aimed, to an unusually degree, at differentiating the brand horizontally. Such horizontally targeted advertising increases WTP primarily for infra-marginal consumers who have a relatively strong preference for Heinz's particular distinguishing (i.e., horizontal) attributes. Second, Heinz has a very large (roughly two-thirds) market share. If Heinz uses advertising to draw in even more consumers, the ketchup market moves even closer to monopoly, and the demand elasticity falls further. Thus, advertising's impact on the demand elasticity facing a brand, while usually positive, is sensitive to the brand's initial market share and to the nature of advertising (i.e., which consumer segment it appeals to).

The paper is organized as follows: Section 2 reviews the literature. Section 3 presents our demand model, and Section 4 our data. Section 5 presents our results on *how* advertising shifts demand curves and the distribution of WTP. Section 6 concludes. There, we stress our results are consistent with several stories of *why* advertising shifts demand.

2. Background and Literature Review

To understand the empirical literature on advertising and consumer price sensitivity, it is useful to first give a simple theoretical background. A firm that produces a differentiated product and has some degree of monopoly power will, in a static framework (where current sales do not influence future demand) choose price P to satisfy the Lerner condition:

$$(1) \qquad P = \frac{\eta}{\eta - 1} mc \qquad \eta \equiv -\frac{P}{Q}\frac{\partial Q}{\partial P}$$

where η>1 is the price elasticity of demand, mc is the marginal cost of production, $Q=f(P, A, z)$ is the demand function, and z is a demand shifter. If we also have a static model of advertising (i.e., current advertising does not influence future demand) then firms will choose advertising expenditure A according to the Dorfman and Steiner (1954) condition:

$$(2) \qquad \frac{A}{PQ} = \frac{\eta_a}{\eta} \qquad \eta_a \equiv \frac{A}{Q}\frac{\partial Q}{\partial A}$$

where η_a<1 is the elasticity of demand with respect to advertising expenditure.

Nerlove and Arrow (1962) showed that if current advertising affects future demand (i.e., the advertising stock depreciates and is augmented by current advertising), but price setting is static (i.e., marginal revenue is set equal to *mc* period-by-period), then (2) can be modified to:

$$\text{(2')} \qquad \frac{A^*}{PQ} = \frac{\eta_A}{(r+\delta)\eta} \qquad\qquad A_t^* = (1-\delta)A_{t-1}^* + A_t$$

where A^* is the advertising stock, δ is the depreciation rate and r is the interest rate.

If advertising does not affect η, then it is straightforward to substitute (1) into (2) and solve for the optimal A. In the more general case where A affects η, numerical joint solution of the two equation system is necessary. Matters are further complicated if current advertising and/or current sales affect future demand.[3] The empirical evidence that current advertising and current sales affect future demand is overwhelming (see, e.g., Ackerberg, 2001; Erdem and Keane, 1996). Thus, equations (1) and (2) are only presented as aids to intuition.

The Dorfman and Steiner condition implies that, *ceteris paribus*, firms will advertise more if they face a lower price elasticity of demand. This might lead us to expect a negative correlation between demand elasticities and advertising if we look across brands or industries or markets. Given (1), we then also expect to see a positive correlation between advertising and markups. And, if demand elasticities are negatively related to concentration, it might lead us to expect a positive correlation between concentration and advertising.

A number of studies have found evidence of these types of patterns. For twenty-two brands marketed in Western Europe, Lambin (1976) found that price elasticity of demand was lower for more advertised brands. Scherer (1980) argues that advertised goods are generally more expensive than similar non-advertised goods. And Strickland and Weiss (1976) found a positive correlation between concentration and advertising. But other studies find different patterns.[4]

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[3] Current sales will affect future demand if there is brand "loyalty." This may be induced by habit formation. Another mechanism through which "loyalty" may arise is if consumers are uncertain about brand attributes and use experience reveals information about brands (see Erdem and Keane, 1996). If we have a simple two period model and current sales affect next period demand, the Lerner condition is modified to:

$$P_1 = \eta(\eta-1)^{-1}[mc - (1+r)^{-1}\partial\pi_2 / \partial Q_1]$$

where π_2 denotes second period profits.

[4] For instance, Wittink (1997) found that price elasticity of demand for a single brand was higher in territories in which advertising intensity was higher. Vanhonacker (1989), looking at two brands in the food category, found that increased ad intensity increased the price elasticity of demand at lower levels of intensity, and reduced it at higher levels. Telser (1964) did not find a positive correlation between concentration and advertising.

Even if such patterns exist, it would not necessarily imply that advertising lowers the price elasticity of demand. The key point that (1) and (2) make clear is that advertising and the price elasticity of demand satisfy a particular relationship in equilibrium. Except in the special case that η is invariant to A, the two variables are jointly determined. Thus, due to the standard problem of reverse causality, it is not possible to measure the effect of advertising on the price elasticity of demand by comparing across markets or brands with different levels of advertising.

Furthermore, Becker and Murphy (1993) argue that (2) may be quite deceptive, because η_a is likely to be greater in markets where η is greater. The argument runs as follows: We expect demand curves facing individual firms to be more elastic than the market demand curve. Hence, in more competitive markets (e.g., oligopoly as opposed to monopoly) the price elasticity facing any one firm will be greater. By the same logic, we expect the advertising elasticity of demand to be greater at the firm than at the industry level. And, we expect η_a to be greater in more competitive markets. Such systematic positive covariation between η_a and η breaks any tendency for advertising levels to be negatively related to the price elasticity of demand.

One way to get around the endogeneity problem is to find a "natural experiment" whereby advertising is restricted in some regions and not others, and compare price levels and/or the price elasticity of demand across regions. In a well-known paper, Benham (1972) found that eyeglass prices in 1963 were higher in states that banned advertising. Maurizi (1972), Steiner (1973) and Cady (1976) obtain similar findings for gasoline, toys and drugs. These studies suggest that allowing advertising increases the price elasticity of demand, thus lowering price in equilibrium.

A key limitation of this experimental work is that it does not reveal why the demand elasticity increased.[5] Did advertising increase consumer price sensitivity (e.g., by raising awareness of substitutes), thus reducing each consumer's WTP for a brand, and flattening demand curves at the individual level? Or did advertising raise the demand elasticity by increasing WTP of marginal consumers, as in the Becker-Murphy story? To distinguish these stories one must estimate the effect of advertising on demand at the individual consumer level. This means estimating a demand system on micro data, as we do here.

[5] The fall in price does reveal something about welfare. Becker and Murphy (1993) show, in a model with fixed preferences where advertising is a compliment with the good advertised, that if advertising lowers the equilibrium price then it increases welfare. Such a welfare comparison is not possible in a model where advertising shifts tastes.

As a simple illustration of the problem, consider the linear (brand level) demand function $P=a-bQ$. In equilibrium, the demand elasticity facing a monopolist is $\eta=(a+mc)/(a-mc)$. Suppose advertising has no effect on WTP for consumers with the highest initial valuations, and has progressively larger effects on those with lower initial valuations (consistent with the Murphy-Becker conjecture on how advertising is likely to be targeted). Then, the impact of advertising is to reduce b while leaving a unchanged. Hence, η is <u>unchanged</u> in equilibrium (i.e., the demand elasticity increases at the initial quantity, and quantity increases to restore equilibrium), despite the fact that the brand level demand function has become more elastic, and many consumer's WTP has increased. Examination of η alone reveals nothing about how advertising affected individual behavior, or how it affected the shape of the brand level demand curve.[6]

Prior empirical work in marketing on the impact of advertising on consumer price sensitivity has produced very conflicting results (see Kaul and Wittink (1995) for a review). In this work, price sensitivity has been measured by either the interaction between price and advertising in a sales response function (e.g., does the price coefficient change with advertising?), the derivative of the brand choice probability with respect to price, or the price elasticity of demand. And, these quantities have been calculated at various levels of aggregation (i.e., the market, brand or individual household levels). As we have discussed, all these measures are quite different conceptually, so there is no reason to expect advertising to affect each in the same way. None of these measures gives a complete picture of how advertising works.

Our work is in part an attempt to resolve the conflicting empirical results on advertising effects obtained in the marketing literature, and to clarify the confusion about alternative measures of the impact of advertising on consumer price sensitivities. As we have argued, to properly understand how advertising affects consumer behavior, it is necessary to estimate a demand system at the micro level. This enables one to fully characterize how advertising affects demand curves at both the individual and brand levels.

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[6] Alternatively, if advertising conveys information about available brands and their prices, making consumers more selective, it might reduce a (the maximum price that anyone is willing to pay for a brand) and also b (since the rate at which consumers are attracted to a brand as its price falls increases with more complete information). In this case η is <u>increased</u>. But a reduction in a holding b constant would have the same effect on η. And this is also a plausible scenario for what might happen if advertising is permitted in a market where it had been banned. A reduction in a holding b fixed would, of course, reduce profits. If advertising has this effect, it would explain why various industry and professional groups have supported advertising bans (see Bond et al., 1980; or Schroeter, Smith and Cox, 1987).

We are certainly not the first to use household level scanner data to estimate demand systems for consumer goods that allow for advertising effects. However, we argue that prior studies of this type have generally suffered from a number of conceptual and/or econometric problems that we attempt to remedy. First, and most importantly, these studies generally summarize advertising effects by one of the various measures we have described above, rather than examining how demand curves are shifted. Second, these studies often suffer from biases that may arise from failure to adequately accommodate consumer heterogeneity.

To our knowledge, the pioneering work in this area was Kanetkar, Weinberg, and Weiss (1992). They were the first to obtain supermarket scanner data linked to household level TV ad exposure data, and use this to estimate brand choice models in which advertising was allowed to influence consumer choice behavior in a flexible way (including both main effects and advertising/price interactions in the conditional indirect utility function). Estimating multinomial logit (MNL) models for the choice among brands of dog food and aluminum foil, they find that the main effect of advertising (measured as ads seen since the last purchase occasion) is positive, while the interaction between advertising and price is negative. They interpret the negative interaction term as indicating that "an increase in television advertising exposures results in higher … price sensitivity." The problem with this conclusion is that the positive main effect implies that at least some consumers' WTP is increased by advertising. But, from the results reported in the paper, one cannot determine how advertising shifts demand curves overall.

Kanetkar at al. also report how advertising alters demand elasticities for individual households, holding price fixed. They calculate that a 10% increase in advertising would increase the demand elasticity for the large majority of households. Of course, this information on how the slope of household demand curves shift at a point is not sufficient to determine how the whole demand curve shifts at the brand level.

Consider a MNL model where the conditional indirect utility given purchase of brand *j* is:

$$V_{ijt} = \alpha_j + \beta P_{ijt} + \gamma A_{ijt} + \lambda P_{ijt} A_{ijt} + \varepsilon_{ijt} \qquad j=1,\dots,J \tag{3}$$

where P_{ijt} denotes the price for brand *j* faced by household *i* at time *t* and A_{ijt} denotes the household's ad exposures for brand *j* since the last purchase occasion. Then, letting $V_{i0t} = 0$ denote the (normalized) utility from the no-purchase option, the expected quantity of brand *j* purchased by household *i* in week *t* is:

$$Q_{ijt} = \frac{\exp(\overline{V}_{ijt})}{1 + \sum_{k=1}^{J} \exp(\overline{V}_{ikt})}$$

The elasticity of the household's expected quantity with respect to price is:

$$\eta_{ijt} \equiv -\frac{P_{ijt}}{Q_{ijt}} \frac{\partial Q_{ijt}}{\partial P_{ijt}} = (\beta + \lambda A_{ijt}) P_{ijt} (1 - Q_{ijt}) \tag{4}$$

This expression makes clear that knowledge of the parameter λ is not sufficient to determine how a household's elasticity of demand varies with A and P. If λ<0 (as Kanetkar et al. find) then advertising has the main effect of increasing the demand elasticity. However, if $\gamma + \lambda P_{ijt} > 0$, then as A_{ijt} increases Q_{ijt} will increase. This reduces the term (1-Q_{ijt}), which tends to drive down the elasticity. Kanetkar et al. show that, given their parameter estimates, for large enough values of A this effect dominates, and household level elasticites tend to fall with further increases in A.

In summary, there are three main limitations of the Kanetkar, Weinberg, and Weiss (1992) analysis. First, while they do estimate a demand system at the household level they do not use their estimated model to show how advertising shifts demand curves at either the household or brand levels. Second, they only examine the short-term (i.e., ads seen since the last purchase) impact of advertising. Third, they do not accommodate consumer heterogeneity.

The failure to accommodate consumer heterogeneity can lead to two types of biases in estimating the effects of advertising on brand choice at the household level:

First, there is a *compositional bias* problem. Suppose consumers are heterogeneous in their tastes. Increased advertising intensity, to the extent that it alters market share of a brand, will change the composition of consumers who buy the brand in terms of their distribution of tastes. If we estimate a brand choice model that does not allow for unobserved heterogeneity in utility function parameters, it will tend to attribute these shifts in the distribution of tastes amongst the consumers who buy a brand to advertising "effects" on utility function parameters.

