Empirically Distinguishing Informative and Prestige Effects of Advertising

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Abstract

This paper introduces techniques to empirically distinguish different effects of brand advertising in non-durable, experience goods markets. We argue that advertisements which provide consumers with product information should primarily affect consumers who have never tried the brand, while advertisements that create prestige or image effects should affect both inexperienced and experienced users. We apply this argument to consumer level data on purchases of a newly introduced brand of Yogurt. Empirical results from a series of discrete choice models allowing for consumer heterogeneity robustly indicate that the advertisements for this brand primarily affected inexperienced users of the brand. We conclude that the primary effects of these advertisements were that of informing consumers.

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0.1 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 must stimulate demand for the product. Otherwise, Molson would not be spending money on them. What is not clear is how such advertisements might 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 paper empirically addresses.

Theoretical work on advertising has long been concerned with different influences of advertising on consumer behavior. Marshall (1919) praised "constructive" advertising, which he described as advertising that conveys economically relevant information to the consumer. On the other hand, he termed the "incessant iteration of the name of a product" as "combative" advertising, and extolled the "social waste" of engaging in 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 models in which firms send out advertising messages that explicitly inform consumers of their product's existence or characteristics. Nelson (1974), Milgrom and Roberts (1986), and others have looked at 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 in equilibrium to implicitly signal their value to consumers. It is interesting to note that 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 may interact in a consumer's utility function with consumption of that brand. In the case where a brand's advertising level interacts positively with consumption, consuming a more advertised good, all else constant, provides more utility to the consumer. This provides a way of modeling the ideas behind Marshall's "combative" advertising or Galbraith's (1958) "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 it is obvious that knowledge of the process or 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 purely provide information on product existence and characteristics. Similarly, the fact that most individuals know of and have tasted Coca-Cola suggests that these advertisements are not providing information on the product's inherent physical characteristics. Perhaps these advertisements are affecting consumers 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.

While the general process by which advertising affects consumers in these two extreme cases may be somewhat obvious, this is certainly not true in general. For many advertisements it is likely that some combination of the above and perhaps other effects are working to influence consumer behavior. Measuring the existence and extent of such effects is an empirical problem, one that

[1]Below we describe these effects as changing consumers' preferences over *products*. This terminology may be a little loose for Becker, Stigler, and Murphy's liking, as one of the main points of their papers is that such effects can (and should) be modeled without a consumer's preferences changing. When we use this terminology, we do not mean that advertising is changing a consumer's underlying preferences (which are defined over both products and advertising for products). We do mean that it is changing the utility derived from consuming a particular product.

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 (for examples see Schmalensee (1972), Roberts and Samuelson (1988) in the Economics literature, Guadagni and Little (1983), Erdem and Keane (1996) in the Marketing literature). The few studies that have attempted to answer more qualitative questions about advertising for consumer non-durables have either 1) looked at cross-industry data (Telser (1964), Boyer (1974)), 2) related advertising levels to product quality (Archibald, Halman, and Moody (1983) and 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)).[2]

This paper introduces an alternative strategy for distinguishing and measuring informative and prestige effects of advertising in consumer goods markets. This method capitalizes on the recent advent of panel data following household grocery purchases and advertising exposures over time. The distinction is made by assessing consumer response to advertising. Specifically, we argue that advertising which informs consumers of a brand's inherent characteristics should relatively affect inexperienced consumers, those who have not purchased the brand in the past. On the other hand, we posit that prestige or image effects of advertising should affect both inexperienced and experienced consumers more equally. Two papers in the marketing literature, Tellis (1998) and Deighton,

[2]Telser and Boyer relate measures of competition to advertising across industries under the general assumption that advertising providing product information should be associated with more competitive markets than advertising that influences consumers through images or prestige. Both find evidence of informative effects of advertising. While very interesting, one important drawback of these cross-industry studies is that they only provide relative conclusions across industries and cannot explicitly differentiate effects of advertising for a given industry or product. In addition, there are clearly endogeneity problems. Archibald, Halman, and Moody and Tellis and Fornell both find positive association between advertising for a brand and the overall quality of that brand. They note that this association strengthens when consumers in the industry become more informed. Although these results suggest that advertising is providing information, they cannot explicitly rule out prestige or image effects. Resnik and Stern examine the content of network television advertisements and find them to be primarily image oriented, with explicit information about a product in only about 50% of the commercials. While these results are interesting, theory suggests that examining advertising content is an inherently flawed approach to distinguishing the afore-mentioned effects of advertising. Advertisements need not contain explicit information to inform consumers of a product's existence or to signal information to consumers. There is also an interesting literature on effects of advertising in health-related markets. Leffler (1981) and Hurwitz and Caves (1988) look at market shares, advertising rates, and generic entry across prescription drugs to distinguish information versus "persuasion".

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 our inexperienced vs. experienced distinction)[3].

In our empirical work, we analyze data on a newly introduced brand of yogurt. Using standard panel discrete choice models allowing for persistent consumer heterogeneity, we find that holding all else equal, the advertisements in our data affect inexperienced consumers more than experienced consumers. In most cases we find a significant effect of advertising on inexperienced users and an insignificant effect on experienced users. We conclude that the advertisements in our dataset primarily affected consumers by providing them with information on inherent product characteristics. This lack of image or prestige effects is interesting as it suggests that advertising may have primarily been a facilitator to competition and entry in this industry (see, e.g. Shapiro (1982)). Even if one chooses not to accept our premise that information is what is generating this differential effect of advertising, we feel the basic empirical result is interesting and has important implications on optimal advertising behavior, at least in this particular market.

Lastly, we note that our approach to distinguishing these effects of advertising is one that can be applied to other products or industries. The household-level panel data necessary for our identification is becoming increasingly available for all kinds of consumer products. We feel that knowing how advertising affects or is able to affect consumers in a particular market can be an important tool in policy making. For example, all else equal one might imagine stricter merger policy to 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

[3] Tellis (1988) interacts advertising with what the marketing literature calls "brand loyalty" (a weighted function of the number of past brand purchases (with 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. Deighton et. al. (1994) interact advertising with an indicator of whether the consumer purchased that particular grocery brand on their 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.

information and quickly gain equal footing. Though we feel that both more theoretical work and empirical work may be necessary to rigorously apply such ideas, the techniques developed here should be an important component.

The remainder of this paper is organized as follows. Section 2 argues that the different types of advertising discussed above have different empirical implications in consumer level data. Section 3 describes the data used in this study. Section 4 presents an empirical model and Section 5 provides results. Section 6 concludes and suggests topics for further research.

