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Empirically distinguishing informative and prestige effects of advertising

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This article introduces techniques to empirically distinguish different effects of brand advertising in nondurable, experience-goods markets. I argue that advertisements that give consumers product information should primarily affect consumers who have never tried the brand, whereas advertisements that create prestige or image effects should affect both inexperienced and experienced users. I apply this empirical argument to consumer-level data on purchases of a newly introduced brand of yogurt. Empirical results indicate that the advertisements for this brand primarily affected inexperienced users of the brand. I conclude that the primary effect of these advertisements was that of informing consumers.

1. Introduction

■ A recent television advertisement for the newly introduced "Molson Ice" beer portrays twenty-somethings dressed in hip clothes in a bar drinking the beer. Clearly such advertisements should stimulate demand for the product. Otherwise, Molson would not be spending money on them. What is not clear is how such advertisements affect rational consumers who view them. Do they alert consumers to the existence of this new product? Does the fact that Molson is advertising the product somehow indicate to consumers that it is a product worth trying? Are there reputation or prestige effects by which consumers simply obtain utility (or disutility) from consuming more advertised products or products that are associated with hip twenty-somethings? Or is there some combination of the above and possibly other effects? It is these questions that this article addresses empirically.

Theoretical work on advertising has long been concerned with different influences of advertising on consumer behavior. Marshall (1919) praised "constructive" advertising, described as advertising that conveys economically relevant information to the consumer. In contrast, he termed the "incessant iteration of the name of a product" as "combative" advertising and lamented the "social waste" of such behavior.

More recently, economists have developed explicit theoretical models to analyze different effects of advertising. Stigler (1961), Butters (1977), and Grossman and Shapiro (1984) examine

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models in which firms advertise to explicitly inform consumers of their product's existence or characteristics. Nelson (1974), Milgrom and Roberts (1986), and others analyze advertising for experience goods, products whose complete characteristics are not observable to consumers before purchase. They find that in the presence of unobservable characteristics such as quality or taste, firms may use advertising to implicitly signal their value to consumers. In these models there need not be anything in the advertising that explicitly informs consumers. Simply the fact that a firm is spending money on advertising is enough to "tell" the consumer that the product tastes good or is of high quality.

Stigler and Becker (1977) and Becker and Murphy (1993) analyze models in which a brand's advertising level or content interacts in a consumer's utility function with consumption of that brand. When this interaction is positive, consuming a more-advertised good, all else constant, provides more utility to the consumer. This provides a way of modelling the ideas behind Marshall's "combative" advertising or Galbraith's (1976) "persuasive" advertising that is consistent with consumer utility maximization. These ideas are that advertising can *in itself* create prestige, differentiation, or association that may change the utility a consumer obtains from consuming a product.[1]

The concern and interest shown above is well deserved. In assessing the impact of advertising on a particular market, knowledge of the processes by which advertisements affect consumers is essential. Consider the polar cases of Coca-Cola advertisements and the classifieds. Most would support the view that classified ads provide information on product existence and characteristics. The fact that most individuals have tasted Coca-Cola suggests that these advertisements are not providing information on the product's inherent physical characteristics. Perhaps these advertisements stimulate demand by creating prestige or associating the product with something or someone. No one would dispute that the ability to place classified ads is a large benefit to society. On the other hand, many would argue that society would be better off if Coca-Cola and Pepsi mutually reduced advertising expenditures.

Although in these two extreme cases the process by which advertising affects consumers may be clear, this is certainly not true in general. For some advertisements it is likely that many effects work to influence consumer behavior. Measuring the existence and extent of such effects is an empirical problem, one that has not received enough attention. The bulk of advertising-related empirical literature, both in economics and marketing, has focused not on *how* advertising affects demand, but only on *how much* advertising affects demand (Schmalensee, 1972; Roberts and Samuelson, 1988; Guadagni and Little, 1983; and Erdem and Keane, 1996). The few studies that have attempted to answer more qualitative questions about advertising for consumer goods have either (1) looked at cross-industry data (Telser, 1964; Boyer, 1974), (2) related advertising levels to product quality (Archibald, Haulman, and Moody, 1983; Tellis and Fornell, 1988), (3) examined actual advertising content (Resnik and Stern, 1978), or (4) used unique natural experiments (Benham, 1972; Ippolito and Mathios, 1990; and Milyo and Waldfogel, 1999). These approaches all have caveats. The cross-industry, aggregate studies have potential endogeneity issues. While the results of Archibald, Halman, and Murphy, and of Tellis and Fornell suggest that advertising provides information, they cannot rule out prestige effects. Resnik and Stern examine television advertisements and find them primarily image oriented. Though this is interesting, theory suggests that examining ad copy is a flawed approach to distinguishing effects of advertising. Advertisements need not contain explicit information to inform consumers of a product's existence or to signal information.[2]

I introduce an alternative strategy for distinguishing and measuring informative and prestige effects of advertising in consumer good markets. I employ panel data following household grocery

[1] Below I describe these effects as changing consumers' preferences over *products*. This terminology may be a little loose for Becker et al.'s liking, as one of their main points is that such effects should be modelled without a consumer's preferences changing. In using this terminology I do not mean that advertising changes consumers' underlying preferences (defined over both products and advertising). It does change the utility derived from consuming a particular product.

[2] There is also an interesting literature on advertising in health-related markets (Leffler, 1981; Hurwitz and Caves, 1988).

purchases and advertising exposures over time. The distinction is made by assessing consumer response to advertising. Specifically, I argue that advertising that informs consumers of a brand's inherent characteristics should primarily affect inexperienced consumers—those who have not purchased the brand in the past. On the other hand, I posit that prestige or image effects of advertising should affect both inexperienced and experienced consumers relatively equally. Tellis (1988) and Deighton, Henderson, and Neslin (1994) have used similar data to examine interactions between previous purchases and advertising. They do not attempt to distinguish informative and prestige effects of advertising and use different functions of previous purchases (in contrast to the inexperienced-versus-experienced distinction).[3,4]

I analyze advertising for a newly introduced brand of yogurt. Employing a panel discrete-choice model allowing for persistent consumer heterogeneity, I find that holding all else equal, these advertisements affected inexperienced consumers more than experienced consumers. In most cases I find a significant effect of advertising on inexperienced users and an insignificant effect on experienced users. I conclude that these advertisements primarily affected consumers by giving them information on inherent product characteristics. The lack of image or prestige effects suggests that advertising may have facilitated competition and entry in this industry (Shapiro, 1982). While I favor this interpretation of the results, others may be more agnostic. Even so, the basic empirical result finding a differential effect of advertising is interesting and has important implications for optimal advertising behavior.

Finally, my approach is one that can be applied to other products or industries. The household-level panel data necessary for identification are becoming increasingly available for all kinds of consumer products. Knowing how advertising affects consumers in a market can be important for policy making. For example, stricter merger policy might be optimal in markets where long-lived prestige effects of advertising create barriers to new entry, in comparison to markets where informative advertising allows new entrants to disseminate information and quickly gain equal footing.

The article is organized as follows. Section 2 argues that different types of advertising have different empirical implications in consumer-level data. Section 3 describes the dataset. Section 4 presents an empirical model, and Section 5 provides results. Section 6 concludes and suggests topics for further research.

2. Some effects of advertising

■ There are many different types of products and many different types of advertisements. To simplify things as well as to match the data, I will be thinking about television advertising by manufacturers of consumer nondurables. Television ads for nondurables such as foodstuffs, clothing, and toiletries typically are the least likely to contain overt product information, rarely mention price, and are most likely to be described as image oriented. As such, it is particularly interesting to examine the effects of these types of ads. However, many of the following arguments could be made for other types of products or advertising.