Second, there is an *endogeneity* problem that arises as follows: Suppose some brands are more differentiated. They therefore face less elastic demand and set higher prices. Suppose, further, that these more expensive brands also advertise more. Then, if there is heterogeneity in price sensitivity, the less price sensitive consumers will tend to buy the high priced, highly advertised brands. This means that demand for these brands will not fluctuate much over time as their price fluctuates. Suppose we then estimate a choice model with homogenous parameters and an interaction term between price and ad exposures, as in equation (3). In order to capture the fact that demand for the high priced highly advertised brands is less price sensitive, such a model will shift the coefficient λ on the advertising price interaction in a positive direction. This might lead one to falsely infer that advertising reduces price sensitivity.[7]

A paper that did allow for unobserved heterogeneity in the conditional indirect utility function parameters was Mela, Gupta and Lehmann (1997). They study the impact of quarterly advertising expenditures on derivatives of brand choice probabilities with respect to price, and find that advertising reduces these derivatives (in absolute value). The main limitation of this study is, again, that it does not examine how advertising affects demand curves as a whole. Also, they only allow for two consumer types, which may not be an adequate control for heterogeneity.

There have been studies that used controlled field experiments to examine advertising effects. Prasad and Ring (1976) examined an experiment in which two groups of consumers received different TV ad exposure levels for one brand of a food product. Regressing market share on price, they found a larger (in absolute value) price coefficient in the high advertising sample.[8] Of course, as we have already discussed, this might occur because advertising raised the WTP of marginal consumers, thus flattening the brand level demand curve, and increasing the demand elasticity facing the brand. Or, alternatively, advertising may have made individual consumers more price sensitive and lowered their WTP. Again, we have to estimate a household level demand system to understand how advertising works.

Krishnamurthi and Raj (1985) and Staelin and Winer (1976) look at "split cable" TV experiments. In these designs, half the households received higher levels of ad exposure for one brand of a frequently purchased consumer good during the second half of the sample period. They find that price sensitivity for that brand dropped among the group that received greater ad exposure. This is considered the strongest evidence that advertising reduces price sensitivity.

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[7] A similar problem may arise if the price coefficient is restricted to be equal across brands. Then a price/advertising interaction term may appear significant, simply because it captures the association that brands with less price sensitive demand advertise more. The bias here is again towards finding that advertising reduces price sensitivity.

[8] Similarly, Eskin and Baron (1977) look at four field experiments in which new products were introduced in a set of test markets accompanied by different levels of (non-price) advertising. Price also varied across stores within each test market. They find that higher ad intensity in a market is usually associated with greater price sensitivity.

But the implications of these split cable TV experiments are, again, ambiguous. For example, more intense advertising for a particular brand could have moved consumers with high WTP (in the category) into the set that buy that brand. This makes the brand's demand curve steeper to the left of the original equilibrium quantity. Advertising is then profitable because it enables the firm to raise price while losing less market share than it would have otherwise. Alternatively, advertising could have made individual consumers less price sensitive.

Krishnamurthi and Raj recognized this compositional problem, and tried to deal with it by classifying consumers as high or low price sensitive (using data from the pre-experiment period). They then examined advertising's effect on price sensitivity within each type. Yet, if there are more than two price sensitivity types, or if consumers are heterogeneous in other dimensions, as seems likely, this will not completely solve the problem. Nor will it solve the problem if advertising alters consumer price sensitivity, and this effect is heterogeneous across consumers.

Finally, some other related work includes Ackerberg (2001), who models the effect of advertising on the demand for a newly introduced product, and Shum (2002), who estimates the differential effect of advertising on demand for established brands by loyal and non-loyal consumers. Shum results imply that advertising can be rather effective at inducing consumers who are loyal to one brand to try another brand (at least relative to the alternative strategy of price promotion). Our work differs in that we focus on the long-term impact of advertising on price sensitivity for established brands. In contrast, Shum examines short run impacts, and Ackerberg does not study the effect of advertising on demand for established brands.

3. The Household Level Brand Choice Model

3.1. Conditional Indirect Utility Function Specification

Consider a model in which on any purchase occasion $t=1,2,\ldots,T_i$, consumer i chooses a single brand from a set of $j=1,2,\ldots,J$ distinct brands in a product category, where T_i is the number of purchase occasions we observe for consumer i. Let the indirect utility function for consumer i conditional on choice of brand j on purchase occasion t be given by:

$$U_{ijt} = \alpha_{ij} + \beta_{ij} P_{ijt} + \gamma_{ij} A_{ijt} + \lambda_i P_{ijt} A_{ijt} + \psi_i E_{ijt} + \phi_i D_{ijt} + \tau_i F_{ijt} + \xi_i C_{ijt} + \varepsilon_{ijt} \tag{5}$$

Here, P_{ijt} is the price faced by household i for brand j on purchase occasion t. The variable A_{ijt} is a measure of household i's cumulative exposure to TV advertisements for brand j up until time t.

We construct A_{ijt} as a weighted average of lagged TV ad exposures. Specifically, letting a_{ijt} denote the number of TV ad exposures of household i for brand j between t-1 and t, define:

(6) $$A_{ijt} = \mu_A A_{ij,t-1} + (1-\mu_A) a_{ij,t-1} \qquad 0< \mu_A <1$$

where μ_A is a decay parameter which we estimate jointly with our logit choice model.

The variable E_{ijt} in (5) is a measure of prior use experience. This is referred to in the marketing literature as the "loyalty" variable, following the usage in the classic original scanner data study by Guadagni and Little (1983). E_{ijt} is constructed as an exponentially smoothed weighted average of past usage experience. Defining d_{ijt} as an indicator equal to 1 if household i bought brand j on purchase occasion t (and zero otherwise) we have:

(7) $$E_{ijt} = \mu_E E_{ij,t-1} + (1-\mu_E) d_{ij,t-1} \qquad 0< \mu_E <1$$

Here, μ_E is a decay parameter that we estimate jointly with our logit choice model.

We intialize A_{ijt} and E_{ijt} at t=1 (the first week we observe a household) to their steady state values given the average ad intensity and purchase frequency of the brand over our sample period. Sensitivity tests in Keane (1997) suggest that results in models similar to ours are not very sensitive to how variables like A_{ijt} and E_{ijt} are initialized. This is not surprising given the rather long observational periods in scanner panel data sets.

Besides advertising and price, we control for several other types of promotional activity. D_{ijt} and F_{ijt} are dummy variables indicating whether brand j was on display or feature in the store visited by household i on purchase occasion t. The variable C_{ijt} is a measure of the expected value of coupons available for purchase of brand j in period t, constructed as described in Keane (1997). It has been common in scanner data for research to use price net of redeemed coupons as the price variable. However, this creates a severe endogeneity problem, because coupons that were potentially available for the non-purchased brands are unobserved.[9] In contrast, C_{ijt} is an exogenous measure of availability of coupons in the marketplace at time t for brand j. Our price variable P_{ijt} is the price marked in the store (prior to any coupon redemption).

[9] Including price net of redeemed coupon value on the right hand side in a logit brand choice model is equivalent to using (P_{ijt} + $d_{ijt}C_{ijt}$) as the price variable, where P_{ijt} is the posted price, d_{ijt} is the dummy for whether brand j was purchased, and C_{ijt} denotes the coupon value that household i had available for purchase of brand j. Thus, one is including a function of the brand choice dummy on the right hand side of an equation to predict brand choice. Erdem, Keane and Sun (1999) provide an extensive analysis of how this procedure can lead to severe upward bias in estimates of the price elasticity of demand.

In equation (5), we allow the intercepts α_{ij} to be household and brand specific. We can think of the brand intercepts as having a mean and a household specific component, so that α_{ij} = $\overline{\alpha}_j + v_{ij}$ where v_{ij} is mean zero in the population. Mean differences capture vertical quality differentiation among brands. That is, if $\overline{\alpha}_j > \overline{\alpha}_k$, then the "typical" consumer views brand j as higher quality than brand k, and is therefore willing to pay more for j. However, since the brand intercepts have a household specific component, consumers may have different opinions about the relative qualities of different brands. This is equivalent to "horizontal" differentiation, where brands differ along several unobserved attribute dimensions, and consumers have heterogeneous preference weights on these attribute dimensions (see Keane (1997) for more discussion).

The slope coefficients β, γ, λ, ψ, ϕ, τ, and ξ in (5) are all allowed to be heterogeneous across households i. And we allow the price and advertising coefficients to be brand specific. This gives the logit model added flexibility in terms of how elasticities of demand with respect to advertising may differ across brands. Also, it is widely recognized in the marketing literature that there are persistent differences across brands in the effectiveness of their advertising (conditional on expenditures). The brand specific advertising coefficients accommodate such differences.

This specification allows for great flexibility in how advertising may affect the demand curve facing a brand. To establish intuition, it is useful to focus on a single brand j, and let $\overline{U}$ denote the maximum utility over all alternatives to buying this brand. Suppress the brand j subscript, and assume that all the parameters in (5) except α_i and ε_i are homogenous. Also, ignore the terms in (5) other than price and advertising. Then, household i will prefer the brand under consideration to all alternatives iff:

$$\alpha_i + \beta P + \gamma A + \lambda PA + \varepsilon_i > \overline{U}$$

This implies that household i's willingness to pay (WTP) or reservation price is:

$$P = \frac{\alpha_i + \gamma A + \varepsilon_i - \overline{U}}{-(\beta + \lambda A)} \quad , \qquad -(\beta + \lambda A) > 0$$

From this expression, we can see that if $\gamma>0$ and $\lambda=0$ then advertising by brand j raises all households' WTP for brand j. In fact, an increase in A by one unit will raise WTP by $\gamma/(-\beta)$ units. Note that a parallel upward shift in the demand curve by $\gamma/(-\beta)$ will reduce the elasticity of demand at any given quantity.

On the other hand, if $\lambda \neq 0$, the effect of A on WTP depends on the household specific taste parameters α_i and ε_i. Note that:

$$\frac{dP}{dA} = \frac{\gamma}{-(\beta + \lambda A)} + \lambda \frac{\alpha_i + \gamma A + \varepsilon_i - \overline{U}}{(\beta + \lambda A)^2}$$

and, starting from an initial position of no advertising, we would have that:

$$\left.\frac{dP}{dA}\right|_{A=0} = \frac{\gamma}{(-\beta)} + \lambda \frac{\alpha_i + \varepsilon_i - \overline{U}}{\beta^2} \tag{8}$$

Thus, if $\lambda<0$, advertising by brand j lowers WTP of infra-marginal consumers with sufficiently large positive values of $\alpha_i+\varepsilon_i-\overline{U}$, while increasing WTP of marginal consumers with values of $\alpha_i+\varepsilon_i-\overline{U}$ that are near zero or negative. Becker and Murphy (1994) call this the "presumptive" case. In contrast, if $\lambda>0$, advertising increases WTP more for the infra-marginal consumers with positive values of $\alpha_i+\varepsilon_i-\overline{U}$. Thus, if $\lambda<0$ advertising flattens the demand curve (tending to increase η), while if $\lambda>0$ advertising makes the demand curve steeper (tending to lower η).[10]

More complex patterns are possible if β, γ, and λ are household specific, and if we allow these parameters to be correlated. For instance, if corr(β_i, γ_i)<0, then the most price sensitive households are the most influenced by ads. Such a negative correlation tends to dampen the population heterogeneity in $\gamma/(-\beta)$. But, if corr(β_i, γ_i)>0, then the least price sensitive households are the most influenced by ads. In that case, advertising is most effective at increasing WTP of households that already have high WTP, which tends to make the demand curve steeper.

3.2. Heterogeneity Specification

In this section we describe our distributional assumptions on the model parameters that are heterogeneous across households. First, we define the following vectors of model parameters:

$$\boldsymbol{\alpha}_i \equiv (\alpha_{i1}, \ldots, \alpha_{iJ})' \qquad\qquad \boldsymbol{\pi}_i \equiv (\boldsymbol{\beta}_i, \boldsymbol{\gamma}_i, \psi_i, \phi_i, \tau_i, \xi_i)'$$

where $\boldsymbol{\beta}_i$ and $\boldsymbol{\gamma}_i$ denote the vectors of the price and advertising coefficients:

$$\boldsymbol{\beta}_i \equiv (\beta_{i1}, \ldots, \beta_{iJ}) \qquad\qquad \boldsymbol{\gamma}_i \equiv (\gamma_{i1}, \ldots, \gamma_{iJ})$$

[10] Note that the set of households who prefer brand j is given by those with taste parameters in the set:

$$S = \{(\alpha_i, \varepsilon_i) \mid \alpha_i + \gamma A + \varepsilon_i > \overline{U} - (\beta + \lambda A)P\}$$

If $\lambda>0$, then $-(\beta+\lambda A)>0$ is decreasing in A. Let $\mu(S)$ denote the measure of set S. The rate at which $Q=\mu(S)$ decreases as P increases is decreasing in A. So dQ/dP is decreased if A is increased, tending to reduce η.

Thus, the column vector $\boldsymbol{\alpha}_i$ contains the brand intercepts, while the column vector $\boldsymbol{\pi}_i$ contains all slope coefficients in equation (5). Finally, λ_i is the advertising and price interaction coefficient.