0.2 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 our data, we will be thinking about television advertising by manufacturers of consumer non-durables, although many of the below arguments could be made for other types of products or advertising. Television ads for non-durables such as foodstuffs, clothing, and toiletries are typically the least likely to contain overt product information, rarely mention price, and are most likely to be described as image oriented. As a result, we feel that it is particularly interesting to examine the effects of these types of ads.

As described in Stigler (1961), we distinguish between search and experience characteristics of a product. Search characteristics are observable and verifiable to consumers before purchase, examples being the calories a brand of cola has, its price, or simply the fact that it is a cola. Experience characteristics are not generally known to consumers before trying the product, e.g. the taste of the cola. This is not to say that consumers have no idea what they are. A consumer might, for example, 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 usually taste bad).

We now argue that in some cases advertising provides very similar information to that obtained from consumption. We suggest that because of this repetition of information these influences of advertising should not affect "experienced consumers", those who have consumed the brand at some point in the past. This is contrasted with situations where advertising provides information that is not learned from consumption. We expect these influences of advertising to affect both inexperienced and experienced consumers. Our empirical work uses this distinction to separately identify different effects of advertising.

Information on Product Existence and Search Characteristics First assume that advertising only informs consumers of our brand's existence and search characteristics. This is the setup of the models of Stigler (1961), Butters (1977) and Grossman and Shapiro (1984). An obvious implication is that such advertising will only affect 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 walking down a supermarket aisle, but in particular it comes from past consumption of the brand. Consumers who have tried the product will generally know of its existence and should know at least the search characteristics that are relevant to their utility function. If this were exactly the case, such advertising would not affect experienced consumers. This does not imply that this advertising would affect all inexperienced consumers - some may have learned this information from other sources and some might dislike the brand enough not to care. The point is simply that if all advertising does is inform consumers of existence and search characteristics, we would generally not see advertising affect the behavior of experienced users.[4]

[4]There are caveats to this argument. For example, this neglects the possibility that search characteristics might change over time. One particular search characteristic, price, is particularly apt to change, and advertising that points out such changes could certainly affect experienced consumers if they were not already aware of them. A second possibility is that consumers might forget such information. It is hard to believe that this never happens, especially if decisions have very marginal affects on utility and there is a cost to remembering. In this case, advertising could remind experienced consumers of the product's existence or characteristics and affect their behavior. Another possibility relates to the fact that we have been discussing consumers' preferences over search characteristics such as calories or fat content. More likely, consumers might have preferences for characteristics like "healthfulness" along with beliefs mapping search characteristics into this healthfulness. If a consumer's knowledge over such a map changed, preferences over our search characteristics might "change" and we could see advertising affect behavior. Another exception is when advertising provides information on how to "use" a product better (e.g. a recipe), in a way that would not be learned from normal consumption. In empirical work it may be possible to eliminate some of

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 many such claims, for example "this brand tastes good" or "this brand is high quality", are not credible and should not affect rational consumers because they are not verifiable and the marginal cost of such claims is zero given that advertising space or time has already been purchased[5]. He proposes a second possibility, that expenditures on advertising might *implicitly signal* information about experience characteristics to consumers. In his intuitive analysis, and in the more formal models solved by Kihlstrom and Riordan (1984), Milgrom and Roberts (1986), and others, firms produce non-durables with different unobservable qualities and are able to advertise, although this advertising contains no explicit information on the firm's product. Equilibria are found in which firms with higher quality products advertise more and consumers justifiably react to this as a signal of this higher quality.

Suppose we are in such an equilibrium where firms are signaling better quality, taste, or some aggregate experience characteristic with high levels of advertising expenditures. First consider the case where a consumer learns a brand's experience characteristics perfectly after one consumption experience with the brand. This might be true for some 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. Inexperienced users, on the other hand, *would* be affected by a brand's advertising level. High levels would likely increase the consumer's expected utility from consumption, low levels decreasing it.

these exceptions as being significant, particularly if we know things about a brand or are able to observe advertising content. For example, we seldom see price mentioned in television advertisements for grocery products. We may know if a product's characteristics have changed and if so whether advertising has mentioned this. In many cases it may be appropriate to assume that forgetting is not significant or at least is not significant as number of previous experiences increases.

[5]Note that both of these sample statements tout experience characteristics (goodness and quality) that are likely unanimously preferred by consumers. If advertising touted experience characteristics that were known to be liked by some consumer and disliked by others, e.g. "this brand is salty" or "this brand is sweet", full or partial credibility might be obtained. If this were the case, we would expect these claims to affect consumers similarly to statements of search characteristics, i.e. they should primarily affect inexperienced users. We would expect the same if claims to experience characteristics were somehow legally binding.

Next consider the case where 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 a very effective pain reliever. In contrast to the simple "one-period" learning process mentioned above, this suggests a more complicated learning process in which consumers continue to learn about experience characteristics on the second and possibly subsequent consumption experiences[6]. Since now even experienced consumers do not know experience characteristics completely, signaling advertising might affect them also. However, for most learning processes, we would expect the effect of advertising on a consumer's behavior to *decrease* in the number of previous consumption experiences. This should be fairly intuitive, consumers who have consumed the brand more times should generally know more about the brand's experience characteristics and should be affected less by advertising that is informing them about these experience characteristics.[7]

Prestige and Image Effects Lastly, consider effects of advertising that, as in Becker and Murphy (1994), directly affect the utility a consumer derives from consuming the brand. Becker and Murphy suggest that this could occur through prestige type effects, i.e. all else equal consumers might derive more utility from consuming a more advertised good. It is also conceivable that consumers might derive utility or disutility from advertising content such as images or personalities — perhaps because it is self-pleasing, perhaps because they want others to associate themselves with

[6]Other possibilities that could lengthen the learning process are variation in product quality or taste, or perhaps that the product is combined with other products or is consumed in different moods or situations that make it hard to tell exactly how much utility to expect from future consumption of the product. The aforementioned signaling equilibrium models use the simpler one-period learning process, Horstmann and MacDonald (1994) examine the possibility of extension to longer learning processes. Eckstein, Horsky, and Raban (1988), Erdem and Keane (1996) and Ackerberg (1996) develop *non-equilibrium* consumer learning models in which Bayesian updating is used to model longer these learning processes.