As described in Stigler (1961), I distinguish between search and experience characteristics. Search characteristics are observable and verifiable to consumers before purchase, e.g., the calories in a cola brand, its price, or the fact that it is a cola. Experience characteristics are not generally known to consumers before trying the product, e.g., taste. This is not to say that consumers have no information on experience characteristics. A consumer might ask a friend about a product, may have tried similar products in the past (e.g., other colas), or may relate experience characteristics with values of search characteristics (e.g., diet sodas taste bad).

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[3] Tellis (1988) interacts advertising with what the marketing literature calls "brand loyalty" (a weighted function of the number of past brand purchases, with the highest weights on recent purchases). His motivation for including these interactions is not to explicitly distinguish different effects of advertising, but to examine how brand loyalty mediates advertising's effect.

[4] Deighton, Henderson, and Neslin (1994) interact advertising with an indicator of whether the consumer purchased that particular grocery brand on his previous shopping trip. They use this interaction to assess alternative "framing" theories of advertising for established brands that have been discussed in the marketing literature.

I argue that in some cases advertising provides information similar to that obtained from consumption. Because of this information duplication, these influences of advertising should not affect "experienced consumers"—those who have consumed the brand at some point in the past. This is in contrast to advertising that provides information not learned from consumption. I expect such advertising to affect *both* inexperienced and experienced consumers. It is this distinction that allows me to separately identify different effects of advertising.

□ **Information on product existence and search characteristics.** Assume that advertising only informs consumers of a brand's existence and search characteristics, as in Stigler (1961), Butters (1977), and Grossman and Shapiro (1984). Such advertising will affect only consumers who do not already know of the brand's existence or those search characteristics. Such knowledge might come from many places, including past advertising, friends, or the supermarket, but particularly from past consumption of the brand. Consumers who have tried the product should know of its existence and the search characteristics that are relevant to their utility function. In this case, such advertising would not affect experienced consumers. Of course, this advertising might not affect all inexperienced consumers—some may have learned from other sources and some might dislike the brand enough not to care. However, the point is that if advertising only informs consumers of existence and search characteristics, it should not affect the behavior of experienced users.[5]

□ **Information on experience characteristics.** Next consider advertising that informs consumers about a brand's experience characteristics. One possibility is that this is accomplished through explicit claims. Nelson (1974) argues that such claims, e.g., "this brand tastes good," should not affect rational consumers because they are not verifiable and their marginal cost is zero given that advertising space has already been purchased.[6] He proposes a second possibility, that expenditures on advertising might *implicitly signal* information about experience characteristics. In his intuitive analysis, and in the more formal models of Kihlstrom and Riordan (1984), Milgrom and Roberts (1986), and others, firms produce nondurables with different unobservable qualities and are able to advertise, although this advertising contains no explicit information on the firm's product. Equilibria are found where firms with higher-quality products advertise more and consumers justifiably react to this signal of higher quality.

Consider such an equilibrium where firms signal better quality or taste with high levels of advertising expenditures. First, suppose a consumer learns a brand's experience characteristics perfectly after one consumption experience. This might be true for food products where the primary experience characteristic is taste. In this case, advertising again should not affect the behavior of experienced users. They already know the brand's experience characteristics from past consumption. In contrast, inexperienced users *would* be affected by a brand's advertising level. High levels would increase the consumer's expected utility from consumption, low levels would decrease it.

Now suppose consumption provides imperfect information on a brand's experience characteristics. If a consumer tries a new pain reliever and his headache immediately goes away, it may be hard to ascertain whether the result was due to a short headache or an effective pain reliever. In contrast to the simple "one-period" learning process above, this suggests a more complicated learning process where consumers continue to learn on the second and subsequent consumption experiences.[7] Since now even experienced consumers do not know experience characteristics

[5] There are caveats. Search characteristics might change over time (e.g., price). Consumers might forget existence or characteristics. In empirical work it may be possible to rule out these caveats, particularly if we know things about a brand or its advertisements. For example, we seldom see price mentioned in television ads for foodstuffs.

[6] Nelson's argument concerns statements that tout experience characteristics (e.g., quality) that are unanimously preferred by consumers. If advertising touted experience characteristics that were liked by some consumers and disliked by others, e.g., "this brand is salty," credibility might be obtained. This would be analgous to providing information on search characteristics.

[7] The aforementioned signalling- equilibrium models use the simpler one-period learning process. Horstmann and MacDonald (1994) examine longer learning processes. Eckstein, Horsky, and Raban (1988), Erdem and Keane (1996),

completely, signalling advertising might affect them as well. But for most learning processes, the effect of advertising on a consumer's behavior should *decrease* in the number of previous consumption experiences. This is fairly intuitive; consumers who have consumed the brand more times should know more about its experience characteristics and be affected less by advertising that informs them about these characteristics.[8]

□ **Prestige and image effects.** Lastly, consider effects of advertising that, as in Becker and Murphy (1993), directly affect the utility a consumer derives from consuming the brand. Becker and Murphy suggest that this can occur through prestige effects, i.e., all else equal, a consumer might derive more utility from consuming a more-advertised good. It is also conceivable that consumers might derive utility (or disutility) from advertising content, e.g., images or personalities—perhaps because it is self-pleasing, perhaps because they want others to associate them with such content, or perhaps as part of some societal equilibrium in which people signal their interests and tastes by associating themselves with particular products. Becker and Murphy suggest thinking of these effects in a characteristics sense. Consumers, as well as having preferences for search and experience characteristics, have preferences for "advertising characteristics" such as how much the brand is advertised or the fact that hip twenty-somethings are in its ads.

I hypothesize that prestige or image effects of advertising should not depend on whether or not consumers are experienced. Although information on search and experience characteristics is gained through consumption, advertising characteristics are generally not. Thus, all else equal (in particular a consumer's preferences for images or prestige), I expect this type of advertising to affect the expected utility of inexperienced and experienced consumers equally. The general idea here is that if a consumer obtains an extra z utils from consuming a product associated with a particular image, seeing such an ad should increase the consumer's expected utility from consuming the product by z, regardless of whether he has purchased in the past.[9] Again, there are exceptions. Consumers might learn advertising characteristics from consumption. Products are sometimes labelled "as advertised on TV."[10] A brand's packaging might convey the images that are portrayed in advertisements. On the other hand, if the consumer is primarily concerned about whether other people (who may not have consumed the product) know the product is associated with an image or advertised heavily, this may not make a difference.

□ **Discussion.** This distinction makes for an interesting empirical application. By comparing the impact of advertising on inexperienced and experienced users, I can distinguish whether advertising provides information similar to that obtained from consumption, provides information different from that learned from consumption, or both. I have argued that this distinction relates very closely to the difference between "informative" and "prestige" influences of advertising. The approach is particularly interesting for examining advertising that primarily contains images. For example, the fact that Michael Jordan is in an ad could be consistent with all three of the above effects of advertising. His presence could attract attention to an ad, making consumers more likely to absorb information on existence or search characteristics. Or the fact that he is being paid tremendous sums of money to be in the ad could be part of a signalling argument, as

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and Ackerberg (1997) develop *nonequilibrium* consumer-learning models in which Bayesian updating is used to model longer these learning processes.

[8] For a more formal model of this effect, see Ackerberg (1997). There are also caveats to this argument. As with search characteristics, there is the possibility that consumers forget or that experience characteristics change. In some cases, experience characteristics might be hard to ascertain even after numerous consumption experiences (e.g., toothpaste).