We assume that $\boldsymbol{\alpha}_i$, $\boldsymbol{\pi}_i$ and λ_i are jointly normally distributed. To prevent a proliferation of covariance matrix parameters, we allow for correlations within each subset of parameters, but not across these subsets of parameters. Thus, we have the following distribution:

(9) $$\begin{bmatrix} \boldsymbol{\alpha}_\mathbf{i} \\ \boldsymbol{\pi}_\mathbf{i} \\ \lambda_{\boldsymbol{i}} \end{bmatrix} \sim N\left\{ \begin{bmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\pi} \\ \lambda \end{bmatrix}, \begin{bmatrix} \boldsymbol{\Sigma}_\alpha & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}_\pi & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & {\sigma_\lambda}^2 \end{bmatrix} \right\}.$$

We further constrain the variance-covariance matrix by imposing that the brand specific price coefficients $(\beta_{\boldsymbol{i}1},\ldots,\beta_{\boldsymbol{iJ}})$ have a common variance (across households), as well as a common set of covariances with the other elements of the $\boldsymbol{\pi}_i$ vector. We impose similar restrictions on the variances and covariances of the brand specific advertising coefficients $(\gamma_{\boldsymbol{i}1},\ldots,\gamma_{\boldsymbol{iJ}})$. We tried relaxing some of our covariance matrix restrictions in the estimation, but this did not alter the results in any significant way, so we chose the current specification for the sake of parsimony.

Finally, one brand intercept must be normalized to achieve identification, since only utility differences determine choices. Without loss of generality we normalize α_J =0, and also zero out the *J*th row and column of the Σ_α matrix.

3.3. Brand Choice Probabilities

In this section, we present the brand choice probabilities and the likelihood function for our model. First, let θ denote the complete vector of model parameters (from equation (9)):

$$\theta \equiv (\boldsymbol{\alpha}, \boldsymbol{\pi}, \lambda, \text{vec}(\Sigma_\alpha), \text{vec}(\Sigma_\pi), \sigma_\lambda, \mu_E, \mu_A).$$

Here, vec(·) is the transformation that stacks the upper diagonal entries of its argument matrix into a vector. Next, it is useful to define $\theta_i \equiv (\alpha_i', \pi_i', \lambda_i)$ as the column vector of household specific parameters for household *i*, and to define $\varpi \equiv (\alpha', \pi', \lambda)$ as the population mean vector of the household parameters. Then, we can rewrite (9) more compactly as θ_i~N(ϖ,Σ). If we define Λ as the Choleski decomposition matrix, such that Σ=ΛΛ′, we can always write that $\theta_i = \varpi + \Lambda\omega_i$, where ω_i is a vector of iid N(0,1) random variables. This enables us to rewrite equation (5) as:

(5') $$U_{ijt} = \overline{U}_{ijt}(X_{ijt}, \theta, \omega_i) + \varepsilon_{ijt}$$

where X_{ijt} includes price, ad exposure, use experience, feature, display and coupon availability.

Thus, we can express the "systematic" part of the conditional indirect utility function for household i, denoted $\overline{U}_{ijt}(X_{ijt},\theta,\omega_i)$, as a function of model parameters θ that are common to all households, along with a vector of standard normal random variables ω_i that, together with θ, determines the household specific utility function parameters (via the equation $\theta_i = \varpi + \Lambda\omega_i$).

The stochastic terms ε_{ijt} capture variation in tastes that is "idiosyncratic" to household i, brand j and purchase occasion t. For example, a household that regularly buys Tide (e.g., it has a high α_i for Tide) might buy Wisk one week because the person who usually does the shopping was sick, and some other household member bought the wrong brand by mistake. The model is not meant to explain such anomalies, so they are relegated to the stochastic terms.

We will assume that the stochastic terms ε_{ijt} have independent standard type I extreme value distributions (see Johnson and Kotz (1970), p. 272) in order to obtain the multinomial logit form for the choice probabilities (see McFadden (1974)) conditional on ω_i:

(10) $$\text{Prob}(\text{d}_{ijt} = 1 \mid X_{it},\theta,\omega_i) = \frac{\exp\left\{\overline{U}_{ijt}(X_{ijt},\theta,\omega_i)\right\}}{\sum_{k=1}^{J}\exp\left\{\overline{U}_{ikt}(X_{ikt},\theta,\omega_i)\right\}}$$

where d_{ijt} is an indicator for whether household i buys brand j on purchase occasion t, and $X_{it} \equiv (X_{i1t},\ldots,X_{iJt})$. The probability that household i makes a particular sequence of choices d_i over $t=1,\ldots,T_i$ is then:

$$Prob(d_i \mid X_i,\theta,\omega_i) = \prod_{t=1}^{T_i}\prod_{j=1}^{J} Prob(d_{ijt} = 1 \mid X_{it},\theta,\omega_i)^{d_{ijt}}$$

Of course, we do not actually observe the household specific vector of stochastic terms ω_i. To obtain the unconditional probability of household i's observed choice history, we must integrate over the population distribution of ω_i. We then obtain:

(11) $$Prob(d_i \mid X_i,\theta) = \int_{\omega_i} Prob(d_i \mid X_i,\theta,\omega_i)\; f(\omega_i)d\omega_i\,.$$

Where $f(\cdot)$ denotes the density of the independent standard normal vector ω_i.

Given (11), the log-likelihood function to be maximized is:

$$Log\ L(\theta) = \sum_{i=1}^{N} ln\, Prob(d_i \mid X_i,\theta)$$

where N is the number of households.

This model is called the "heterogeneous" or "mixed" logit since the choice probabilities for a particular household, conditional on its vector of unobserved household specific utility function parameters, have the multinomial logit form given by (10). But, to form unconditional choice probabilities, we must take a mixture of the conditional probabilities, as in (11). The heterogeneous logit implies the IIA property for individual households, but it allows a flexible pattern of substitution at the aggregate level. See Train (2003) for further discussion.

Construction of the likelihood function requires evaluation of the integrals appearing in (11). Since ω_i is high dimensional, it is not feasible to do this analytically. Instead, we adopt the simulated maximum likelihood (SML) approach, using Monte Carlo methods to simulate the high dimensional integrals (see, e.g., Pakes 1987, McFadden 1989, Keane 1993). Specifically, we replace the analytic integration in (11) with the following integration by simulation:

$$(12) \qquad \hat{P}rob(d_i \mid X_i, \theta) = \sum_{r=1}^{R} Prob(d_i \mid X_i, \theta, \omega^r)$$

where ω^r denotes a draw from $f(\cdot)$. We set the simulation size R=100.

It is important that the draws $\{\omega^r\}_{r=1}^{R}$ be held fixed when searching over θ to find the maximum of the likelihood function. Otherwise, the simulated log-likelihood is not a smooth function of the model parameters, and it will change across iterations simply because the draws change. This is why we wrote the household specific parameters as $\theta_i = \varpi + \Lambda\omega_i$. Then, θ_i will vary smoothly as we vary the parameter vector θ, because ϖ and Λ are smooth functions of θ.

3.4. Identification

To estimate our model, we need exogenous variation in prices and advertising intensity. Crucially, we assume the price P_{ijt} of brand j faced by household i at time t varies exogenously over time. That is, we assume the over-time fluctuations in supermarket prices faced by an individual consumer are exogenous to that consumer. This assumption is quite standard in the literature on estimating discrete choice demand models using scanner data. Yet, at the same time, there is a substantial IO literature on how to deal with endogenous prices when estimating discrete choice demand models on other types of data (see Berry; 1994). Since many readers may be more familiar with the latter literature than the former, it may be helpful to explain why the exogenous price assumption is entirely plausible in the scanner data context, even while it has been implausible in most applications of discrete choice demand models in IO.

Supermarket prices for frequently purchased consumer goods typically exhibit patterns where prices may stay flat for weeks at a time, while also exhibiting occasional sharp, short-lived price cuts, or "deals." Price endogeneity would arise if such deals were responses by retailers, wholesalers, or manufacturers to taste shocks. We find such arguments extremely implausible. Why would tastes for a good like ketchup, toothpaste or detergent suddenly change every several weeks or so and then return to normal? Even if they did, how could retailers detect it quickly enough to influence weekly price setting? Recently, Pesendorfer (2002) and Hong, McAfee and Nayyar (2002) have argued that such price patterns can best be explained by a type of inter-temporal price discrimination, in which retailers play mixed strategies. Under this scenario, price fluctuations are exogenous to the consumer since they are unrelated to taste shocks.[11]

In typical IO applications of discrete choice models (see again Berry; 1994), the data lack the extensive over-time price variation present in supermarket scanner data. The sample period is often short, so identification relies heavily on cross-sectional price variation. Then price may be endogenous because it is correlated with unobserved attributes of a brand (e.g., a high quality brand will tend to be relatively expensive). Failure to measure quality then leads to downward bias in price elasticities. But in scanner data, because we do have extensive over-time variation in prices, we can wash out the cross-sectional price variation entirely, and also control for unobserved brand attributes, simply by including brand specific intercepts, as in equation (5).

We would make similar arguments regarding the other forcing variables in equation (5). We observe considerable over-time variation in advertising intensity and in the other marketing mix activities (feature, display and couponing activity). We again expect that the over-time variation in these activities is largely unrelated to variation in consumer tastes. Of course, a brand's overall level of advertising is likely to be related to the brand's quality (see Horstmann and MacDonald (2003) for a recent empirical analysis of various models of the relation between advertising and quality). But again, since we rely on over-time variation in advertising to identify its effects, we can use brand intercepts to control for quality. In our view, the great strength of scanner panel data for demand estimation is the extensive and plausibly exogenous over-time variation in prices and other marketing activities that these high-frequency data provide.

[11] Of course, predictable changes in tastes over time may arise due to seasonal factors and holidays. We can deal with this simply by including seasonal/holiday dummies in (5). Our results were not affected by adding such controls.

4. Data

4.1 The Four Product Categories

We estimate our models on scanner panel data provided by A.C. Nielsen for the toothpaste, toothbrush, ketchup and detergent categories. The data sets record household purchases in these categories on a daily basis over an extended period of time.

The toothpaste and toothbrush panels cover 157 weeks from late 1991 to late 1994. They include households in Chicago and Atlanta. The Chicago panel is used for model calibration, while the Atlanta panel is used to assess out-of-sample fit. In these data we observe weekly TV advertising intensity, as measured by Gross Rating Points (GRP), for each brand in each market.

The ketchup and detergent panels cover 130 weeks from mid-1986 to the end of 1988. These data sets include households from test markets in Sioux Falls, South Dakota and Springfield, Missouri. The Sioux Falls data is used for estimation, and the Springfield data is used to assess out-of-sample fit. In each city, 60% of households had a telemeter connected to their television for the last 51 weeks of the sample period, so commercial viewing data at the household level is available for that period. Only these 51 weeks are used in the analysis.

As is typical in brand choice modeling, we only consider the several largest brands in each category. Consideration of the many small brands available would greatly increase the computational burden involved in estimating the choice model, without conveying much additional information. Table 1 reports the market shares for the brands used in the analysis. The analysis covers four brands in the toothbrush and toothpaste categories, with combined market shares of 71% and 69% of all purchases, respectively. In the ketchup category we model choice among three brands with a combined market share of 89%, and in the detergent category we examine seven brands with a combined market share of 82%. Purchase occasions where a household bought a brand other those listed in Table 1 were ignored in constructing the data set.

Nielsen made the toothbrush and toothpaste panels available to us specifically for this research. Therefore, in Table 1, we cannot report brand names in these categories for confidentiality reasons. The ketchup and detergent panels are publicly available and have been widely used in previous research, so we do report brand names for these categories in Table 1.

We wished to restrict the analysis to households who were relatively frequent buyers in each category. Therefore, in each category, we restricted the sample to households who bought at least 3 times over the estimation period. Given these screens, the sample sizes used in estimation are as follows: The toothpaste panel contains 345 households who made 2880 purchases of toothpaste (an average of 8.35 purchases per household). The toothbrush panel contains 167 households who made 621 purchases, the ketchup panel contains 135 households who made 1045 purchases, and the detergent panel contains 581 households who made 3419 purchases. Each purchase occasion provides one observation for our choice model. For example, our toothpaste brand choice model is fit to data on 2880 purchase occasions. Thus, we are modeling brand choice conditional on purchase, and not attempting to model purchase timing.

Table 1 also provides summary statistics on average price for each brand and the frequency with which each brand is on display or feature. The Nielsen data come with "price files" that contain measures of price, as well as display, feature and coupon activity, for each size of each brand in every (large) store in the four markets (Sioux Falls, Springfield, Chicago, Atlanta) during each week of the sample period. We use these files to construct our price, feature display and coupon variables. Of course, data is not available for small "mom and pop" stores.

The price variable we use in our model is the unit price for the most standard size container in each category. For example, the price we use for Heinz ketchup in a particular store in a particular week is the price for the 32oz size, since that is by far the most commonly purchased size. According to Table 1, the mean 32oz Heinz price is $1.36, where this mean is taken over all 1045 purchase occasions in the ketchup data set. This is a mean "offer" price, which, of course, tends to exceed the mean "accepted" price.