[7]For a more formal model of this effect, see Ackerberg (1996), Chapter 1. There are also caveats to this general conclusion about signalling advertising. As with search characteristics there is the possibility that consumers might forget or that a manufacturer might change a brand's experience characteristics. In both cases we could see advertising affect experienced users. In some cases, experience characteristics might be hard or impossible to ascertain even after numerous consumption experiences. Health products provide a good example. We hardly expect a consumer to learn very much about a toothpaste's cavity prevention ability, even after years of use. Sometimes advertising promotes these types of experience characteristics, e.g. "3 out of 4 dentists recommend". Such claims might be fully or partially credible in a legal sense and could affect the behavior of experienced users.

such content, or perhaps as part of some societal equilibrium where people signal their interests and tastes by what products they consume and what these products are associated with. 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 their ads. Images in or amounts of advertising define these advertising characteristics.

We hypothesize that prestige or image effects of advertising on consumers should not depend on whether consumers are experienced or not. While information on search and experience characteristics are typically learned through consumption, advertising characteristics are generally not learned through consumption. Thus, all else equal (in particular a consumer's preferences for images or prestige), we 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 that is 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[8]. Again, there are exceptions. Occasionally consumers might learn advertising characteristics from consumption. We sometimes see products labeled "as advertised on TV"[9]. A brand's packaging might convey some of the images that are portrayed in advertisements. On the other hand, if what the consumer is primarily concerned about is whether other people (who may not have consumed the product) know that the product is associated with a particular image or is advertised heavily, this may not make much of a difference.

[8]One case where we wouldn't have this result is if for some reason prestige advertising interacts with *previous* purchases of the brand in the consumer's utility function (e.g. a consumer who prefers a **more** advertised brand **less** when he has purchased it **more** times in the past). Although one might argue that number of previous purchases affects the utility from consuming the product (e.g. habit formation), we can think of no obvious reason for such an interaction between previous purchases and advertising.

[9]This brings up an interesting point relating to Nelson's signaling argument as well as to consumers having preferences for consuming more advertised goods. If either were the case, one might wonder why firm's generally don't advertise how much they advertise. The answer is not so clear in the signaling case. In the preference case we might argue that consumers do not like this behavior, i.e. it might be prestigious to consume a more advertised good only when it doesn't advertise it is more advertised!

Discussion In summary, we think that this distinction makes for an interesting empirical application. By comparing the impact of advertising on inexperienced and experienced users of a brand, we can distinguish how much of advertising's influence provides similar information to that obtained from consumption and how much provides different information than that learned from consumption. We have argued that in general this distinction relates very closely to the difference between influences of advertising in which consumers are informed of the inherent search and experience characteristics of a brand and influences of advertising based on images and prestige. This approach is particularly interesting in looking at advertising that primarily contains images. The fact that Michael Jordan is in an advertisement, for example, could be consistent with all three of the above general effects of advertising. His presence could simply 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 signaling argument, as the signaling argument suggests that consumers should weigh more expensive advertisements more, e.g. Michael Jordan's presence or advertisements during the Superbowl. Lastly, consumers might simply obtain more utility from consuming a product that has Michael Jordan in its advertisements. Our approach can distinguish the relative extent of these effects by comparing how much this advertising affects inexperienced users to how much it affects experienced users.

Another interesting point is that this approach avoids problems in defining what are inherent characteristics of the product. Taplin (1963), for example, 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)). Our approach can potentially answer this question for us by asking whether such advertising affects experienced consumers or not.

We lastly note that this is not the only interesting conclusion on the qualitative effects of advertising that might be derived from analyzing consumer response to advertising. One could investigate whether consumers seem to 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 likely be a function of the number of advertisements seen. On the other hand, a signaling effect would likely depend on intensity, as the consumer really wants to know how much the brand is spending on advertising.[10] Although we briefly touch upon these additional points in our empirical work, we focus on the inexperienced-experienced distinction. One reason is that we think it is a clearer argument and that what is distinguished (inherent product information vs. images or prestige) is more economically interesting. A second reason is that we feel that it more robust to our particular data than are the others.

0.3 The Data

We use consumer level panel data on grocery purchases and television advertising exposures to empirically examine the above arguments. This data, collected by A.C. Nielsen, is referred to as "scanner data" because the grocery purchases were recorded by supermarket UPC scanners. In each of two geographic markets, Sioux Falls, SD and Springfield, MO, shopping trips and purchases of approximately 2000 households in more than 80% of area drugstores and supermarkets were recorded over three years (1986-1988). There is also data on weekly prices so it is possible to reconstruct the price situation on each household's shopping trips[11]. In addition to containing this extremely detailed data on purchases over time, A.C. Nielsen TV meters were used to collect

[10] Another possible distinguishing factor that might be identified and exploited is heterogeneity in the effects of advertising on consumers. Given that we do not observe all sources of consumers' information, we would expect response to information about existence or search characteristics to be fairly heterogeneous. Inexperienced consumers who have learned these things elsewhere or previously wouldn't be affected while those who haven't could be. Signaling effects might be more homogeneous or continuous in their effects (Although clearly this would depend on any heterogeneity in consumer's preferences for better quality or tasting products). Prestige effects and image effects could also potentially be distinguished from one another. Consumers may be more likely to react either positively or negatively to images they favor or disfavor than to prestige.

[11] On shopping trips in which a particular product was purchased, we observe the exact price of the transaction. A price file has been created (Kolaczyk (1989)) in order to obtain prices on shopping trips in which the product was not purchased. This price file was generated by interpolating prices on observed purchases (of other households) of the product in the same week in the same supermarket.

information on household TV advertising exposures for about half the households in the last year of the data. We thus know, along with when and what each household bought, when their television set was tuned to advertisements for each brand[12].

The publicly available Nielsen data contains data on four product categories: ketchup, laundry detergent, soap, and yogurt. We choose to focus on the yogurt data for two reasons. First, although we do have data on purchase amounts, i.e. how much of a brand a household buys on a shopping trip, we have chosen not to use it. This is because keeping things in a discrete choice framework greatly simplifies our analysis. As a result, we really have no way to account for household inventories or stockpiling behavior, i.e. consumers purchasing many units at low prices and consuming them during high prices. Of the above products, Yogurt is likely the least affected by this limitation. We hope that its comparatively short shelf life (about 2-6 weeks) and comparatively high storage costs[13] prevent significant amounts of such behavior from occurring.

A second reason for this choice 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 because we wouldn't know which households had experienced the brand beforehand. Using a newly introduced brand alleviates this problem[14] and the yogurt data had such a product, Yoplait 150. In our empirical work we focus specifically on our consumers' decisions whether to purchase Yoplait 150 and the effect of television advertisements for this brand on these decisions.