[9] One counterexample is if prestige advertising interacts with *previous* purchases of the brand in the consumer's utility function (e.g., the consumer prefers a *more*-advertised brand *less* when he has purchased it *more* in the past). Although one might argue that the number of previous purchases affects the utility from consuming the product (e.g., habit formation), I can think of no obvious reason for such an interaction.

[10] This brings up a point relating to Nelson's signalling argument as well as to preferences for consuming more-advertised goods. In either case, its not clear why firms generally don't advertise how much they advertise. The answer is not so clear with signalling. In the preference case, one could argue that consumers are not accepting of this behavior.

signalling suggests that consumers should weight more-expensive advertisements more heavily. Lastly, consumers might simply obtain more utility from consuming a product that has Michael Jordan in its advertisements. My empirical approach can distinguish informative and prestige effects by comparing how advertising affects inexperienced users and experienced users.

Another point is that this approach avoids problems in defining what are inherent characteristics of a product. Taplin (1963) argued that the images of flowers in liquor advertisements may "get closer to the essential experience of consuming liquor than would a precise description of the alcoholic content" (Boyer, 1974). My approach can answer this question by asking whether such advertising affects experienced consumers.

Lastly, note that this is not the only conclusion on the qualitative effects of advertising that can be derived from analyzing consumer response to advertising. One could investigate whether consumers respond to the absolute number of advertisements they see or some measure of advertising intensity, e.g., advertisements divided by possible exposure time. If advertising primarily provides explicit information, consumer reaction would most likely be a function of the number of advertisements seen. A signalling effect would probably depend on intensity, as the consumer really wants to know how much the brand is spending on advertising.[11] Although these additional points are briefly discussed in my empirical work, I focus on the inexperienced-experienced distinction. One reason is that what is distinguished (inherent product information versus images or prestige) is more economically interesting. A second reason is that it is probably more robust to my particular dataset than the others.

3. The data

■ I use consumer-level panel data on grocery purchases and television advertising exposures to empirically examine the above arguments. These data, collected by A.C. Nielsen, are called "scanner data" because the grocery purchases were recorded by supermarket UPC scanners. In each of two geographic markets, Sioux Falls, South Dakota (SF) and Springfield, Missouri (SP), shopping trips and purchases of approximately 2,000 households in more than 80% of area drugstores and supermarkets were recorded over three years (1986–1988). There are also data on weekly prices, so it is possible to reconstruct the price situation on each household's shopping trips.[12] In addition, A.C. Nielsen TV meters were used to collect information on household TV advertising exposures for 50% of the households in the last year of the data. I thus know, along with when and what each household bought, when their television set was tuned to advertisements for each brand. These data have primarily been analyzed in the marketing literature with classical discrete-choice models (e.g., Gaudagni and Little, 1983; Pedrick and Zufryden; 1991) or Bayesian methods (e.g., Rossi, McCulloch, and Allenby, 1994; McCulloch and Rossi, 1994), allowing for varying degrees of consumer heterogeneity.[13] These studies usually measure an overall effect of advertising and do not distinguish different effects of advertising. As mentioned in the Introduction, Tellis (1988) and Deighton, Henderson, and Neslin (1994) contain the empirical specifications most similar to those used here.

The publicly available Nielsen data covers four product categories: ketchup, laundry detergent, soap, and yogurt. I choose to focus on the yogurt data for two reasons. First, although there is information on purchase amounts, i.e, how much of a brand a household buys on a shopping trip, I have chosen not to use it. Keeping things in a discrete-choice framework greatly simplifies the analysis. As a result, there is no way to account for household inventories or stockpiling behavior.

[11] Another distinguishing factor that might be exploited is heterogeneity in response to advertising. Since one does not observe all sources of consumer information, response to search characteristic information might be heterogeneous. Signalling effects might be more homogeneous.

[12] On a shopping trip where a consumer purchases a product, we observe the exact price of the transaction. A price file has been created (E. Kolaczyk) to compute prices on a consumer's shopping trips where a product wasn't purchased. This is done using other households' purchases at the same week in the same store (prices change weekly).

[13] There are also a number of articles (e.g., Bell, Chiang, and Padmanabhan (1999) and the references cited therein) that examine purchase amounts as well as brand choice.

TABLE 1 **Summary Statistics**

Variable	SF	SP
Households	950	825
Average shopping trips per household	70.58 (33.39)	65.82 (31.82)
Average price of Yoplait 150 (cents)	.645 (.060)	.663 (.079)
Shopping trips with Yoplait 150 purchase	302	656
Manufacturers' coupons redeemed for Yoplait 150	16	238
Shopping trips with other Yogurt purchase	5,432	3,863
Households trying Yoplait 150	123	184
Households trying other yogurts	648	512
Commercial exposures per household	13.60 (10.81)	15.22 (9.96)
Advertising share of Yoplait 150	.35	.37
Market share of Yoplait 150	.05	.14

Note: Standard deviations in parentheses.

Of the above products, yogurt is probably the least affected by this limitation. Its comparatively short shelf life (about 2–6 weeks) and comparatively high storage costs should prevent significant amounts of such behavior from occurring.[14]

A second reason is that the arguments of Section 3 rely crucially on a distinction between experienced and inexperienced consumers of a brand. Starting at an arbitrary point in a brand's lifetime would result in an initial condition problem—one would not know which households had experienced the brand beforehand. Using a newly introduced brand alleviates this problem, and the yogurt data had such a product, Yoplait 150.[15] My empirical work focuses on consumers' decisions whether to purchase Yoplait 150 and on how Yoplait 150 television advertisements affect these decisions.[16]

Yoplait, the second-largest yogurt manufacturer in the United States, introduced Yoplait 150 in April 1987, about 15 months before the end of the Nielsen data. It was Yoplait's first venture into the low-calorie, low-fat yogurt market (Jorgensen, 1994). Table 1 presents summary statistics for the data following the introduction.[17] Comparing advertising shares to market shares, the data suggest that Yoplait 150 was (at least initially) a heavily advertised yogurt. Note the large variation in the number of advertising exposures per household. The large difference in market shares between SF and SP may be due to the existence of two, high-share, local brands in SF and the large number of manufacturer's coupons that were available in SP. Figure 1 indicates, for the

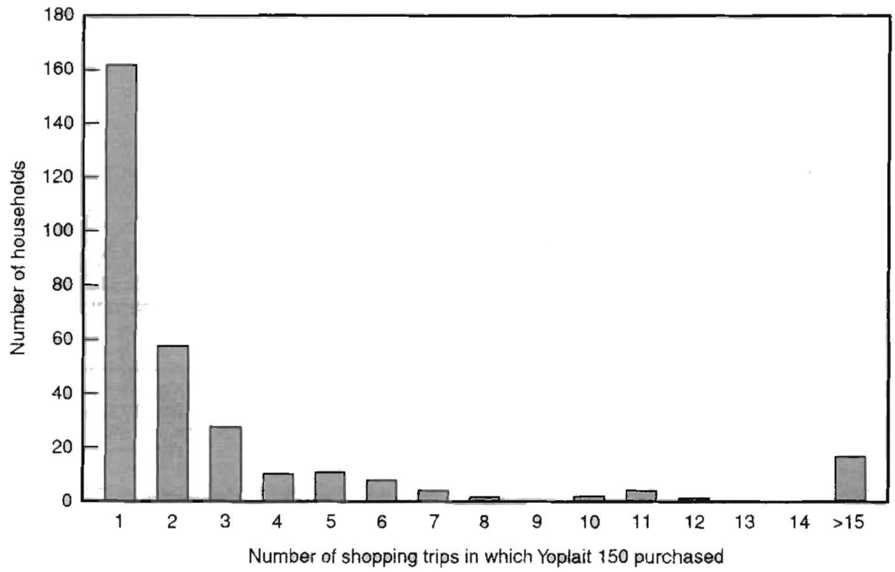
[14] Although its containers may be smaller than those of the other products, yogurt must be stored in the refrigerator, which probably has much higher storage costs per unit of volume than a closet or basement.