Many scanner data studies have used price net of redeemed coupons as the price variable. But, as we discussed in section 3.1, this creates a serious endogeneity problem, since coupon redemptions are only observed if a brand is bought. Coupon availability for non-chosen brands is unobserved. Thus, we use posted store prices as our price variable. Then, we construct a measure of coupon availability for each brand in each week, and use this as an additional predictor of brand choice. To construct this measure, we first form the average coupon redemption amount for each brand in each week, and then smooth this over time (see Keane (1997) for details). The last column of Table 1 reports the mean of this measure of "coupon availability" for each brand. For example, in a typical week there is a 10.5 cent coupon available for Wisk.

4.2. The Alternative Advertising Measures

The weekly GRP for a brand is defined as a weighted sum of the number of TV ads aired for that brand in that week. The weights are the Nielsen rating points for the TV shows on which the ads were aired. These rating points are the percentage of television-equipped homes with sets tuned to a particular program. Our GRP statistics are specific to Chicago or Atlanta.

The TV ad exposure data, on the other hand, are collected at the household level. A telemeter measures total time that a household had a TV tuned to a particular channel during the airing of a commercial on that channel. We assumed a household was exposed to a brand's ad if it had a TV tuned to the channel on which its ad aired for the full duration of the commercial. Thus, if the household changes stations during the commercial, it is not counted as exposed.

Table 1 column 4 reports summary measures of the intensity of advertising by each brand in the analysis. In the toothbrush and toothpaste categories we report the average weekly GRP for each brand (including zeros for weeks in which the brands were not advertised). For example, in an average week, Brand 2 of toothpaste has ads that appear on shows with a total of 27 rating points. Note that toothpaste Brands 3 and 4 did not advertise at all. In the ketchup and detergent categories we report the percentage of households exposed to at least one ad for a brand in a typical week. For instance, Hunt's reaches 24% of households in an average week.

An interesting feature of the data is that advertising is not very closely related to market share. For instance, in toothpaste, Brand 2 advertises about twice as much as Brand 1, yet its market share is about 50% lower. In detergent, Cheer reaches only 10% of households in a given week (on average), compared to 69% for Wisk. Yet these brands have similar market shares. Nor is there a clear positive correlation with price. For example, in toothpaste, the highest priced brand does not advertise at all, and in detergent the brand with the highest level of advertising (Wisk) is moderately priced. The substantial independent variation of price and ad intensity is encouraging from the perspective of identification of price and advertising effects.

Regardless of whether we use GRP or household-level TV ad exposures as our measure of advertising, our advertising stock variable A_{ijt} is constructed in the same basic way, using the updating formula in equation (6). In the case of TV ad exposure data, a_{ijt} is defined as the number of commercials seen by household i for brand j in a particular week. In the case of GRP, which is measured at the brand level, $a_{ijt} = a_{jt} \; \forall \; j$ is defined as the GRP of brand j in week t.

Note that the interpretation of the parameters γ and λ, the advertising main effect and the advertising/price interaction, differs in the two cases. In the model that utilizes household level TV ad exposure data, the parameters γ_i and λ_i capture household i's response to the number of ads it actually sees. But, in the case of GRP data, γ_i and λ_i embed both a household's TV commercial viewing habits, and its responsiveness to ads seen. For instance, a household that rarely watches TV would tend to have small values of γ_i and λ_i simply because it is unlikely to see many ads even if GRP is high. Since the TV and commercial viewing habits of consumers are not under the direct control of firms - the control variable for firms is GRP rather than TV exposures – one could make a case that GRP is actually the more interesting variable to examine.

5. Empirical Results

5.1. Some Simple Descriptive Statistics

Before presenting the estimates of our brand choice models, we first present some simple descriptive statistics that illustrate how the composition of consumers who buy a brand is strongly affected by prices, and their interaction with advertising and consumer characteristics. These results are presented in Table 2, for two brands of detergent, Tide and Cheer.

In this table, we decompose offer prices for each brand into "high," "medium" and "low" ranges. We made this distinction by looking at the offer price distribution for each brand, and finding what appeared to be break points. Notice that the "low" range is a bit lower for Cheer, because it is a lower priced brand on average (see Table 1).

We also divide consumers into types in three different ways. First, we categorize their brand loyalty as "high," "medium" and "low," based on their purchase frequency for a brand over the whole sample period. For example, consumers who bought Tide 75%-100% of the time are categorized as having "high" Tide loyalty. For Cheer the "high" category is 67%-100%. The difference arises because it has a smaller market share than Tide (13% vs. 34%).

Next, we group consumers by ad exposures for a brand. Here we have "high," "medium" and "low" and none. Finally, we group consumers based on their willingness to pay in the category as a whole. This is based on the average price the consumer paid for detergent over the whole sample period. This is a category specific rather than a brand specific construct, as it does not depend on which brands the consumer bought.

Each cell of Table 2 contains a purchase frequency. Thus, e.g., on purchase occasions when the price of Tide is "high," 81.3% of the Tide loyal consumers buy Tide. This increases only slightly to 88.7% when the price of Tide is "low." In contrast, for low loyalty consumers, the percent choosing Tide increases from 11.0% to 22.9% when price goes from high to low.

The table reveals a number of other interesting ways that the composition of consumers who buy a brand changes as price changes. For instance, as price goes from high to low, the percent of high WTP consumers who buy Tide only increases from 42% to 44%. In contrast, for low WTP consumers, the percent buying Tide increases from 12.6% to 35.1%. The effect is even stronger for Cheer (a lower priced brand – see Table 1). The percentage of high WTP consumers who buy Cheer is 14% (17%) when its price is high (low). But the percent of low WTP consumers buying Cheer increases from 0.8% to 13.6% as price goes from high to low.

From our perspective, the most interesting statistics concern advertising. *Prima facie*, the figures in Table 2 appear consistent with the notion that high advertising exposure (i) raises WTP for a brand, and (ii) flattens the demand curve. Consumers exposed to a high level of Tide ads buy Tide 47% (52%) of the time when price is high (low). But for those who see no ads (perhaps because they rarely watch TV, or do not watch programs where Tide is advertised) the percent buying Tide increases from 13.2% to 32.5% as price goes from high to low. Thus, the level of demand for Tide is higher (at any given price) amongst consumers who are heavily exposed to Tide ads, and the demand curve is much flatter as well. The pattern is similar for Cheer.

While these statistics suggest that consumers who are exposed to more ads have higher WTP, we cannot yet conclude this is a causal relationship. What Table 2 does make clear is that, as a brand cuts its price, it draws in less loyal consumers with less exposure to its ads and lower WTP in the category. Thus, as we have argued, any choice model must account for heterogeneity in WTP, and interactions between WTP and advertising. Of course, since so many variables are moving at once, we need a multivariate analysis to understand the shape of the demand curve.

5.2. Parameter Estimates and Goodness of Fit

We estimated the general model described in Section 3, equations (5), (6), (7) and (9), as well as two nested models. The first nested model (NM1) imposes the restriction that the model parameters are homogenous across households. The second (NM2) allows for heterogeneity in the parameters of the conditional indirect utility function, but rules out correlations among them.

Table 3 reports the likelihood function value for each model, as well as the Bayesian Information Criterion (BIC) statistic for comparing alternative models, due to Schwarz (1978). The BIC is based on the likelihood but includes a penalty term that adjusts for the number of parameters and observations. Specifically, BIC = $-log\text{-}L + (1/2)\cdot q\cdot\log(N)$, where q is the number of parameters and N is the sample size. As we see in Table 2, the general model with correlated heterogeneity distributions outperformed the nested models both in sample and out-of-sample.

Table 4 presents the parameter estimates for the full model. All the main effects are statistically significant and have the expected signs. That is, the main effects of price are all negative and significant, while the main effects of advertising, display, feature and coupon availability are positive. There is also strong evidence of positive state dependence, since the coefficient on the "loyalty variable" (i.e., the exponentially smoothed weighted average of prior use experience) is positive and highly significant.

The estimates also provide clear evidence of heterogeneity in consumer tastes, marketing mix sensitivities, and the effect of prior use experience. Taste heterogeneity is captured by the estimated standard deviations (across consumers) of the brand specific constants (see equation (9)). These are usually more than half the size of the means of the brand specific constants.

A key parameter in our model is the price times advertising interaction term, which we denote λ. Our estimate of λ is negative and significant in the toothpaste, toothbrush and detergent categories. It is only significant and positive in the ketchup category.

One might think a negative λ implies advertising increases consumer price sensitivity (by driving the price coefficient more negative). However, as we discussed in Section 3.1, especially the discussion of equation (8), how advertising affects a consumer's WTP depends on λ in a rather complex way that varies with his/her position in the taste distribution. Thus, an assertion that knowledge of λ alone tells us how advertising affects price sensitivity is overly simplistic. We address this issue in Section 5.3 using simulations of the model to see how advertising shifts the demand curve. It will turn out that advertising tends to flatten the demand curve in the toothpaste, toothbrush and detergent categories. But in ketchup the effect differs by brand.

The correlations of the consumer specific parameters are reported on the second page of Table 4. Most of these correlations are statistically significant at 5% level or higher, and many of them are substantively interesting. The correlation between the price coefficient and the ad exposure coefficient is negative in all four categories, implying that consumers who are more responsive to advertising also tend to be more price sensitive. The correlation between the "loyalty" (or use experience) coefficient and the price coefficient is positive in all four categories, suggesting that people who exhibit stronger "loyalty" formation also exhibit less price sensitivity.

The correlations between the price (advertising) coefficients and the display, feature and coupon coefficients are negative (positive) in all four categories. Thus, consumers who are sensitive to price or advertising tend to be sensitive to displays, features and coupons as well. If one constructs, for each category, a 5 by 5 matrix with entries for correlations of price, ad, coupon, display and feature sensitivities, all entries would be positive.[12] This implies that, in the language of factor analysis, the covariance between these five coefficients is driven by a single factor, which is interpretable as sensitivity to marketing variables in general.

But, when one considers the coefficient on past use experience (i.e., the loyalty" variable) the picture grows more complex. The correlation between sensitivities to use experience and to price, coupons, features and displays is <u>negative</u>, while that between sensitivity to use experience and to ad exposures is <u>positive</u>. A natural interpretation of this covariance structure is a two-factor model, where factor one captures sensitivity to marketing variables and insensitivity to use experience, while factor two captures sensitivity to both advertising and use experience. Loosely speaking, one could then think of there being four basic types of consumers. For example, a type that was high on factor one and low on factor two would be sensitive to price, coupon, display and feature activity, while being relatively insensitive to both advertising and use experience.

5.3. Simulations of How Advertising Affects Demand

In this section, we use our estimated demand model to simulate how advertising affects demand curves. The top panel of Figure 1 shows the *ceteris paribus* effect of increasing the ad stock variable for Brand 1 of toothpaste by 20%. As we see, advertising increases demand at any given price, implying that it increases willingness to pay. At the same time, advertising flattens the demand curve, because WTP increases more among consumers whose WTP was relatively low initially. This is consistent with the Becker-Murphy conjecture about the most likely scenario for how advertising should shift demand. Because of the flattening of the demand curve, the price

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[12] Assuming we reverse the signs of all correlations with the price coefficient, since for price a larger negative coefficient implies greater sensitivity.

elasticity of demand increases at any given price level. Thus, this simulation clearly illustrates the point that advertising can simultaneously increase WTP while reducing the price elasticity of demand. As Becker-Murphy argue, “advertising is profitable not because it lowers the elasticity of demand for the advertised good, but because it raises the level of demand.”

Table 5 shows how advertising affects the price elasticity of demand. For each consumer and purchase occasion, we calculate the consumer’s price elasticity of demand as implied by our model, given the marketing mix variables the consumer actually faced. In Table 5 we report the average of these elasticities across all consumers and purchase occasions in the row labeled “Baseline Price Elasticities.” We then increase the ad stock by 20% and recalculate the elasticity in the same way. Our model implies that such an increase in advertising would increase the price elasticity of demand for toothpaste Brand 1 (at initial prices) from 2.99 to 3.07. The effect is bigger for Brand 4, which has a substantially higher mean offer price and a smaller market share. For this brand, the price elasticity of demand would increase from 3.70 to 4.09.

The bottom panel of Figure 1 reports results of a dynamic simulation in which advertising intensity for toothpaste brand 1 is increased by 20%. This has little effect initially, because the advertising stock variable is subject to substantial inertia. Our estimate of μ_A, the coefficient of the lagged advertising stock in equation (6), is 0.63 (see Table 4). Thus, it takes several weeks for the ad stock to reach its new steady state level, which, of course, is 20% higher. But it takes even longer for demand to reach its new steady state level. This is because, as the ad stock variable grows, demand grows. This in turn causes the use experience (or loyalty) variable to grow. Overall, our model implies that adjustment to a new steady state demand level takes about 20 weeks. At this new steady state, demand for Brand 1 is 33% higher than it was initially.

We can also calculate what would happen to demand under the hypothetical that the ad stock is increased 20% while use experience is held fixed. We estimate this would increase demand for toothpaste Brand 1 by 11.3%. Thus, nearly two-thirds of the increase in demand resulting from an increase in advertising intensity is the indirect feedback effect whereby advertising increases sales, which in turn generate additional sales due to “habit persistence” or “loyalty.”[13] Of course, all of these calculations ignore competitor reaction. Such reactions would

[13] We estimate that the elasticity of demand for toothpaste Brand 1 with respect to the prior use experience stock (i.e., the “loyalty” variable) is 0.61. Note that this elasticity must be less than 1.0 for stability of the model.

presumably dampen the advertising effects we describe here. Our object in presenting these simulations is simply to present various *ceteris paribus* calculations of how advertising shifts demand, not to predict what would actually happen if a particular brand raised its ad intensity.