[12]This data has primarily been used in the marketing literature. They (e.g. Gaudagni and Little (1983), Pedrick and Zufryden (1991)) typically use classical discrete choice models or Bayesian methods (e.g. Rossi, McCulloch, and Allenby (1994) and McCulloch and Rossi (1994)) allowing for varying degrees of consumer heterogeneity to analyze the data. When analyzed, advertising typically enters as a reduced form explanatory variable (with one notable exception the structural learning model of Erdem and Keane (1996)) but these studies usually concern themselves with measuring an overall effect of advertising, not distinguishing different effects of advertising. As mentioned in the introduction, Tellis (1988) and Deighton, et. al. (1994) contain the most similar empirical specifications to those used here.

[13]While the size of Yogurt containers may be smaller that the other products, it must be stored in the refrigerator, which probably has much higher storage costs per unit of volume than a closet or basement, for example.

[14]Of course there are other possible problems with prior experience variables. We obviously don't 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.

Yoplait, the second largest yogurt manufacturer in the U.S., 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 (*Encyclopedia of Consumer Brands* (1994)). Table 1 gives some summary statistics for the data following the introduction[15]. The data suggest that Yoplait 150 was (at least initially) a fairly heavily advertised yogurt, as can be seen by comparing advertising shares to market shares. Note the large variation in the number of advertising exposures per household. The large difference in market shares between markets 1 and 2 may be due to the existence of two, high-share, local brands in market 1 and the significant number of manufacturer coupons that were available in market 2. Chart 1 indicates, for the 307 households who purchased Yoplait 150, the number of shopping trips in which the brand was purchased. As a majority purchased the product only once, we really don't have a tremendous amount of data on multiple purchasers.

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

There are a couple of notable data problems. One is the existence of manufacturer coupons, usually distributed in newspaper pullouts or mailings. We optimally would like to know whether or not a consumer had access to a manufacturer coupon for Yoplait 150 on a particular shopping trip. Unfortunately, we only observe redeemed manufacturers coupons, i.e. conditional on a purchase actually being made. This prevents its straightforward use as an explanatory variable because of its correlation with any unobservables influencing purchases. As the data indicate that manufacturers

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

coupons were much more prevalent in the second market than the first, we use a market dummy as a proxy for the availability of manufacturers coupons[16].

Another significant problem is that TV advertising exposures were 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. This was another motivation for the choice of Yoplait 150 because this was the latest advertised product introduction and minimized the period in which advertising exposures are not observed. We generally assume zero advertising exposures for this period. Our justification for this is that for three weeks after TV measurement started, there were no Yoplait 150 advertisements observed. We hope that this may indicate that Yoplait did not start advertising the product until this time[17].

Chart 3 divides the quantity series of Chart 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 our identification hypothesis. Table 3 presents results from separate OLS regressions of daily initial purchases and repeat purchases on a market dummy, time trend, current price, and number of recent advertising exposures[18]. As these aggregates ignore a significant

[16]Fortunately, we did not expect such problems with store coupons, which 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. We did not feel uncomfortable assuming that all consumers in the store that week were making decisions based on the store coupon value. However, since we were not sure as to the exact nature of the store coupons (e.g. $0.50 off one purchase, $0.50 off two purchases), *store coupon* is included as a separate explanatory variable, not subtracted off price. We also consider the dummy variables *in display* and *in circular*. These capture whether Yoplait 150 was featured in a special display or was advertised in the store circular in a given week.

[17]Another problem with measured advertising exposures it that it appears that the Nielsen TV meters were not all that reliable. For a considerable number of households, there are significant TV viewing gaps in the data. To ameliorate this problem, two steps were taken. First, households with very large viewing gaps were eliminated from the study (In the data used for the following results, households with viewing gaps larger than 100 days were eliminated. Similar results were obtained when the cutoff point was changed to 50 and 30 days.). Second, to avoid problems of unmeasured TV watching, our advertising variables are usually defined as number of Yoplait 150 advertising exposures per TV watching hour. We compare using these advertising "intensities" to using absolute levels of advertising in our empirical work. Note that this does not solve other measurement error problems inherent in using this TV meter data, particularly the fact that we don't observe who in a household (if anybody) actually saw or paid attention to a commercial.

[18]In most cases this variable is total advertising exposures the past 4 days. Note that we are not suggesting that only recent advertising exposures affect individual behavior (and later the individual level data will agree with us). The problem with a lengthier lag is that past advertising which generates past initial purchases in turn allows for more current repeat purchases. One can see this effect in the column where we change the Ads variable to include advertising exposures over the past two weeks. This is the one case where the effect of Ads on repeat purchases is

source of variation (i.e. across households) to identify 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 half that in the initial purchase regression[19]. The last two columns attempt simple adjustments for the missing advertising data and the results don't change. Though these results suggest that these advertisements primarily affected inexperienced consumers, there are enough potential problems[20] that we hesitate to make any strong conclusions, instead moving to more fully exploit our consumer choice model and the panel nature of our data.

0.4 The Empirical Model

Recalling the arguments of section 3, we 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 fairly complicated, even for very simple utility function specifications (e.g. Ackerberg(1996)). Alternatively, and the tack taken in this paper, one can estimate a reduced form representation of the discrete decision

significantly positive. Supporting the above explanation is the fact that this significant coefficient tends to disppear when we add lagged dependent variables to control for past initial purchases, though we haven't investigated how sensitive this is to possible serial correlation bias.

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

[20]Including, among others, a lack of strong identification of the repeat purchase advertising coefficient, potential endogeneity of prices which we don't have instruments for (though probably not advertising since this is done at the national level), probable lack of correct specification because of missing lagged endogenous variables, and, maybe most importantly, the fact that we are not explicitly conditioning on consumers' probabilities of purchase. This last potential problem can be exemplified by a situation in which experienced consumers have expected utilities significantly above price, while inexperienced consumers' expected utilities are right below price. A burst of prestige advertising (increasing all expected utilities by a certain amount) would then cause many inexperienced consumers to switch from not buying to buying, but not affect purchase behavior of experienced consumers (they already purchase) . This exemplifies the need for a comparison of behavior *conditional* on purchase probability, which the discrete choice models of the next section do.

whether or not to purchase Yoplait 150. We consider the model:

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

where c_{it} indicates whether consumer i purchased Yoplait 150 on shopping trip t[21]. 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.