[15] Of course, there are other possible problems with prior-experience variables. We obviously cannot observe, for example, whether a consumer tried a brand at a friend's house, had it in a cafeteria, or purchased it at a supermarket that did not participate in the data collection.

[16] In some store-weeks there were no Yoplait 150 purchases by consumers in the sample. Prices for these store-weeks (33.2% of the sample) were imputed by prices at the same store in adjacent weeks or prices at other stores in the same chain, making measurement error a possibility. However, my focus is not on these price coefficients but on the effects of advertising.

[17] Only households whose television viewing was recorded are included both here and in estimation. I believe that this was a randomly selected group from the total sample of households.

FIGURE 1



307 households that purchased Yoplait 150, the number of shopping trips in which the brand was purchased. Because most households purchased the product only once, there is not a large amount of data on multiple purchasers.

Figure 2 displays time series of weekly market shares, prices, and advertising for each market. Table 2 exhibits some current and lagged correlations of these series. Market share is the percentage of shopping trips in that week in which at least one unit of Yoplait 150 was purchased. Weekly price is the average price over all consumer shopping trips in that week. Advertising is the total number of 30-second ads for Yoplait 150 observed by consumers in that week. There is a strong correlation between price and market share and serial correlation in price and advertising.

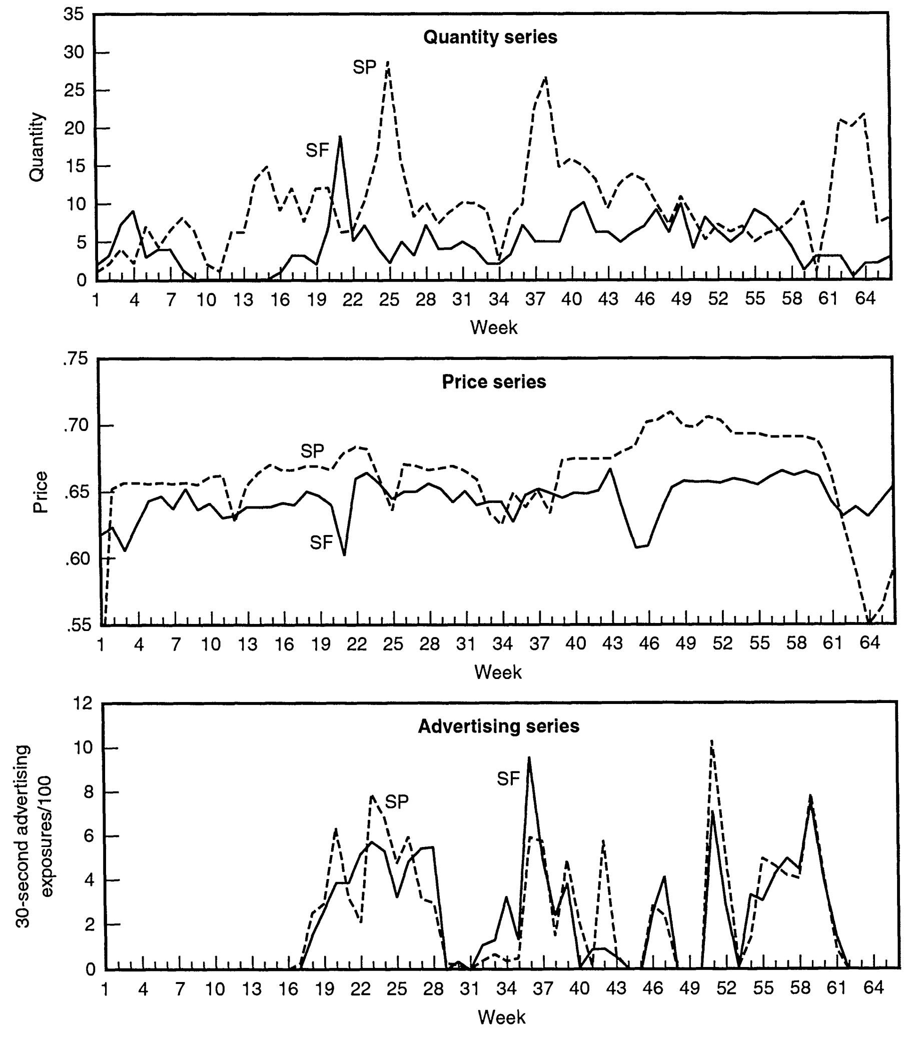
There are two notable data problems. One is the existence of manufacturer's coupons, usually distributed in newspaper pullouts or mailings. One would like to know whether or not a consumer had access to a coupon for Yoplait 150 on a particular shopping trip. Unfortunately, only redeemed manufacturer's coupons are observed, i.e., conditional on a purchase being made. This prevents its

TABLE 2 **Weekly Correlations**

Variable	SF	SP
p_t, q_t	$-.326^{**}$	$-.499^{**}$
p_t, a_t	.106	$.285^{*}$
q_t, a_t	.122	.030
q_t, a_{t-1}	.028	.194
p_t, p_{t-1}	$.274^{*}$	$.744^{**}$
p_t, a_{t-1}	.141	.249
a_t, p_{t-1}	.216	.216
a_t, a_{t-1}	$.486^{**}$	$.387^{**}$

Note: **.01 significance, *.05 significance.