Figures 2 and 3 report analogous simulations for the toothbrush and detergent categories. The results are similar. As we see in Figure 2, *ceteris paribus*, a 20% increase in the ad stock increases WTP for the Brand 2 toothbrush. The increase is greater for marginal than for high-WTP consumers, so the demand curve is flattened. From Table 5 we see that the price elasticity of demand increases from 2.89 to 3.06 at initial prices. In the lower panel of Figure 2 we see that a 20% increase in ad intensity raises demand 36% in the long run. Of this, 13% is a direct effect of higher long run ad stocks, and 23% is an indirect effect due to higher use experience stocks.

In Figure 3, we see that, *ceteris paribus*, a 20% increase in the ad stock increases WTP for Tide, and flattens the demand curve. The price elasticity of demand for Tide increases from 4.79 to 5.03 at initial prices (see Table 5). In the bottom panel of Figure 3 we see that a 20% increase in ad intensity raises demand 20% in the long run. Of this 8% is a direct effect of the higher long run ad stock, and 12% is an indirect effect due to higher use experience stocks.

The effects of advertising on the demand curve are more complex in the Ketchup category. The situation for Hunt's ketchup, described in Figure 4a is similar to what we have described for brands in other categories. Advertising again raises WTP, flattens the demand curve, and raises the price elasticity of demand at initial prices (see Table 5). The long run simulation in the bottom panel of Figure 4a implies that a 20% increase in ad intensity raises demand by 18.6% in the long run. Of this, 10.5% is a direct effect of the higher long run ad stock, and the remaining 8.1% is an indirect effect due to higher use experience stocks.[14]

However, the situation for Heinz ketchup, show in Figure 4b, is very different. Here advertising raises WTP more for infra-marginal consumers who would have already bought Heinz even at relatively high prices. Thus, advertising makes the demand curve steeper. As we see in Table 5, the price elasticity demand is <u>falls</u> from 3.98 to 3.80 at initial prices.[15]

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[14] We estimate that the elasticities of demand for toothbrush Brand 2, Tide detergent, and Hunts ketchup with respect to the prior use experience stock (i.e., the "loyalty" variable) are 0.60, 0.54 and 0.48, respectively.

[15] The dynamic simulation in the bottom panel of Figure 4b implies that the LR effect of a 20% increase in Heinz advertising is to increase demand for Heinz by 22.3%, of which 8.9% is a direct effect of the higher long run ad

We see that, while Becker and Murphy may be correct in asserting that a flattening of the demand curve due to advertising should be "the presumptive case," this pattern does not hold universally. It is interesting to ask what might be different about the ketchup category in general, and the Heinz brand in particular, that leads to a different pattern in this case.

A mechanical explanation may simply involve the fact the Heinz, unlike all the other brands under study, is very dominant in its market, with a market share of 61%. In the discussion surrounding equation (4), we noted that, in the logit model, the price elasticity of demand is eventually decreasing with market share, once market share grows sufficiently large. The reason is that, as market share increases, the marginal consumer is further out in the tail of the taste distribution.[16] So long as the taste density declines sufficiently rapidly as we move out into the tail, the demand elasticity will fall. This is in fact the case in the logit model. But it is true much more generally, since consumer taste distributions assumed in choice modeling typically have the property that densities decline fairly rapidly as one moves out into the tails.[17]

We illustrate this mechanical effect of market share on the price elasticity of demand in Table 4 by simulating the impact of increasing the mean brand intercept for each brand by 20%. That is, we simulate what would happen if market share increased simply because consumers' decided they like a brand more (for no particular reason), holding price and marketing activity fixed. Note that the price elasticity of demand for Heinz falls from 3.98 to 3.20. In contrast, the elasticity increases for all the other brands, all of which have much smaller market shares.

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stock, and the remaining 13.4% is an indirect effect due to higher values of the use experience stock. We estimate that the elasticity of demand for Heinz ketchup with respect to the prior use experience stock is 0.57.

[16] Say we have two brands. A consumer buys brand 1 if $\overline{V}_1+\varepsilon_1>\overline{V}_2+\varepsilon_2$, where $\overline{V}_j$ is the deterministic part of the conditional indirect utility function for brand j (determined by price, advertising and other promotional activity), and ε_j represents consumer tastes. Suppose that $\overline{V}_1>>\overline{V}_2$, so brand 1 has a substantial market share. Then, the critical value of ε_2-ε_1 such that a consumer would buy brand 2 is well out in the right tail of the distribution of ε_2-ε_1. As long as the density of ε_2-ε_1 declines sufficiently quickly as one moves further out into the tail, an increase in advertising for brand 1 that raises $\overline{V}_1$ and shifts the cutoff point further right will reduce the derivative of market share with respect to $\overline{V}_1$. This reduces the demand elasticity, provided the derivative falls more rapidly than P/Q increases.

[17] A reverse pattern holds for low market share brands. An increase in advertising that raises market share of such a brand will bring the cutoff point for buying that brand up into the "fat" part of the taste heterogeneity distribution. This tends to raise the derivative of demand with respect to price. This is one factor driving up the price elasticity of demand.

But this mechanical explanation is far from being the whole story of how adverting affects demand elasticities, because it ignores interactions between advertising and price in the conditional indirect utility function. Specifically, it fails to explain what is different about ketchup such that the interaction term λ is positive in the ketchup category and negative in the other three categories we examined.

One argument is that the nature of advertising is different in the ketchup category vs. the toothpaste, toothbrush and detergent markets, due to differences in category characteristics. Comanor and Wilson (1979) argued that the impact of advertising on price elasticities, as well as advertising's pro-or-anti competitive effects in general, should depend on product category characteristics. Nelson (1974) argued that advertising is more likely to increase price sensitivity and lead to more pro-competitive effects when the information contained in advertising is "hard" (e.g. relative quality information) rather than "soft" (e.g. image oriented).[18]

It could be argued that advertising provides more "soft" information in the ketchup category, and more "hard" information in the toothpaste, toothbrush and detergent categories. In the later categories, TV advertising focuses on vertically differentiated dimensions of quality, such as cavity fighting power in toothpaste, removal of plaque in toothbrush and cleansing power in detergent. By contrast, in the ketchup category, much of the TV advertising for Heinz concerns the "thickness" dimension, along which it is clearly differentiated. According to Quelch (1985), "thickness" as an attribute was "created" by Heinz's past advertising. In contrast, the cleansing power of a detergent, and the cavity fighting or tartar removing capability of a toothpaste or toothbrush, respectively, are not attributes created by advertising.

"Thickness" is a <u>horizontal</u> attribute that may be valued heavily by some consumers and not by others. Thus, it is not surprising that advertising that aims to reinforce the differentiation of Heinz on the thickness dimension would raise the WTP of infra-marginal consumers who place a high value on thickness (and hence strongly prefer Heinz already) more than it raises the WTP of marginal consumers who place less value on thickness. Thus, Heinz seems to be an exception the Becker-Murphy argument that advertising should be aimed at marginal consumers.

[18] The "brand equity" literature in marketing asserts that emotional or self-expressive benefits (intangible, "soft" benefits) are more difficult to copy than functional benefits; and that positioning and communications strategies focusing on non-functional benefits create more differentiation (see Aaker, 1991).

6. Concluding Remarks

In this paper, we have used Nielsen scanner panel data on four categories of consumer goods to examine how TV advertising affects demand for a brand. Advertising can affect consumer demand in many different ways. Becker and Murphy (1993) have argued that the "presumptive case" should be that advertising works by raising marginal consumers' willingness to pay (WTP) for a brand. This has the effect of flattening the demand curve, thus increasing the equilibrium price elasticity of demand and lowering the equilibrium price. Thus, "advertising is profitable not because it lowers the elasticity of demand for the advertised good, but because it raises the level of demand." We find that, for 17 of the 18 brands across the four categories we examine, advertising does indeed work in this way. That is, it increases WTP more for marginal than infra-marginal consumers, thus flattening the demand curve while shifting it right.

Many prior studies estimated effects of advertising on equilibrium prices or equilibrium price elasticities of demand, without attempting to estimate how it shifts the demand curve for a brand as a whole. In many instances, the observation that advertising causes prices to fall and/or demand elasticities to increase, has misled authors into concluding that consumer "price sensitivity" must have increased, meaning the number of consumers' willing to pay any particular price for a brand was reduced – perhaps because advertising increases awareness of substitutes, as in Nelson (1970). But Becker and Murphy clarify that an equilibrium increase in the price elasticity of demand, or decrease in price, does not imply that advertising made consumers more "price sensitive" in this sense. In fact, decreases in price and increases in demand elasticities are perfectly consistent with a scenario where consumer WTP is generally increased by advertising.

Thus, if one wants to understand how advertising works, it is not sufficient to see how it alters a single parameter like the price elasticity of demand in equilibrium. Rather, one must estimate how it shifts the whole distribution of WTP in the population. This means estimating how it shifts the shape of the demand curve as a whole, which in turn means estimating a complete demand system for all brands in a category – as we do here.

We find one important exception to the pattern that advertising primarily increases the WTP of marginal consumers. This is the case of Heinz ketchup. Heinz advertising has a greater positive effect on WTP of infra-marginal consumers. This is not surprising, because Heinz focuses on differentiating its brand on the "thickness" dimension. This is a horizontal dimension that is highly valued by some consumers and not others. The consumers who most value this dimension have the highest WTP for Heinz. By focusing on this dimension, Heinz advertising raises the WTP of these infra-marginal consumers further. Such advertising is profitable because it reduces the market share loss that the brand would suffer from any given price increase.

This suggests that the effects of advertising on the shape of the demand curve depends on whether goods are vertically and/or horizontally differentiated, and on whether firms design their advertising to stress vertical or horizontal attributes of their products. Advertising that stresses vertical characteristics would appeal to marginal consumers, while advertising that stresses horizontal characteristics (in which a brand is perceived as having an advantage) will increase WTP most for those infra-marginal consumers who most value those horizontal attributes.

Our work is differentiated from previous work on the effect of advertising on consumer demand both by our focus on how advertising shifts demand curves as a whole and by our attention to consumer heterogeneity in tastes and in sensitivity to marketing variables. Unlike previous work in this area, we allowed for a rich heterogeneity structure to avoid the compositional biases that may exist if there is unobserved heterogeneity and if advertising affects the composition of consumers who purchase a brand.

For all 18 brands examined, advertising reduces consumer price sensitivity in the sense of increasing the number of consumers willing to pay any given price for a brand. This result is consistent with Becker-Murphy's view that advertising is complimentary to brand consumption, but also consistent with models where advertising increases WTP for a brand by producing "artificial" differentiation, or conveying information about brand attributes. A more structural approach is needed to distinguish these behavioral stories of why advertising shifts demand.[19]

We only examined non-price advertising. Milyo and Waldfogel (1999) note that price advertising can affect stores' demand curves differently if consumers have different costs of acquiring price information, and different types of consumers visit each store. This is analogous to our point that non-price advertising can differentially affect consumers with different tastes.

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[19] For example, a positive effect of advertising on WTP is consistent with Erdem and Keane (1996), where consumers are uncertain about brand attributes and risk averse with regard to attribute variation. If advertising provides noisy signals of brand attributes, a more advertised brand is "lower variance." Risk averse consumers have a greater WTP for a "familiar" brand than for a higher variance alternative, even if the alternative has the same expected attributes. This is obviously an informational story.

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Table 1: Summary Statistics*

Brand Name	Market Share	Mean Price	Ad Frequency	Display Frequency	Feature Frequency	Mean Coupon Availability
Toothpaste						
Brand 1	31.3%	$1.83	13.54	2.0%	2.9%	$0.073
Brand 2	20.0%	$1.90	27.07	1.6%	2.8%	$0.068
Brand 3	10.6%	$1.75	0	1.4%	3.2%	$0.082
Brand 4	9.5%	$2.52	0	1.2%	1.8%	$0.091
	(71.4%)					
Toothbrush						
Brand 1	10.2%	$2.36	12.62	1.2%	2.6%	$0.074
Brand 2	21.8%	$1.99	19.75	1.1%	3.1%	$0.063
Brand 3	19.4%	$2.36	22.84	0.6%	3.2%	$0.085
Brand 4	17.3%	$1.96	0	0.7%	3.3%	$0.069
	(68.7%)					
Ketchup						
Brand 1 (Heinz)	61.3%	$1.36	19%	10.9%	14.2%	$0.056
Brand 2 (Hunt's)	15.2%	$1.19	24%	11.5%	20.1%	$0.062
Brand 3 (Del Monte)	12.8%	$0.89	0	8.2%	27.3%	$0.029
	(89.3%)					
Detergent						
Brand 1 (Tide)	27.9%	$3.91	54%	20.9%	12.6%	$0.097
Brand 2 (Wisk)	11.5%	$3.40	69%	3.10%	16.7%	$0.105
Brand 3 (CH)	10.8%	$3.61	10%	12.0%	11.8%	$0.086
Brand 4 (Surf)	9.7%	$3.20	22%	18.9%	12.0%	$0.093
Brand 5 (Oxydol)	8.6%	$3.19	20%	14.1%	8.0%	$0.100
Brand 6 (Era)	7.0%	$4.29	56%	10.0%	7.8%	$0.092
Brand 7 (All)	5.5%	$3.92	36%	1.0%	21.5%	$0.094
	(82.0%)					

*Mean price: Mean "offer" price is per 50 oz of toothpaste, per unit of toothbrush, per 32 oz of ketchup and per 64 oz of detergent.