Our observables X_{it} contain variables such as household and consumer characteristics, functions of a household's previous purchases of Yoplait 150 or yogurt, and advertising exposures. As we are particularly interested in looking for a differential effect of advertising on the behavior of experienced and inexperienced consumers, we allow for cross-partials between a consumer's advertising exposures and his previous purchases of Yoplait 150 by including *interactions* between advertising exposures and previous purchases in X_{it}. p_{it} is the price of Yoplait 150 faced by consumer i on shopping trip t, while Z_{it} contains functions of the prices of other Yogurts. We include variables such as calender time and functions of previous Yoplait 150 purchases in X_{it} to either1) better approximate the value function or 2) accommodate habit persistence. Unobservables ϵ_{1it} and ϵ_{2it} allow

[21]Note that we have decided to assume that the consumer's choice occasion is the shopping trip, i.e. the consumer chooses whether or not to purchase Yoplait 150 on each shopping trip and only on each shopping trip. We feel that this is the most reasonable way to to define a choice occasion for this dataset, although there are certainly problems. First, we can't be sure that a consumer had the opportunity to purchase on each shopping trip. We have eliminated shopping trips at stores that seem to have not sold Yoplait 150 (essentially all the drug stores in the sample) and also eliminated shopping trips on which a consumer spent less than $10 and did not buy yogurt to alleviate this problem. Second, any type of durability of the product across shopping trips calls into question the independence of ϵ_{1it} and ϵ_{1it+1} (In particular, one might expect negative correlation). We include a "bought last shopping trip" dummy variable in X_{it} to hopefully alleviate this problem. Third, we must assume that consumers' decisions when and where to shop are exogenous (see below).

for idiosyncratic, time-specific shocks to a consumer's behavior that are known to the consumer but not to the econometrician.

The above is a standard binary choice model. Assumptions that the ϵ's are i.i.d. normals or Type 1 Extreme Value deviates that are independent of (X_{it}, p_{it}, Z_{it})[22] result in binary probit and binary logit models respectively. Given that we have data on multiple shopping trips for each consumer, one might think such an i.i.d. assumption to be extreme. In particular, one could imagine our consumers having preferences for Yoplait 150 or yogurt that are fixed over time and unobservable to us as econometricians. In our primary models, we allow for such persistent unobservables α_i, i.e.

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

and treat them as random effects by specifying a parameterized distribution and integrating out choice probabilities over this distribution[23,24]. As lagged endogenous variables (e.g. number of previous Yoplait 150 purchases) are included as explanatory variables, we need to be careful as our random effects will likely be correlated with them on any given shopping trip. To avoid this problem we derive the likelihood of observing a given household's data by integrating the probability of the household's entire purchase sequence over the distribution $(f(d\alpha_i \mid \theta))$ of this random effect. The

[22]Our 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. We 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).

[23]If computation were not an issue we could explicitly model choices of the other yogurts. We have estimated three choice models where the consumer chooses between Yoplait 150, another brand of Yogurt, or nothing. These three choice models increase computational time significantly because in these models we allow for two persistent unobservables, one general taste for yogurt and one specific taste for Yoplait 150. These obtained very similar results, so we only include estimates from the binary choice model in this paper.

[24]This random effects formulation is used in a number of the marketing literature cites above. We typically assume these effects are normally distributed independently of the explanatory variables, though in our empirical work we examine the possibility that advertisers can focus ads towards consumers with high α_i's. We have also tried estimation without distributional assumptions on the α_i's. One option is to condition on a households total purchases over the entire period . For the logit model one can then derive a likelihood where the α_i's drop out (Chamberlain (1980)). This method is not computationally feasible given the length of our data, but we have estimated linear probability models (where one can difference out α_i) on the data. However, in this case one must instrument for the lagged endogenous variables and we had trouble finding efficient instruments.

likelihood function for consumer i is thus:

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

where superscripts represent histories, T_i is the number of shopping trips of consumer i, W_i^t is the subset of our 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 our assumption on the ϵ's, and $X_{it}(c_i^{t-1})$ explicitly writes the explanatory variables as depending on previous choices. Note that as we have 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.

0.5 Econometric Results

Table 5 presents results of the above model. The first and fourth columns contain maximum likelihood estimates of standard logit models with no persistent, household specific, random effect. In the second and fifth columns, we allow for a normally distributed random effect[25] and see large increases in the likelihoods. In the third and last two columns we use additional data to "predict" more of this random effect. Specifically, we use information on a household's yogurt, lowfat yogurt, and regular Yoplait purchases in the two years of data *prior* to Yoplait 150's introduction on the market. We assume that this "presample" information is exogenous to our model. As evidenced by the increase in likelihood values, this additional data seems to contain quite a bit of information on α_i. Note that the coefficients on the non-advertising related variables, in particular *price*, *store*

[25] We assume a 101 point discretized normal distribution as an alternative to dealing with simulation and simulation error.

coupon, and *competitor's price*[26], seem fairly robust across the models except for the simple logits.

The first and second sets of columns in Table 5 differ in their specification of the interaction between a household's number of previous Yoplait 150 purchases and *advertising*[27]. In the first three columns, we 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 might correspond with a case where all the brand's experience characteristics are learned after one consumption. According to our arguments, 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 our informational effects of advertising. In all three 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. Note that although there is generally a very 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 the these advertisements primarily provided information on inherent product characteristics to consumers.

The economic significance of these advertising coefficients seem fairly reasonable. In the third 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, as the average advertising intensity is only one commercial every 4 weeks, a doubling of advertising at the mean has the same effect as only a 2.5 cent price decrease.

[26]This variable is defined as $\min_j\{(p_{ijt} - \overline{p_j})/\overline{p_j}\}$, the minimum percentage deviation from average price, where j indexes the other brands of yogurt. We tried alternative sets of j, including only those of lowfat Yogurts, i.e. Yoplait 150's likely strongest competitors. Using all yogurts had the best predictive power.

[27]Because of the short time period of our data and because nothing suggested otherwise, we start 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). We examine both the unweighted assumption (that recent and past ad exposures are equally important) and use of intensity (rather than, e.g., the absolute number of ads) below.

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 F.O.C.'s, our simulated price elasticity of 2.8 corresponds to a 35% markup and implies that advertising expenditures are 5% of total revenue[28].