FIGURE 2

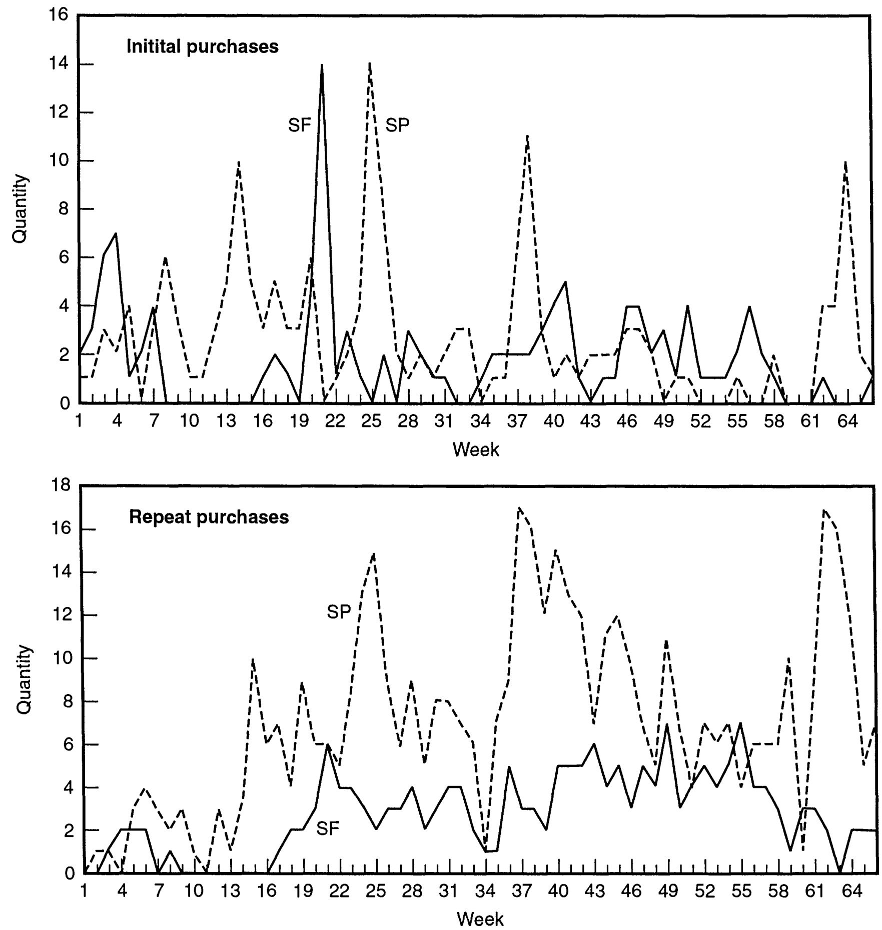


straightforward use as an explanatory variable because of its correlation with any unobservables that influence purchases. Because the data indicate that manufacturer's coupons were much more prevalent in SF than in SP, I use a market dummy as a proxy for the availability of manufacturer's coupons. Such problems are not expected with store coupons, as they are typically available and announced at the point of purchase. During weeks where store coupons were available at a particular store, virtually every consumer who purchased the product used the store coupon. I assume all consumers in the store that week were making decisions based on the store coupon value.[18]

Another problem is that TV advertising exposures are only measured in the last year of the Nielsen study. This leaves about three months during which Yoplait 150 was on the market but advertising was not measured (up to week 13 on Figure 2). This was another motivation for the choice of Yoplait 150, as it minimized the period in which advertising is not observed. I generally assume zero advertising exposures for this period. Justification for this is that for three weeks after TV measurement started, there were no Yoplait 150 advertisements observed (up to week

[18] However, since the data do not reveal the exact nature of the store coupons (e.g., \$.50 off one purchase, \$.50 off two purchases), *Store Coupon* is included as a separate explanatory variable, not subtracted off price.

FIGURE 3



16). This may indicate that Yoplait did not start advertising the product until this time—perhaps waiting until the product was distributed nationally.[19]

Figure 3 divides the quantity series of Figure 2 into initial purchases (purchases by inexperienced consumers) and repeat purchases (purchases by experienced consumers). These time series allow for a simple first look at my identification hypothesis. Table 3 presents results from separate OLS regressions of daily initial purchases and daily repeat purchases (the unit of observation is a day) on a market dummy, time trend, average price (across all shopping trips in that day), and number of recent advertising exposures (in the past four days).[20] As these aggregates ignore a significant source of variation (i.e., across households) to identify the effects of advertising, it is surprising that the coefficients measuring advertising's effect on initial purchases are significantly positive in all but one of the different specifications. On the other hand, the effect of advertising on repeat purchases is rarely significant, and the magnitude of the coefficient is usually less than

[19] Another problem is that the Nielsen TV meters were not particularly reliable. For a few households, there are significant TV viewing gaps. To ameliorate this problem, households with very large viewing gaps (>100 days) were eliminated from the study. Also, the advertising variables are usually defined as the number of Yoplait 150 advertising exposures per TV watching hour.

[20] I am not suggesting that only recent advertising exposures affect individual behavior. The problem with a lengthier lag is that past advertising generates past initial purchases, which generate current repeat purchases. This could be solved by including a measure of the number of inexperienced users, but given apparent serial correlation, this would lead to endogeneity problems.

TABLE 3 **OLS Regressions**

	Dependent Variable: Initial Purchases				Dependent Variable: Repeat Purchases			
	1	2	3	4	1	2	3	4
N	918	918	678	918	918	918	678	918
R^2	.066	.085	.107	.066	.162	.149	.120	.162
Market	.222	.002	.224	.223	.700	.006	.832	.700
Dummy	(.062)	(.000)	(.069)	(.062)	(.089)	(.000)	(.111)	(.089)
Price	−5.298	−.038	−7.388	−5.354	−3.954	−.029	−5.512	−3.942
	(1.568)	(.013)	(1.726)	(1.585)	(1.829)	(.014)	(2.207)	(1.838)
Ads	.044	.030	.042	.044	.020	.014	.014	.016
	(.022)	(.015)	(.021)	(.022)	(.023)	(.017)	(.024)	(.024)
t-value	1.981	1.925	2.046	1.988	.873	.818	.596	.679

Notes: Unit of observation is a market day. Constant term and third-order polynomial in time not reported. SEs corrected for serial correlation using Newey-West.

Specifications: Column 2 uses market shares (quantity/shopping trips) as dependent variables (Ads coef $*$ 100); column 3 eliminates data when advertisements not observed (first three months); column 4 uses mean advertising level for first three months.

half that in the initial purchase regression.[21] The last two columns attempt simple adjustments for the missing advertising data, and the results don't change significantly. Though these results suggest that these advertisements primarily affected inexperienced consumers, there are enough potential problems—endogeneity of prices (probably not advertising, since it is decided nationally) or missing lagged endogenous variables[22]—that I hesitate to make any strong conclusions, instead moving to more fully exploit a consumer-choice model and the panel nature of the data.

4. The empirical model

■ Recalling the arguments of Section 3, I want to compare the effects of Yoplait 150 advertising on the behavior of inexperienced and experienced users of the brand. There are at least two possibilities at this point. The first is to posit a fully structural model of optimal consumer behavior. In the case where consumers are learning from past consumption or advertising, this can get complicated, even for simple utility-function specifications (e.g., Erdem and Keane, 1996; Ackerberg, 1997). Alternatively, one can estimate a reduced-form representation of the discrete decision whether or not to purchase Yoplait 150. I consider the following model:

$$c_{it} = \begin{cases} 1 & \text{iff } X_{it}\beta_1 - \gamma p_{it} + \epsilon_{1it} > Z_{it}\beta_2 + \epsilon_{2it} \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

[21] This is even though the mean of initial purchases is less than half the mean of repeat purchases. There is even more disparity when one does the regression in logs (adjusting for zeros) to get percentage changes. I have also estimated specifications with "day of the week" dummies and obtained similar results.

[22] In addition, unlike the discrete-choice models of the next section, this does not explicitly condition on consumers' purchase probabilities. Suppose experienced consumers have expected utilities significantly above price, while inexperienced consumers' expected utilities are right below price. A burst of prestige advertising induces many inexperienced consumers to start buying but doesn't affect purchase behavior of experienced consumers (they already purchase).

where c_{it} indicates whether consumer i purchased Yoplait 150 on shopping trip t.[23] If one were not worried about dynamic behavior on the part of consumers, $(X_{it}\beta_1 - \gamma p_{it} + \epsilon_{1it})$ might be interpreted as the expected net utility from purchasing and consuming Yoplait 150. If one does want to allow for dynamics, it can be thought of as a reduced-form approximation to the value function (i.e., the PDV of future utilities) conditional on purchasing Yoplait 150. Similarly, $(Z_{it}\beta_2 + \epsilon_{2it})$ is the expected value of (or the value function conditional on) purchasing either another brand or no yogurt.