Ad Frequency: For toothpaste and toothbrush, we report average GRP. For ketchup and detergent, we report the percentage of households exposed to at least one ad in a typical week. These measures represent the intensity of advertising.

Display frequency and feature frequency: The percentage of all purchase occasions that the brand was on display or feature, regardless of which brand was bought.

Mean coupon availability: This is an average over all purchase occasions, regardless of whether a coupon was used (and including zeros when no coupon was available), and regardless of which brand was bought.

Table 2: Some Descriptive Statistics about Demand

Conditional Purchase Probabilities - Tide

Marketing Variables	Percentage of Purchases									
	Brand loyalty			Ad Viewing Habit				Category WTP		
	H (75-100%)	M (40-67%)	L (1-33%)	H (30-51)	M (20-30)	L (1-19)	N (0)	H (3.69-4.46)	M (3.33-3.68)	L 2.34-3.30
Offer Prices										
H (4.07-4.97) 44.92%	.813	.471	.110	.471	.342	.149	.132	.423	.315	.126
M (3.56-4.40) 24.39%	.822	.657	.195	.485	.456	.309	.295	.423	.326	.294
L (2.94-3.52) 30.69%	.887	.733	.229	.518	.498	.366	.325	.440	.420	.351

Conditional Purchase Probabilities - Cheer

Marketing Variables	Percentage of Purchases									
	Brand Loyalty			Ad Viewing Habit				Category WTP		
	H (63-100%)	M (33-62%)	L (1-33%)	H (26-40)	M (16-25)	L (1-15)	N (0)	H (3.69-4.46)	M (3.33-3.68)	L (2.34-3.30)
Offer Prices										
H (4.303-4.99) 25.86%	.672	.317	.024	.209	.183	.068	.045	.139	.093	.008
M (3.31-4.29) 46.62%	.698	.431	.059	.221	.195	.133	.106	.167	.157	.130
L (2.20-3.30) 26.97%	.709	.456	.065	.234	.230	.137	.125	.167	.164	.136

Note: Each cell of the Table reports the probability that a particular type of consumer buys the indicated brand on a particular purchase occasion, given the price of the brand is in the indicated range. The unconditional purchase probabilities are 34% for Tide and 13% for Cheer.

Table 3: Model Selection ***

Parameters		NM1	NM2	Full Model
In-Sample*				
Toothpaste	**-Log-Like**	3410.4	2965.9	2872.6
	BIC	3474.1	3081.4	3047.8
Toothbrush	**-Log-Like**	1228.5	1110.9	1041.7
	BIC	1279.9	1207.4	1186.4
Ketchup	**-Log-Like**	1422.1	1291.6	1213.4
	BIC	1470.8	1375.0	1349.0
Detergent	**-Log-Like**	5814.3	5069.3	4956.7
	BIC	5924.2	5293.1	5241.5
Out-of-Sample**				
Toothpaste	**-Log-Like**	1361.6	1260.1	1215.6
Toothbrush	**-Log-Like**	699.4	642.7	595.4
Ketchup	**-Log-Like**	935.4	859.4	820.2
Detergent	**-Log-Like**	2930.5	2775.2	2722.1

* 345 households made 2880 purchases of toothpaste. 167 households made 621 purchases of toothbrush. 135 households made 1045 purchases of ketchup. 581 households made 3419 purchases of detergent.

** 102 households made 1014 purchases of toothpaste. 110 households made 922 purchases of ketchup. 90 households made 414 purchases of toothbrush. 230 households made 1898 purchases of detergent.

*** The Bayes Information Criterion (BIC) includes a penalty based on the number of parameters. It is calculated as BIC=-Log-likelihood+0.5*# of parameters*ln(# of observations). In the Full Model there are 44, 45, 39 and 70 parameters in the toothpaste, toothbrush, ketchup and detergent models, respectively. In Nested Model One (NM1) there are 16, 17, 14 and 27 parameters, respectively. In Nested Model Two (NM2) there are 29, 30, 24 and 55 parameters, respectively.

Table 4: Parameter Estimates – Full Model*

Parameter	Toothpaste	Toothbrush	Ketchup	Detergent
Brand specific constants α:				
(Brand 1)	0.64 (0.10)	-0.63 (0.07)	1.75 (0.38)	0.60 (0.12)
(Brand 2)	0.26 (0.09)	0.14 (0.03)	-0.15 (0.07)	0.60 (0.17)
(Brand 3)	0.04 (0.02)	-0.05 (0.01)		0.20 (0.08)
(Brand 4)				0.17 (0.06)
(Brand 5)				-0.88 (0.23)
(brand 6)				-0.50 (0.10)
Standard deviation of Brand Intercepts σ_α:				
(Brand 1)	0.38 (0.18)	0.56 (0.19)	1.27 (0.08)	0.25 (0.09)
(Brand 2)	0.16 (0.09)	0.09 (0.04)	0.14 (0.06)	0.47 (0.15)
(Brand 3)	0.05 (0.02)	0.03 (0.01)		0.18 (0.07)
(Brand 4)				0.10 (0.03)
(Brand 5)				0.59 (0.14)
(brand 6)				0.43 (0.20)
Price coefficient β:				
Brand specific means (Brand 1):	-1.03 (0.36)	-0.72 (0.20)	-1.79 (0.16)	-1.81 (0.46)
(Brand 2):	-1.21 (0.38)	-0.79 (0.21)	-1.99 (0.15)	-1.65 (0.60)
(Brand 3):	-1.42 (0.42)	-1.06 (0.10)	-2.10 (0.20)	-1.90 (0.57)
(Brand 4):	-1.72 (0.41)	-1.29 (0.24)		-2.31 (0.59)
(Brand 5):				-2.22 (0.69)
(Brand 6):				-2.47 (0.70)
(Brand 7):				-2.41 (0.65)
Standard deviation of Price Coefficient σ_β:	0.92 (0.20)	0.63 (0.13)	1.10 (0.19)	0.75 (0.60)
Advertising coefficient γ:				
Brand specific means (Brand 1):	0.49 (0.10)	0.50 (0.02)	0.26 (0.08)	0.51 (0.14)
(Brand 2):	0.18 (0.07)	0.41 (0.07)	0.10 (0.03)	0.30 (0.06)
(Brand 3):		0.013 (0.004)		0.25 (0.05)
(Brand 4):				0.12 (0.06)
(Brand 5):				0.17 (0.06)
(Brand 6):				0.10 (0.06)
(Brand 7):				0.14 (0.04)
Standard deviation of Ad coefficients σ_γ:	0.15 (0.06)	0.04 (0.02)	0.07 (0.03)	0.09 (0.04)
Mean Price*Advertising coefficient λ:	**-0.16 (0.04)**	**-0.21 (0.07)**	**0.28 (0.08)**	**-0.23 (0.09)**
Standard deviation σ_λ:	0.08 (0.03)	0.12 (0.05)	0.19 (0.06)	0.18 (0.25)
Mean Use Experience coefficient ψ:	3.20 (0.16)	2.49 (0.16)	3.89 (0.20)	4.02 (0.18)
Standard deviation σ_ψ:	2.62 (0.19)	2.04 (0.51)	0.70 (0.18)	2.23 (0.20)
Mean Display coefficient ϕ:	1.51 (0.20)	1.14 (0.09)	2.20 (0.90)	2.12 (0.43)
Standard deviation σ_ϕ:	1.00 (0.26)	0.80 (0.30)	0.74 (0.22)	1.21 (0.52)
Mean Feature coefficient τ:	1.06 (0.29)	0.74 (0.32)	2.94 (0.30)	1.93 (0.12)
Standard deviation σ_t:	1.10 (0.47)	0.70 (0.16)	1.83 (0.28)	0.46 (0.20)
Mean Coupon coefficient ξ:	0.57 (0.12)	0.91 (0.12)	2.44 (0.37)	1.50 (0.20)
Standard deviation σ_ξ:	0.40 (0.17)	0.73 (0.28)	1.23 (0.31)	0.42 (0.10)

Table 4 continued: Parameter estimates	**Toothpaste**	**Toothbrush**	**Ketchup**	**Detergent**
Use Experience Smoothing Parameter μ_A:	0.79 (0.20)	0.79(0.06)	0.95 (0.11)	0.79 (0.17)
Media Smoothing Parameter μ_E:	0.63 (0.10)	0.62(0.24)	0.63 (0.17)	0.57 (0.20)
Correlation Between:				
Price and Ad coefficients $\rho_{\pi 12}$:	-0.34 (0.12)	-0.29(0.07)	-0.29 (0.10)	-0.23 (0.09)
Price and Use Experience coefficients $\rho_{\pi 13}$:	0.20 (0.08)	0.30(0.08)	0.35 (0.10)	0.21 (0.10)
Price and Display coefficients $\rho_{\pi 14}$:	-0.12 (0.05)	-0.14(0.06)	-0.13 (0.06)	-0.17 (0.08)
Price and Feature coefficients $\rho_{\pi 15}$:	-0.20 (0.08)	-0.23(0.08)	-0.18 (0.11)	-0.17 (0.06)
Price and Coupon coefficient $\rho_{\pi 16}$:	-0.25 (0.10)	-0.22(0.10)	-0.28 (0.12)	-0.23 (0.10)
Ad and use experience coefficients $\rho_{\pi 23}$:	0.10 (0.06)	0.12 (0.06)	0.13 (0.07)	0.19 (0.10)
Ad and display coefficients $\rho_{\pi 24}$:	0.08 (0.04)	0.10 (0.06)	0.20 (0.07)	0.12 (0.07)
Ad and feature coefficients $\rho_{\pi 25}$:	0.14 (0.10)	0.18 (0.07)	0.09 (0.09)	0.17 (0.07)
Ad and coupon coefficients $\rho_{\pi 26}$:	0.27 (0.12)	0.26 (0.08)	0.25 (0.10)	0.20 (0.08)
Use Experience and display coeff. $\rho_{\pi 34}$:	-0.03 (0.01)	-0.04 (0.02)	-0.07 (0.04)	-0.05 (0.02)
Use Experience and feature coeff. $\rho_{\pi 35}$:	-0.03 (0.05)	-0.06 (0.04)	-0.04 (0.04)	-0.04 (0.04)
Use Experience and coupon coeff. $\rho_{\pi 36}$:	-0.12 (0.04)	-0.07 (0.04)	-0.16 (0.06)	-0.07 (0.03)
Display and Feature coefficients $\rho_{\pi 45}$:	0.26 (0.05)	0.19 (0.06)	0.21 (0.13)	0.29 (0.11)
Display and Coupon coefficients $\rho_{\pi 46}$:	0.24 (0.10)	0.20 (0.07)	0.16 (0.07)	0.20 (0.09)
Feature and Coupon coefficients $\rho_{\pi 56}$:	0.17 (0.11)	0.13 (0.04)	0.11 (0.04)	0.19 (0.08)
Correlations Among Brand Intercepts				
$\rho_{\alpha 12}$	-0.19 (0.06)	0.35 (0.010)	-0.24 (0.11)	-0.42 (0.11)
$\rho_{\alpha 13}$	-0.23 (0.06)	-0.24 (0.11)		-0.59 (0.17)
$\rho_{\alpha 14}$				0.19 (0.04)
$\rho_{\alpha 15}$				0.10 (0.18)
$\rho_{\alpha 16}$				-0.67 (0.27)
$\rho_{\alpha 23}$	0.20 (0.17)	-0.20 (0.09)		0.48 (0.21)
$\rho_{\alpha 24}$				-0.32 (0.10)
$\rho_{\alpha 25}$				-0.30 (0.19)
$\rho_{\alpha 26}$				0.51 (0.19)
$\rho_{\alpha 34}$				0.10 (0.04)
$\rho_{\alpha 35}$				-0.16 (0.10)
$\rho_{\alpha 36}$				0.18 (0.31)
$\rho_{\alpha 45}$				0.15 (0.09)
$\rho_{\alpha 46}$				-0.008(0.004)
$\rho_{\alpha 56}$				-0.08 (0.03)

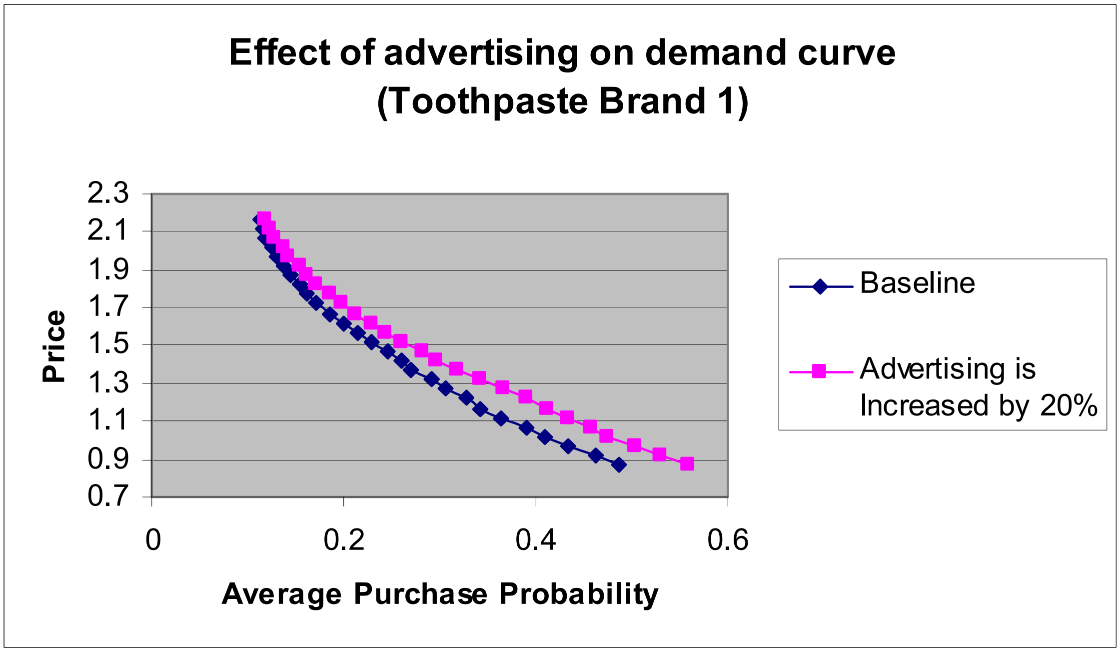
* Standard errors are reported in the parenthesis.