In the specification of the next three columns, we allow the effect of advertising to change linearly in the number of previous purchases of Yoplait 150[29]. This functional form corresponds with a model where consumers continue to learn about experience characteristics after the first consumption experience. In this case we argued that effects of advertising which inform consumers of experience characteristics should decline in the number of previous consumption experiences. In all three sets of estimates, we obtain a positive, significant coefficient on the *advertising* term, measuring the effect of advertising on inexperienced consumers. Our 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. The size of these slope coefficients are generally large, indicating that the effect of advertising is going down fairly quickly. We expect such a result with yogurt, where consumers should be learning experience characteristics fairly quickly with consumption. Optimally one would want to find an asymptote of the effect of advertising in number of previous purchases. This asymptote would measure our image and prestige effects of advertising. Unfortunately, richer functional forms which would allow for such an asymptote haven't resulted in very precise results, likely due to our lack of data on very inexperienced consumers. The results in the last column of Table 5 estimate a slightly richer specification with 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

[28]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 we are not modeling purchase amounts, these elasticities are not necessarily the elasticity of total quantity (units) purchased with respect to price (or advertising). Also note that the FOCs assume single product firms, which is not the case in this industry.

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

driven by the difference between having 0 or 1 previous purchases.

Robustness Checks Table 6 presents some additional results that give a brief indication of the robustness of this differential effect of advertising. The first two columns utilize different specifications on the shopping trip specific error terms. The first assumes the ϵ's are normal, a probit model. The second column addresses a characteristic of standard logit and probit models that the map from observables (in our case $X_{it}\beta_1 - \gamma p_{it} - Z_{it}\beta_2$) into purchase probabilities has its maximum derivative when the purchase probability is .5. This means that the consumers affected most (probability wise) by advertising (holding number of previous purchases constant) 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 the 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 our data. As a simple check of robustness, we 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 results in a quasi-logit model where the maximum probability of purchase is .5 and the maximum derivative is at .25 rather than .5. 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.

Columns 3 through 5 examine alternative specifications of the advertising variables. Column 3 adds the explanatory variable *recent advertising,* measuring the number of advertising exposures in the month prior to a shopping trip. Its complete insignificance indicates that for at least this short time period, our unweighted measure of advertising intensity does fairly well. We obtained similar results when we defined recent ads as those either one week or two weeks prior to a shopping trip.

Column 4 changes our definition of the advertising variables from advertisements per unit of exposure time to advertisements divided by calendar time. Although we still find a significant differential effect of advertising, these variables do not do as good a job of our explaining the data. Likelihood values are even worse when we use the absolute number of advertisements observed so far[30]. One possibility is that these results, along with the arguments at the end of section 3, support the idea that our informative effects of advertising are more of the signaling variety than of providing explicit information. However, we hesitate to make any strong conclusions about this result because it also might be due to more measurement error in the absolute numbers[31].

The fifth column 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_i's that we don't[32] and aim advertising towards consumers with high α_i's, our advertising variables will be correlated with our random effect. In a manner similar to Mundlak (1978), (though without his robustness to alternative functional forms because of the non-linearity of our model) we 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 our other advertising coefficients by much. It does at least suggest, however, that advertisers might be succeeding in aiming advertising towards consumers who like the brand.

Column 6 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 given store in a given week. *In Circular* equals 1 if Yoplait 150 was featured in a store circular or advertisement.

[30]We have also checked robustness to alternative parametric forms for our advertising variable. In particular, we were worried about potential declining returns to a possible prestige effect (if this were the case, an incorrect linear specification could generate spurious results because of positive correlation between advertising (and thus a lower marginal utility of advertising) and previous purchases). Models using $\sqrt{\text{ads}_{it}}$ and $\ln(\text{ads}_{it}+\text{constant})$ have also generated strong differential effects of advertising and worse likelihoods than the linear model.

[31]If we were not so worried about measurement error and had more data, we could include both measures in a specification and potentially distinguish between them. Also, regarding potential measurement error due to potential advertising in the first three months of Yoplait 150's introduction, we obtained similar results when we estimated the model without these first three months of data. In these specifications, consumers who purchased in the first three months were dropped from the sample to avoid initial condition problems.

[32]"What we know" is this linear combination of variables that we are using to predict α_i. *Additional* information known by advertisers could, in particular, come from data sets such as this (e.g. whether consumers who watch Seinfeld like yogurt) .

As one might expect, both these promotional variables enter positively and significantly. Unlike our 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 "advertise" a new sale price, which might be new information for all types of consumers. Lastly, Column 6 also interacts our 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.

The last two columns of Table 6 examine the possibility of heterogeneity in consumer response to advertising by adding consumer specific but time invariant random coefficients to our effects of advertising. In the sixth column, the random coefficient is on our informational effect of advertising; in the seventh, it is on our image or prestige effect of advertising[33]. We assume that these random coefficients are independent of our linear random effect and our explanatory variables. In both cases there is still a large differential effect of advertising at the mean, but in both cases the significance goes down. Although imprecise, the estimates of the standard deviations of these random coefficients in both case are very large compared to their means. This at least suggests a large degree of consumer heterogeneity in response to advertising. Unfortunately, these large but inaccurate estimates may be due more to measurement error in our advertising measure than

[33]Recall that the dummy variable model is:

$$\beta_1 \text{ad*inexp.} + \beta_2 \text{ad*exp.} = (\beta_1 - \beta_2)\text{ad*inexp.} + \beta_2 \text{ad}$$

where $(\beta_1 - \beta_2)$ measures our informative effects advertising, β_2 our prestige effects. The specification in the 6th column is:

$$(\beta_1 - \beta_2 + \sigma \upsilon_i)\text{ad*inexp.} + \beta_2 \text{ad}$$

where ν_i is $N(0,1)$ i.e. a random coefficient on informative effects, and the specification in the 7th column is:

$$(\beta_1 - \beta_2)\text{ad*inexp.} + (\beta_2 + \sigma \upsilon_i)\text{ad}$$

i.e. a random coefficient on the prestige effect. The reason we add the random coefficients to the dummy specification is because of the easier interpretation of the coefficients relating to the different effects of advertising. Putting a random coefficient on the slope term in the linear specification does not change the significant, negative, (mean) slope coefficient.

heterogeneity[34]. Such a procedure might be more fruitful with more data.