The observables X_{it} contain variables such as *Advertising*,[24] household and consumer characteristics (e.g., *Income*, a categorical variable ranging from 1 to 14, *Family Size*, and a *Market Dummy* (= 1 for SP)), functions of a household's previous purchases of Yoplait 150 (*Number of Previous Purchases, Never Previously Purchased, Once Previously Purchased, Days Since Last Purchase*, and *Purchased Last Shopping Trip*), *Store Coupon*, and a *Time Trend*. The *Time Trend* and functions of previous Yoplait 150 purchases are included in X_{it} to (1) better approximate the value function or (2) allow for habit persistence. p_{it} is the *Price* (in \$) of Yoplait 150 faced by consumer i on shopping trip t, while Z_{it} contains an index of the prices of other yogurts (*Competitors Prices*[25]). Unobservables ϵ_{1it} and ϵ_{2it} allow for idiosyncratic, time-specific shocks a consumer's behavior that are known to the consumer but not to the econometrician. Table 4 contains descriptive statistics of the observables.

Lastly, since I am particularly interested in looking for a differential effect of advertising on the behavior of experienced and inexperienced consumers, I allow cross-partials between a consumer's advertising exposures and his previous purchases of Yoplait 150 by including *interactions* between *Advertising* and previous purchases in X_{it}. (1) is a standard binary choice model. Assuming the ϵ's are Type 1 Extreme Value deviates that are independent of (X_{it}, p_{it}, Z_{it})[26] results in a binary logit model. Given data on multiple shopping trips for each consumer, this iid assumption might be extreme. One could imagine consumers having unobserved preferences for Yoplait 150 or yogurt that persist over time. I allow for such persistent unobservables α_i, i.e.,

$$c_{it} = 1 \qquad \text{iff } \alpha_i + X_{it}\beta_1 - \gamma p_{it} + \epsilon_{1it} > Z_{it}\beta_2 + \epsilon_{2it},$$

and treat them as random effects by specifying a parameterized distribution and integrating out choice probabilities over this distribution.[27,28] The random effects will be correlated with the lagged endogenous variables (e.g., number of previous Yoplait 150 purchases) that are included as explanatory variables. Thus, the likelihood of observing a given household's data needs to be computed by integrating the probability of the household's entire purchase *sequence* over the

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[23] There are potential problems with this definition of a purchase occasion. For example, one can't be sure that consumers had the opportunity to purchase on each shopping trip. In response, I eliminated shopping trips at stores that did not sell Yoplait 150 and those in which a consumer spent less than \$10 (and did not buy yogurt).

[24] Because of the short time period of the data and because nothing suggested otherwise, I started by defining *Advertising* as the unweighted average of a household's past advertising intensities (i.e., the total Yoplait 150 advertisements seen up to t/the total hours of television watched up to t). Results are robust to weighting recently seen advertisements more and to using the absolute number of ads observed rather than the intensity measure.

[25] This variable is defined as $\min_j\{(p_{jt} - \overline{p_j})/\overline{p_j}\}$, the minimum percentage deviation from average price on a given household's shopping trip, where j indexes the other brands of yogurt. I tried alternative measures, such as the exact prices of low-fat yogurts, i.e., Yoplait 150's likely strongest competitors. Using the above index had the best predictive power.

[26] My primary concern with regard to this assumption is endogenous supermarket (or shopping time) choice, e.g., a consumer with a high ϵ_{1it} draw searching out a supermarket with a low price of Yoplait 150. I think that the small share of yogurt in shoppers' overall budgets prevents significant amounts of such behavior. If not, the primary biases would likely be on the price coefficients (making them stronger).

[27] If computation were not an issue, I could explicitly model choices of the other yogurts. I have estimated three choice models where the consumer chooses between Yoplait 150, another brand of yogurt, or nothing. In these models I allow for two persistent unobservables, one general taste for yogurt and one specific taste for Yoplait 150. Very similar results were obtained.

[28] Another option is Chamberlain's (1980) conditional logit, but this method is not computationally feasible given the length of the data. Linear probability models (where one can difference out α_i) are also attempted. But in this case one must instrument for the lagged endogenous variables, and I had trouble finding reasonably efficient instruments.

TABLE 4 **Explanatory Variable Descriptive Statistics**

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Advertising	121,359	.0544	.0605	.0000	.8333
Price	121,359	.6528	.0702	.2000	.7900
Store coupon	121,359	.0014	.0284	.0000	.6700
Competitor's prices	121,359	−.1695	.1623	−.6859	.0838
Number of previous purchases	121,359	.3144	1.6251	.0000	42.0000
Dummy—never previously purchased	121,359	.8830	.3215	.0000	1.0000
Dummy—once previously purchased	121,359	.0679	.2516	.0000	1.0000
Days since last purchase (0 if never)	121,359	13.1016	49.0667	.0000	472.0000
Time trend	121,359	.5550	.2592	.0143	1.0000
Dummy—purchased last shopping trip	121,359	.0078	.0879	.0000	1.0000
Dummy—market	1,775	.4648	.4989	.0000	1.0000
Income Classification	1,775	6.3673	2.8564	1.0000	14.0000
Family size	1,775	2.8310	1.3433	1.0000	8.0000
Presample yogurt purchases	1,775	14.1132	26.6221	.0000	355.0000
Presample regular Yoplait purchases	1,775	3.4980	10.8332	.0000	170.0000
Presample low-fat yogurt purchases	1,775	7.8214	16.0411	.0000	212.0000

Note: First 10 variables vary by Household-Shopping Trip, last 6 vary across households.

distribution ($f(d\alpha_i \mid \theta)$) of this random effect. The likelihood function for household i is

$$\begin{aligned} L_i(\theta) &= \Pr\left[c_{i1}, \ldots, c_{iT_i} \mid W_i^t, Z_i^t, p_i^t; \theta\right] \\ &= \int \Pr\left[c_{i1}, \ldots, c_{iT_i} \mid W_i^t, Z_i^t, p_i^t, \alpha_i; \theta\right] f(d\alpha_i \mid \theta) \\ &= \int \prod_{t=1}^{T_i} \Pr\left[c_{it} \mid X_{it}(c_i^{t-1}), Z_{it}, p_{it}, \alpha_i; \theta\right] f(d\alpha_i \mid \theta), \end{aligned}$$

where superscripts represent histories, T_i is the number of shopping trips of consumer i, W_i^t is the subset of the explanatory variables X_{it} that is completely exogenous, and θ is a vector of all parameters to be estimated (including β_1, β_2, γ, and the parameters of the α_i distribution). Pr[$\cdot$] is defined by the assumption on the ϵ's, and $X_{it}(c_i^{t-1})$ explicitly writes the explanatory variables as depending on previous choices. As there is data from Yoplait 150's introduction, initial conditions on the lagged endogenous variables are deterministic and known (i.e., previous purchases = 0), so there is no problem of their being correlated with this random effect.