Table 5. Price Elasticities of Demand*

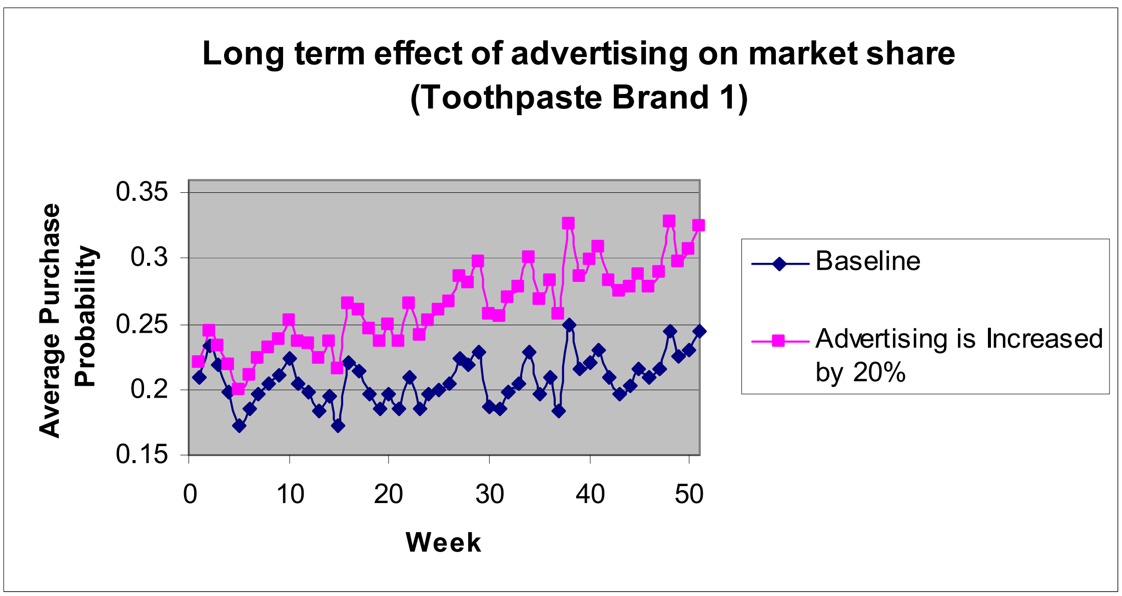
Simulation	Toothpaste		Toothbrush		Ketchup		Detergent	
	High MS Brand 1	Low MS Brand 4	High MS Brand 2	Low MS Brand 1	High MS Heinz	Low MS Hunt's	High MS Tide	Low MS All
Baseline Price Elasticities	-2.99	-3.70	-2.89	-3.65	-3.98	-4.57	-4.79	-5.14
Advertising is increased by 20%	-3.07	-4.09	-3.06	-3.81	-3.80	-4.93	-5.03	-5.52
Price is increased by 20%	-2.89	-3.57	-2.75	-3.58	-4.29	-3.99	-4.52	-4.85
Brand Intercept is increased by 20%	-3.07	-3.75	-3.11	-3.83	-3.20	-5.15	-4.98	-5.43

Note: In the counterfactual simulations where advertising and the brand intercept are increased, the elasticity is calculated at the initial prices observed in the data. In each category, we report results for a relatively high market share brand (in the "High MS" column) and for a relatively low market share brand (in the "Low MS" column).

Figure 1

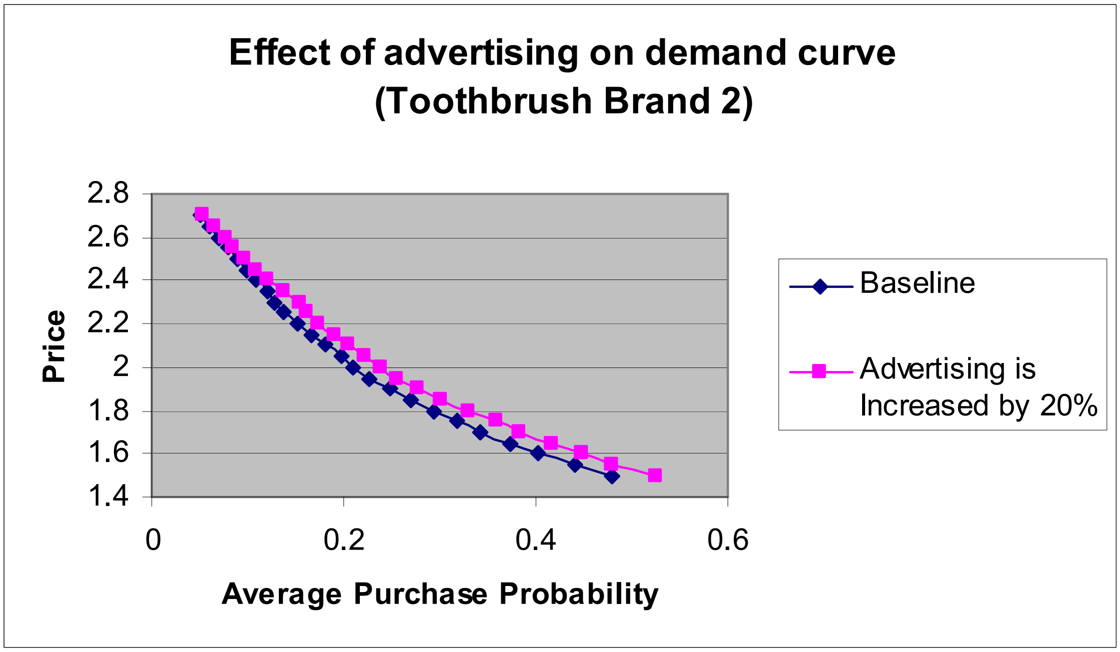


Effect of advertising on demand curve
(Toothpaste Brand 1)
2.3
2.1
1.9
1.7
1.5
1.3
1.1
0.9
0.7
Price
0
0.2
0.4
0.6
Average Purchase Probability
Baseline
Advertising is Increased by 20%

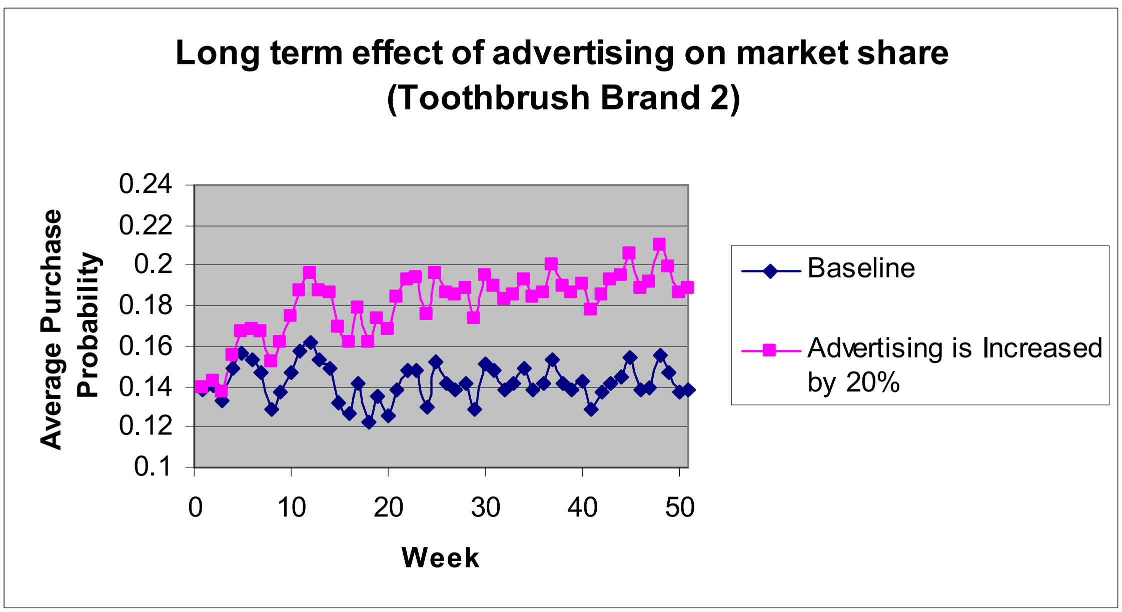


Long term effect of advertising on market share
(Toothpaste Brand 1)
0.35
0.3
0.25
0.2
0.15
Average Purchase Probability
0
10
20
30
40
50
Week
Baseline
Advertising is Increased by 20%

Figure 2

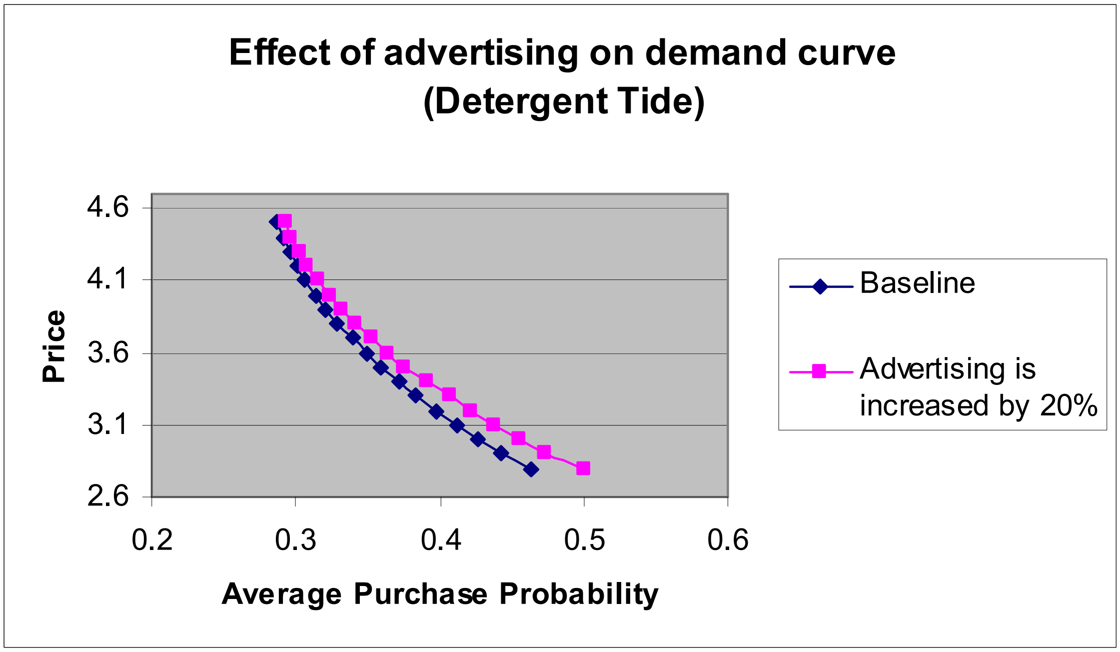


Effect of advertising on demand curve
(Toothbrush Brand 2)
Price
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
0
0.2
0.4
0.6
Average Purchase Probability
Baseline
Advertising is Increased by 20%



Long term effect of advertising on market share
(Toothbrush Brand 2)
Average Purchase Probability
0.24
0.22
0.2
0.18
0.16
0.14
0.12
0.1
0
10
20
30
40
50
Week
Baseline
Advertising is Increased by 20%

Figure 3


Effect of advertising on demand curve
(Detergent Tide)
4.6
4.1
3.6
3.1
2.6
Price
0.2
0.3
0.4
0.5
0.6
Average Purchase Probability
Baseline
Advertising is increased by 20%