0.6 Conclusions

We feel that these are strong and interesting empirical results. We have argued that advertising providing information on inherent brand characteristics should primarily affect inexperienced consumers of a brand, while advertising creating prestige or association should affect both inexperienced and experienced consumers. Our data indicate a significant effect of advertising on inexperienced consumers and either a declining or insignificant effect on experienced consumers. We 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. We make a couple of additional notes. First, the explicit linking of a household's grocery purchases to their 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 analyzing established products are 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 period of time as experienced. Another would be to use more sophisticated econometric techniques to deal with the initial condition

[34] Because we define our advertising variables as averages of all past exposures, measurement error in advertising exposures will be somewhat persistent over time. Thus one might expect a time invariant random coefficient to pick it up. Note that one could could conceivably model such measurement error, for example having a probability a consumer actually sees or pays attention to an advertising exposure. We doubt that we would be able to identify this very well with our limited amount of data. In addition, the long time frame of the model would make this computationally very difficult. We have also tried including both random coefficients above simultaneously and allowing correlation with our linear random coefficient. Unfortunately, we still get imprecise and likely inconclusive results.

problems. It should prove interesting to compare results across different industries and products, and as noted in the introduction, we feel that such analyses should make valuable contributions to policy work.

Regarding our current results, a significant amount of experimentation has shown the differential effect of advertising we find to be very robust over this type of model (i.e. reduced form, discrete choice) as long as we allow for unobserved, persistent, consumer heterogeneity. However, this does not mean that there are not possible problems. A first problem is that if one believes that consumers dynamically optimize, these reduced form models rely on an approximations to optimal dynamic decision rules. The quality of our results are 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 us in answering important welfare questions about advertising. The fact that we have found this advertising to primarily be providing product information brings up many questions about its affects on the functioning of this market. First of all, we 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, we want to assess the impact of advertising on variables such as pricing, entry, and innovation in this industry. If we assume that 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 which act as entry barriers, anti-trust policy should be more lenient, all else equal, towards the yogurt industry. Unfortunately, we cannot formalize such arguments without more rigorous study of the information structure of the market and firm behavior under this structure.

We feel that the above problems point to an obvious next step. Our argument is an informational one, and we expect advantages to explicitly modeling such information. What we are suggesting is a structural approach to this problem, one in which primitives such as utility functions and information structure are modeled 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 our ability to examine different functional forms or specifications. We therefore consider such an approach not as a replacement to but as an interesting complement to the present one.

Table 1: Summary Statistics

Variable	Market 1	Market 2
Households	950	825
Total Shopping Trips	67051	54308
Average Shopping Trips per Household	70.58 (33.39)	65.82 (31.82)
Average Price of Yoplait 150 (Cents)	0.645 (0.060)	0.663 (0.079)
Shopping Trips with Yoplait 150 Purchase	302	656
Manufacturers Coupons Redeemed for Yoplait 150	16	238
Shopping Trips with Other Yogurt Purchase	5432	3863
Households Trying Yoplait 150	123	184
Households Trying Other Yogurts	648	512
Commercial Exposures	12918	12563
Commercial Exposures per Household	13.60 (10.81)	15.22 (9.96)
Advertising Share of Yoplait 150	0.35	0.37
Market Share of Yoplait 150	0.05	0.14

Note: Standard Errors in parentheses where applicable

Table 2: Weekly Correlations

Variable	Market 1	Market 2
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

Table 3: OLS Correlations of Time Series

	1	2	3	4	5	6	7	8	9	10
Dependent Variable: Initial Purchases										
N	918	918	918	459	459	896	306	132	678	918
R^2	0.066	0.085	0.066	0.087	0.074	0.084	0.147	0.201	0.107	0.066
Constant	3.559	0.033	3.556	5.707	2.003	5.473	12.036	21.855	19.858	3.530
	(0.655)	(0.005)	(0.655)	(1.010)	(0.986)	(0.841)	(2.359)	(5.755)	(5.353)	(0.654)
Market	0.222	0.002	0.224			0.259	0.705	1.479	0.224	0.223
Dummy	(0.047)	(0.000)	(0.047)			(0.048)	(0.163)	(0.429)	(0.054)	(0.047)
Time	0.424	0.020	0.254	8.592	-8.427	6.056	0.694	-1.295	55.645	0.934
	(2.592)	(0.023)	(2.594)	(3.122)	(4.161)	(3.267)	(2.937)	(3.135)	(18.858)	(2.594)
$\text{Time}^{1/2}$	0.131	-0.022	0.157	-6.659	7.387	-4.705	-0.004	4.034	-54.503	-0.029
	(1.980)	(0.017)	(1.980)	(2.400)	(3.159)	(2.602)	(3.885)	(6.277)	(18.627)	(1.982)
Time^2	-0.770	-0.007	-0.627	-3.557	2.359	-2.775	-0.309	-0.015	-16.665	-1.076
	(1.097)	(0.009)	(1.102)	(1.313)	(1.779)	(1.309)	(0.415)	(0.192)	(5.472)	(1.095)
Price	-5.298	-0.038	-5.285	-6.509	-4.811	-6.628	-17.976	-35.511	-7.388	-5.354
	(0.812)	(0.007)	(0.812)	(1.515)	(1.067)	(0.881)	(3.003)	(7.994)	(0.955)	(0.816)
Ads	0.044	0.030	0.093	0.068	0.025	0.021	0.088	0.180	0.042	0.044
	(0.014)	(0.013)	(0.031)	(0.018)	(0.021)	(0.005)	(0.036)	(0.092)	(0.014)	(0.015)
t-value	3.043	2.299	2.974	3.713	1.152	3.865	2.437	1.950	2.870	2.942
Dependent Variable: Repeat Purchases										
N	918	918	918	459	459	896	306	132	678	918
R^2	0.162	0.149	0.162	0.093	0.102	0.162	0.333	0.559	0.120	0.162
Constant	2.499	0.018	2.517	0.582	3.518	3.910	9.091	14.414	12.729	2.463
	(0.939)	(0.007)	(0.939)	(1.053)	(1.597)	(1.215)	(3.272)	(6.728)	(8.750)	(0.938)
Market	0.700	0.006	0.701			0.736	2.143	4.793	0.832	0.700
Dummy	(0.068)	(0.000)	(0.068)			(0.070)	(0.226)	(0.502)	(0.088)	(0.068)
Time	7.528	0.027	7.420	10.548	6.890	10.924	7.793	6.181	40.238	7.739
	(3.712)	(0.028)	(3.715)	(3.257)	(6.741)	(4.723)	(4.074)	(3.665)	(30.822)	(3.715)
$\text{Time}^{1/2}$	-2.755	-0.007	-2.746	-6.517	-0.773	-5.739	-5.057	-4.602	-35.813	-2.807
	(2.836)	(0.021)	(2.836)	(2.504)	(5.117)	(3.762)	(5.389)	(7.339)	(30.444)	(2.839)
Time^2	-4.638	-0.018	-4.544	-5.079	-5.293	-5.813	-1.592	-0.580	-13.756	-4.774
	(1.571)	(0.012)	(1.577)	(1.369)	(2.882)	(1.892)	(0.575)	(0.225)	(8.944)	(1.569)
Price	-3.954	-0.029	-3.972	0.839	-5.657	-5.141	-14.274	-25.102	-5.512	-3.942
	(1.164)	(0.008)	(1.163)	(1.580)	(1.729)	(1.274)	(4.167)	(9.345)	(1.562)	(1.169)
Ads	0.020	0.014	0.050	0.020	0.020	0.016	0.059	0.114	0.014	0.016
	(0.020)	(0.016)	(0.044)	(0.019)	(0.035)	(0.008)	(0.050)	(0.107)	(0.024)	(0.021)
t-value	1.001	0.882	1.132	1.081	0.573	2.052	1.177	1.056	0.589	0.770