5. Econometric results

■ Table 5 presents empirical results. The first and third columns contain maximum-likelihood estimates of standard logit models with no persistent, household-specific, random effect. In the

TABLE 5 **Estimates**

Parameter	Simple Logit	Normal Random Effect	Simple Logit	Normal Random Effect	Flexible Ad Coefs	.5 Logit	With Mean Advertising	Extra Promotional Variables
Advertising *	2.04073	2.30566	—	—	2.32360	—	—	—
Inexperienced	(.72313)	(.77561)			(.78683)			
Advertising *	.90371	.43304	—	—	1.33200	—	—	—
Experienced	(.63504)	(1.21180)			(1.39850)			
t-statistic on diffference	1.47662	1.58703	—	—	—	—	—	—
Advertising	—	—	1.71550	2.01370	—	2.10570	1.73080	2.40619
			(.76392)	(.79037)		(.85627)	(.82047)	(.89738)
Advertising *	—	—	−.14812	−.35627	−.29487	−.27106	−.35253	−.39207
Num prev pur			(.06282)	(.10803)	(.12079)	(.14411)	(.10904)	(.11248)
Mean	—	—	—	—	—	—	2.48400	—
ads							(2.40050)	
Own price	−4.89980	−5.58440	−4.89500	−5.61630	−5.61890	−7.21680	−5.60710	−5.02189
	(.33114)	(.34993)	(.33501)	(.35604)	(.35541)	(.43486)	(.35583)	(.38633)
Store	2.72990	2.88690	2.73590	2.87050	2.88770	3.23160	2.88460	2.91887
coupon	(.74368)	(.85073)	(.74214)	(.85707)	(.85558)	(.95421)	(.86097)	(.86565)
Competitor	.76070	.76116	.76215	.76848	.76809	1.00150	.76963	.63461
price	(.19214)	(.21745)	(.19180)	(.21904)	(.21889)	(.24940)	(.21953)	(.23211)
Number prev	.10810	−.26717	.10314	−.27046	−.27303	−.55373	−.27129	−.27843
purchases	(.06370)	(.09312)	(.06227)	(.09152)	(.09235)	(.15038)	(.09161)	(.09715)
Number prev	−.00360	.00085	−.00340	.00110	.00117	.00019	.00119	.00130
purchases^2	(.00053)	(.00096)	(.00057)	(.00099)	(.00099)	(.00124)	(.00099)	(.00106)
Never	−2.78400	−.81135	−2.72150	−.58661	−.70453	−.22113	−.655 61	−.59998
purchased	(.11685)	(.22343)	(.11042)	(.21866)	(.22804)	(.29160)	(.21907)	(.22796)
Once	−.59088	−.08104	−.59857	.00169	−.06915	.11842	−.07050	−.03513
purchased	(.11515)	(.15986)	(.11430)	(.16046)	(.16103)	(.18864)	(.16181)	(.16683)
Prev purch/	.84429	.46907	.84135	.46784	.46557	0.85689	0.46457	0.46080
time	(.08562)	(.10757)	(.08571)	(.10882)	(.10903)	(.16457)	(.10940)	(.11785)
Purchased	.17144	.47774	.19047	.51778	.51009	1.12970	.51200	.51312
last s. trip	(.10042)	(.15667)	(.09691)	(.15421)	(.15550)	(.28121)	(.15559)	(.16910)
Days since	−.00577	−.00487	−.00582	−.00511	−.00499	−.00470	−.00504	−.00552
last purch	(.00072)	(.00091)	(.00073)	(.00092)	(.00092)	(.00103)	(.00092)	(.00096)
Time trend	−1.65580	−.36393	−1.64200	−.26339	−.30594	−.19387	−.28784	−.01729
	(.17406)	(.26303)	(.17325)	(.27417)	(.27314)	(.30920)	(.27332)	(.29203)
Constant	.27671	−3.83780	.22409	−4.18620	−4.03510	−3.05580	−4.26380	−4.32983
	(.29693)	(.60556)	(.29907)	(.62472)	(.62341)	(.72518)	(.64286)	(.68434)
Market	.60162	1.44070	.60805	1.48240	1.47340	1.51620	1.47950	1.48370
dummy	(.06177)	(.17311)	(.06305)	(.17744)	(.17654)	(.19088)	(.17636)	(.18329)
Income	.05070	.06871	.05235	.06952	.06907	.08332	.07173	.08032
	(.01344)	(.03118)	(.01334)	(.03210)	(.03209)	(.03267)	(.03171)	(.03123)
Family	−.00719	−.06382	−.01268	−.06363	−.06352	−.07723	−.05176	−.06171
size	(.02568)	(.06886)	(.02715)	(.07127)	(.07086)	(.07293)	(.07264)	(.07872)
On display	—	—	—	—	—	—	—	1.59054
								(.48198)
On display *	—	—	—	—	—	—	—	.02305
Num prev purchase								(.19642)
In circular	—	—	—	—	—	—	—	1.48767
								(.17613)
In circular *	—	—	—	—	—	—	—	−.04596
Num prev purchase								(.04516)
Ads * Num	—	—	—	—	—	—	—	−14.23809
presample purchase								(2.69371)
Random effect	—	1.72610	—	1.80080	1.78410	1.88010	1.77310	1.81363
Standard Deviation		(.14227)		(.14951)	(.14754)	(.18230)	(.15277)	(.15305)
Presample	N	Y	N	Y	Y	Y	Y	Y
purchase variables								
Ln Likelihood	−4090.4248	−3919.6631	−4090.2372	−3918.8530	−3918.4795	−3906.0805	−3918.0326	−3865.1329

Note: Standard errors in parentheses.

second and fourth columns, I allow for a normally distributed random effect.[29] Some additional data are used to "predict" more of this random effect. Specifically, I use information on a household's yogurt, low-fat yogurt, and regular Yoplait purchases in the two years of data *prior* to Yoplait 150's introduction on the market. I assume that this "presample" information is exogenous to the model. As evidenced by the increase in likelihood values, there is strong support for the random effect.[30] The coefficients on the non-advertising-related variables, in particular *Price*, *Store Coupon*, and *Competitors Prices*, seem fairly robust across the models except for the simple logits.

The first and second columns in Table 5 differ from the third and fourth columns in their specification of the interaction between a household's number of previous Yoplait 150 purchases and *Advertising*. In the first two columns, I estimate separate effects of advertising on inexperienced and experienced consumers. This assumes that advertising affects all experienced consumers equally, regardless of the number of times they have purchased in the past. This specification corresponds to the case where all the brand's experience characteristics are completely learned after one consumption. The coefficient on *Advertising* $*$ *Experienced* can be interpreted as measuring image and prestige effects of advertising, while the difference between the two coefficients (*Advertising* $*$ *Inexperienced* $-$ *Advertising* $*$ *Experienced*) measures the informative effects of advertising. In both specifications, the estimate of advertising's effect on inexperienced consumers is positive and significant. Although also positive, the estimate of advertising's effect on experienced consumers is relatively close to zero and insignificant. While there is generally a high standard error on the experienced coefficient, high positive correlation between the estimates give t-statistics on the difference between the two coefficients around 1.5. The results support the hypothesis that these advertisements primarily provided information to consumers on inherent product characteristics.

The economic significance of these advertising coefficients seems reasonable. In the second column of estimates, an additional 30-second commercial every week for the average inexperienced household (26 hours of TV/week) has the same effect on purchase probability as a 10-cent price decrease. On the other hand, since the average advertising intensity is only one commercial every four weeks, a doubling of advertising at the mean has the same effect as only a 2.5-cent price decrease. Simulations using these point estimates indicate that the advertising elasticity of demand for Yoplait 150 is about .15. This is consistent with a static, single-product firm, advertising and price-setting model where a positive profit condition implies that this elasticity must be less than unity. Using the same first-order conditions, the simulated price elasticity of 2.8 corresponds to a 35% markup and implies that advertising expenditures are 5% of total revenue.[31]

In columns 3 and 4, I allow the effect of advertising to change linearly in the number of previous purchases of Yoplait 150.[32] This functional form corresponds to a model where consumers continue to learn about experience characteristics after the first consumption experience. In this case I argued that effects of advertising that inform consumers of experience characteristics should decline in the number of previous consumption experiences. In both sets of estimates, I obtain a positive, significant coefficient on the *Advertising* term, measuring the effect of advertising on inexperienced consumers. The estimated interactive coefficient is significantly negative in all cases, indicating that the marginal effect of advertising is going down as a consumer's number of previous purchases increases. These slope coefficients are generally large, indicating that the effect of advertising is going down quickly. I would expect such a result with yogurt, where consumers

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[29] Given that the unobserved heterogeneity is only one-dimensional, I assume a 101-point discretized normal distribution as an alternative to dealing with simulation and simulation error.