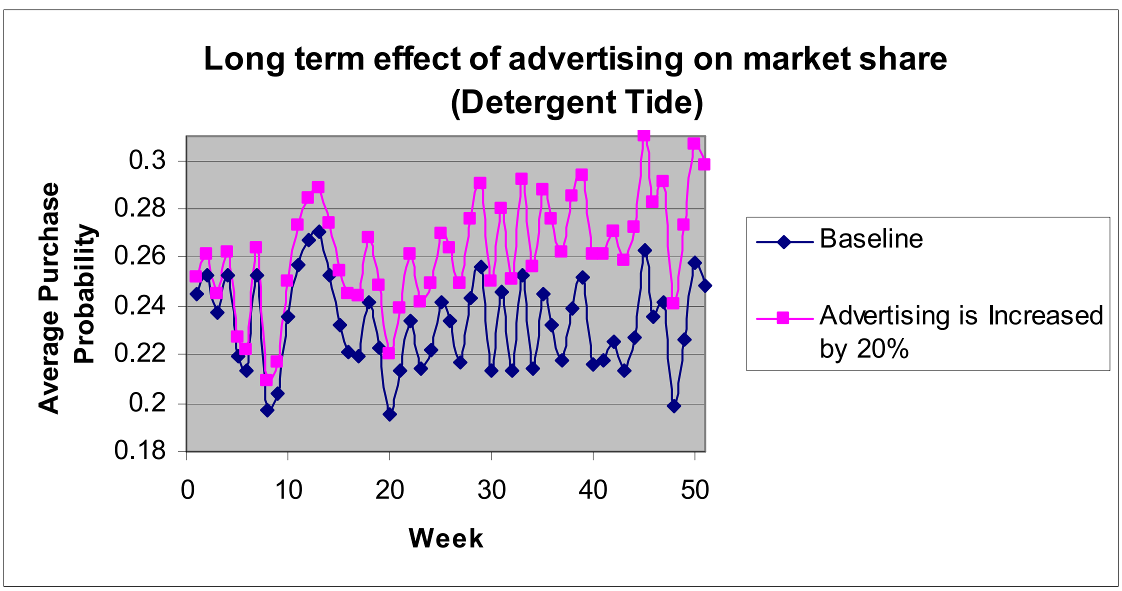
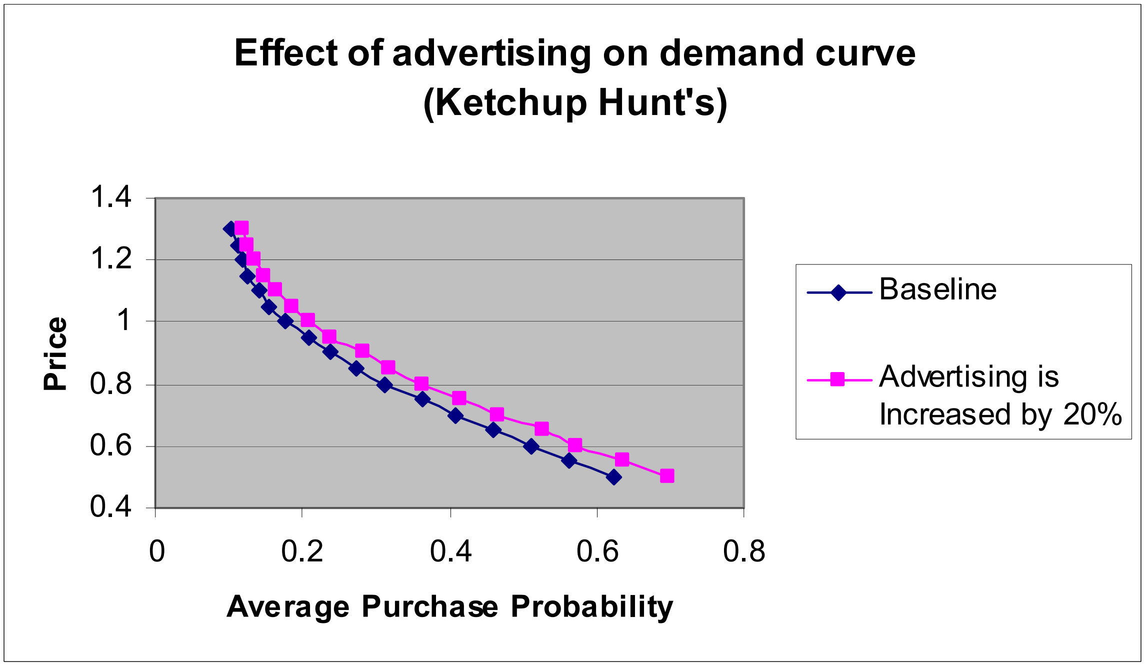

Long term effect of advertising on market share
(Detergent Tide)
0.3
0.28
0.26
0.24
0.22
0.2
0.18
Average Purchase Probability
0
10
20
30
40
50
Week
Baseline
Advertising is Increased by 20%

Figure 4a


Effect of advertising on demand curve
(Ketchup Hunt's)
Price
1.4
1.2
1
0.8
0.6
0.4
0
0.2
0.4
0.6
0.8
Average Purchase Probability
Baseline
Advertising is Increased by 20%

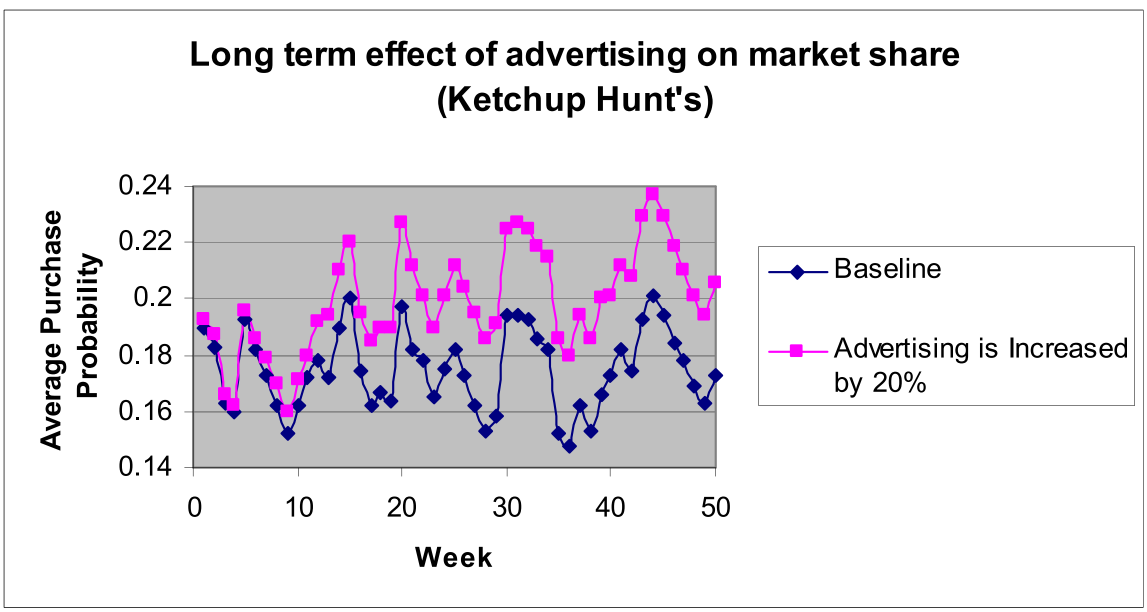
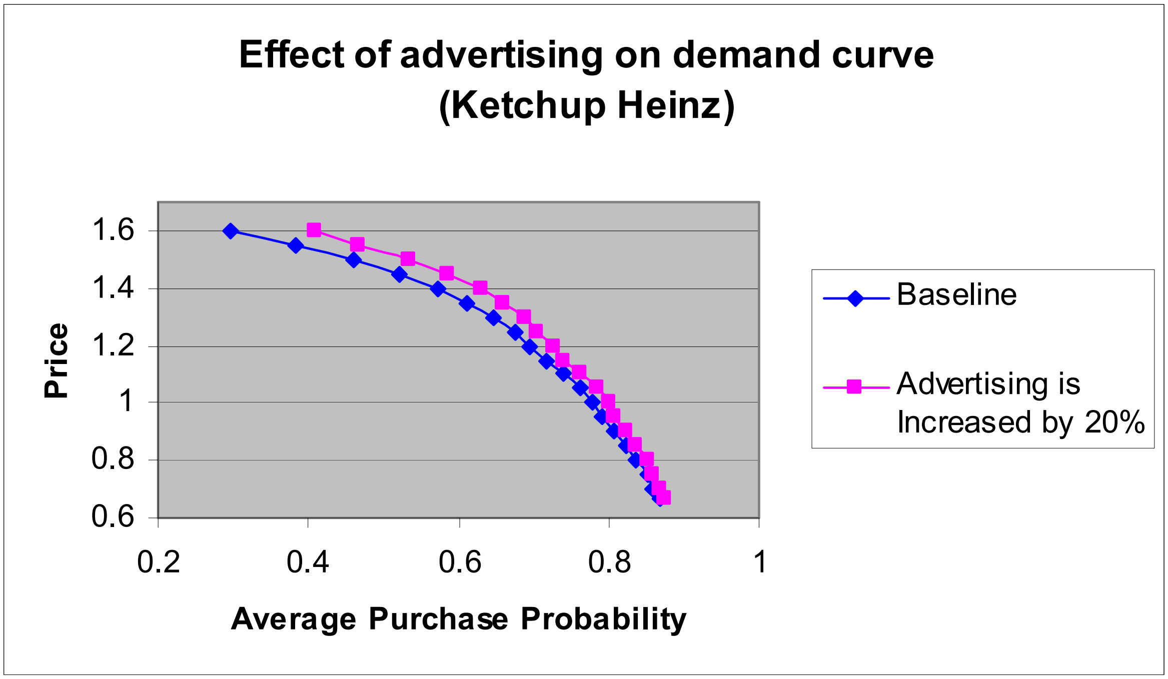
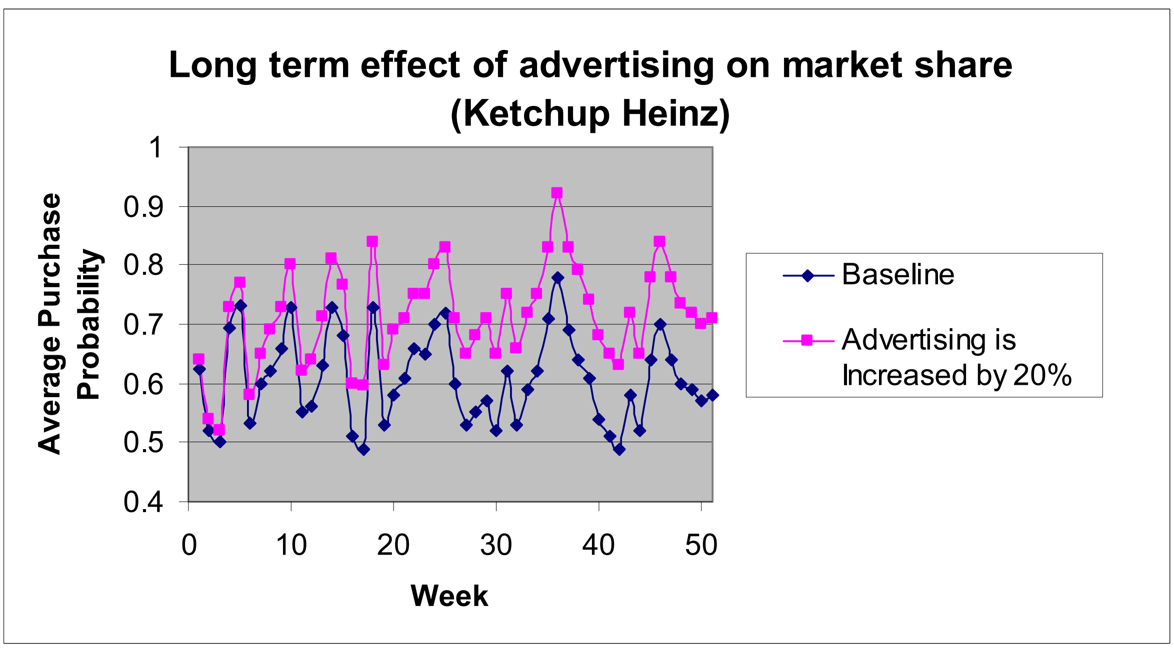

Long term effect of advertising on market share
(Ketchup Hunt's)
Average Purchase Probability
0.24
0.22
0.2
0.18
0.16
0.14
0
10
20
30
40
50
Week
Baseline
Advertising is Increased by 20%

Figure 4b



Effect of advertising on demand curve
(Ketchup Heinz)
Price
1.6
1.4
1.2
1
0.8
0.6
0.2
0.4
0.6
0.8
1
Average Purchase Probability
Baseline
Advertising is Increased by 20%



Long term effect of advertising on market share
(Ketchup Heinz)
Average Purchase Probability
1
0.9
0.8
0.7
0.6
0.5
0.4
0
10
20
30
40
50
Week
Baseline
Advertising is Increased by 20%