[30] Estimates of the coefficients on the presample data are not presented due to space considerations.

[31] This seems to be a reasonable result. According to *Advertising Age*, in 1988 total Yoplait advertising expenditures were about 7% of total sales. Note, however, that because I do not model purchase amounts, these elasticities are not necessarily the elasticity of total quantity (units) purchased. Also note that the first-order conditions assume single-product firms, which is not the case in this industry.

[32] This is measured as the number of shopping trips on which any number of units of Yoplait 150 was purchased.

should be learning experience characteristics quickly through consumption. Optimally, one would want to find an asymptote of the effect of advertising in the number of previous purchases. This asymptote would measure the image and prestige effects of advertising. Unfortunately, richer functional forms allowing for such an asymptote haven't resulted in very precise results, probably due to the lack of data on very experienced consumers. Column 5 estimates a slightly richer specification with a separate effect of advertising on inexperienced users as well as a slope term for experienced users. This slope term is still significantly negative, indicating that the original negative slope coefficient is not completely driven by the difference between having zero or one previous purchases.

□ **Robustness checks.** The last three columns of Table 5 present some additional results that give a brief indication of the robustness of this differential effect of advertising. Column 6 addresses a characteristic of standard logit and probit models that the map from observables (i.e., $X_{it}\beta_1 - \gamma p_{it} - Z_{it}\beta_2$) into purchase probabilities has its maximum derivative when the purchase probability is .5. This means that the consumers affected most (in terms of probability) by advertising are those whose purchase probability is .5. Any sort of durability or inventory behavior might call this into question because, for example, a consumer purchasing every other shopping trip (i.e., with .5 probability) could be at a "limit" in terms of consumption. In a standard logit or probit model, such "saturation" doesn't occur until the probability of purchase approaches one, something that is clearly not happening much in the data. As a simple check of robustness, I assume that the distribution of $\epsilon_{1it} - \epsilon_{2it}$ has a mass of .5 on $-\infty$ but is proportional to a logistic distribution on the rest of its support. This quasi-logit model has a maximum probability of purchase of .5 and a maximum derivative at .25. The estimates again show a significant differential effect of advertising, although overall advertising elasticities in this model are slightly smaller. Note that the likelihood is quite a bit higher in this model.

Column 7 addresses a potential endogeneity problem due to an advertiser's ability to choose when and where to advertise. If advertisers know information about consumers' α_is that I don't[33] and aim advertising toward consumers with high α_is, the advertising variables will be correlated with the random effect. In a manner similar to Mundlak (1978), (though without his robustness to alternative functional forms because of the nonlinearity of the model), I address this by including consumer i's mean advertising intensity over the entire sample as a predictor of α_i. Although positive and fairly large, the coefficient is not significant and does not affect the other advertising coefficients by much. It does at least suggest, however, that advertisers might be succeeding in aiming advertising toward consumers who like the brand.

The last column adds some additional promotional variables to the specification. *On Display* is a dummy variable taking the value of 1 if Yoplait 150 was in a special display in a given store in a given week. *In Circular* equals 1 if Yoplait 150 was featured in a store circular or advertisement. As one might expect, both these promotional variables enter positively and significantly. Unlike the television advertising variable, however, these variables don't seem to interact with the number of previous Yoplait 150 purchases. Recalling some of the caveats of Section 2, perhaps this is because in contrast to television advertising, these promotions typically "advertise" a new sale price, which might be new information for all types of consumers. Column 8 also interacts the regular advertising variable with a dummy variable indicating that a family *never* purchased *any* brand of yogurt in the presample period. The strong negative coefficient suggests that these households are not affected by Yoplait 150 advertising. Apparently, those affected most by television advertising are those who are inexperienced with Yoplait 150 but who do buy yogurt in general.[34]

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[33] "What I know" is this linear combination of variables that I am using to predict α_i. Additional information known by advertisers could, in particular, come from datasets such as this (e.g., whether consumers who watch Seinfeld also like yogurt).

[34] The results were robust to a number of other perturbations such as a probit model, weighting recently seen advertisements more, and using the absolute number of ads observed or ads per calender time rather than our advertising intensity variable. These results are reported in Ackerberg (1997).

6. Conclusions

■ I believe that these are strong and interesting empirical results. I have argued that advertising that provides information on inherent brand characteristics should primarily affect inexperienced consumers of a brand, while advertising that creates prestige or association should affect both inexperienced and experienced consumers. The data indicate a significant effect of advertising on inexperienced consumers and either an insignificant or declining effect on experienced consumers. I conclude that these Yoplait 150 advertisements were influencing consumer behavior primarily by informing them about search and experience characteristics, not by creating prestige or associating the product with favorable images.

This approach to distinguishing informative and prestige effects of advertising is one that can fairly easily be applied to other products or industries. I make a couple of additional notes. First, the explicit linking of a household's grocery purchases to its television advertising exposures is not a necessity for this analysis. As long as one has significant (and frequent, e.g., weekly) time-series variation in advertising expenditures, one could distinguish these effects by treating household-level exposures as unobservables distributed around weekly expenditures. Perhaps a more significant problem if one is analyzing established products is the presence of initial-condition problems regarding a consumer's past experiences with a product. One solution, given a long-enough panel, would be to treat consumers who haven't purchased a product in a long time as experienced. Another would be to use more sophisticated econometric techniques to deal with the initial-condition problems. It should prove interesting to compare results across different industries and products, and as noted in the Introduction, I believe that such analyses should make valuable contributions to policy work.

Regarding the current results, a significant amount of experimentation has shown this differential effect of advertising to be very robust over this type of model (i.e., reduced form, discrete choice). However, this does not mean that there are not possible problems. A first problem is that if one believes consumers dynamically optimize, these reduced-form models rely on an approximation to optimal dynamic decision rules. The quality of the results is only as good as the quality of this approximation. A second problem with these reduced-form models is that they are unable to explicitly help answer important welfare questions about advertising. The fact that advertising primarily provides product information brings up many questions about its effects on the functioning of this market. First, one would like to assess the value of the information contained in this advertising and compare it to the resources spent by the economy on advertising. Second, one might want to assess the impact of advertising on variables such as pricing, entry, and innovation in this industry. If this result applies to all yogurt advertising, it may suggest that advertising facilitates rather than prevents entry and innovation in the yogurt industry. Perhaps, for example, in comparison to another industry where advertising creates long-lived prestige effects that act as entry barriers, antitrust policy should be more lenient, all else equal, toward the yogurt industry. Unfortunately, one cannot formalize such arguments without more rigorous study of the information structure of the market and firm behavior under this structure.

The above problems point to an obvious next step. My argument is an informational one, and I expect advantages to explicitly modelling such information. What I am suggesting is a structural approach to this problem, one in which primitives such as utility functions and information structure are modelled and estimated. As noted above, when a consumer's current decision affects future states of knowledge, optimal consumer behavior implies a dynamic optimization problem. Although better able to deal with the above issues, such an approach also has problems. In particular, computational issues become more significant, requiring stricter assumptions and reducing the ability to examine different functional forms or specifications. I therefore consider such an approach not a replacement of but an interesting complement to the present one.

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