Specifications:
2 - Uses market shares rather than quantities as dependent variables.(Note: Ad coef. mult. by 100)
3 - Uses sqrt(advertising) as independent variable.
4 - Only Market 1 data.
5 - Only Market 2 data.
6 - Ads for past 2 weeks rather than past 4 days.
7 - 3 day time series rather than daily.
8 - Weekly time series rather than daily.
9 - Throwing out data when advertisements not observed (first 3 months).
10 - Putting in mean advertising level first 3 months.

Table 4: Explanatory Variable Descriptive Statistics

Variable	N	Mean	S.D.	Min	Max
Advertising	121359	0.0544	0.0605	0.0000	0.8333
Recent Advertisements	121359	0.0206	0.0390	0.0000	0.56000
Price	121359	0.6528	0.0702	0.2000	0.7900
Store Coupon	121359	0.0014	0.0284	0.0000	0.6700
Competitor's Price	121359	-0.1695	0.1623	-0.6859	0.0838
Number of Previous Purchases	121359	0.3144	1.6251	0.0000	42.0000
Dummy - Never Purchased	121359	0.8830	0.3215	0.0000	1.0000
Dummy - Once Purchased	121359	0.0679	0.2516	0.0000	1.0000
Days Since Last Purchase (0 if never)	121359	13.1016	49.0667	0.0000	472.0000
Time Trend	121359	0.5550	0.2592	0.0143	1.0000
Dummy - Purchased Last Shopping Trip	121359	0.0078	0.0879	0.0000	1.0000
Dummy - On Display	121359	0.0032	0.0573	0.0000	1.0000
Dummy - In Circular	121359	0.0151	0.1218	0.0000	1.0000
Dummy - Market	1775	0.4648	0.4989	0.0000	1.0000
Income Classification	1775	6.3673	2.8564	1.0000	14.0000
Family Size	1775	2.8310	1.3433	1.0000	8.0000
Presample Yogurt Purchases	1775	14.1132	26.6221	0.0000	355.0000
Presample Regular Yoplait Purchases	1775	3.4980	10.8332	0.0000	170.0000
Presample Lowfat Yogurt Purchases	1775	7.8214	16.0411	0.0000	212.0000

Table 5: Primary Estimates

Parameter	Simple Logit	Normal R.C.	Normal w/ presample Info	Simple Logit	Normal R.C.	Normal w/ presample Info	Normal w/ presample Info
Advertising* Inexperienced	2.04073 (0.72313)	2.17918 (0.76249)	2.30566 (0.77561)	-	-	-	2.32360 (0.78683)
Advertising* Experienced	0.90371 (0.63504)	0.55710 (1.22320)	0.43304 (1.21180)	-	-	-	1.33200 (1.39850)
T-Stat on Dif	1.47662	1.38641	1.58703	-	-	-	-
Advertising	-	-	-	1.71550 (0.76392)	1.85380 (0.78109)	2.01370 (0.79037)	-
Advertising* Num Prev Pur	-	-	-	-0.14812 (0.06282)	-0.24085 (0.11199)	-0.35627 (0.10803)	-0.29487 (0.12079)
Own Price	-4.89980 (0.33114)	-5.56750 (0.34183)	-5.58440 (0.34993)	-4.89500 (0.33501)	-5.57540 (0.34233)	-5.61630 (0.35604)	-5.61890 (0.35541)
Store Coupon	2.72990 (0.74368)	2.91050 (0.81432)	2.88690 (0.85073)	2.73590 (0.74214)	2.91290 (0.81708)	2.87050 (0.85707)	2.88770 (0.85558)
Competitor Price	0.76070 (0.19214)	0.73598 (0.21746)	0.76116 (0.21745)	0.76215 (0.19180)	0.74430 (0.21822)	0.76848 (0.21904)	0.76809 (0.21889)
Number Prev Purchases	0.10810 (0.06370)	-0.21309 (0.08616)	-0.26717 (0.09312)	0.10314 (0.06227)	-0.21512 (0.08423)	-0.27046 (0.09152)	-0.27303 (0.09235)
Number Prev Purchases^2	-0.00360 (0.00053)	0.00037 (0.00094)	0.00085 (0.00096)	-0.00340 (0.00057)	0.00065 (0.00094)	0.00110 (0.00099)	0.00117 (0.00099)
Never Purchased	-2.78400 (0.11685)	-1.36590 (0.26303)	-0.81135 (0.22343)	-2.72150 (0.11042)	-1.23120 (0.24307)	-0.58661 (0.21866)	-0.70453 (0.22804)
Once Purchased	-0.59088 (0.11515)	-0.23091 (0.15891)	-0.08104 (0.15986)	-0.59857 (0.11430)	-0.22264 (0.15454)	0.00169 (0.16046)	-0.06915 (0.16103)
Prev. Purch/ Time	0.84429 (0.08562)	0.45504 (0.10346)	0.46907 (0.10757)	0.84135 (0.08571)	0.45508 (0.10482)	0.46784 (0.10882)	0.46557 (0.10903)
Purchased Last S. Trip	0.17144 (0.10042)	0.42182 (0.14933)	0.47774 (0.15667)	0.19047 (0.09691)	0.43981 (0.14197)	0.51778 (0.15421)	0.51009 (0.15550)
Days Since Last Purch	-0.00577 (0.00072)	-0.00405 (0.00088)	-0.00487 (0.00091)	-0.00582 (0.00073)	-0.00416 (0.00088)	-0.00511 (0.00092)	-0.00499 (0.00092)
Time Trend	-1.65580 (0.17406)	-0.90517 (0.25331)	-0.36393 (0.26303)	-1.64200 (0.17325)	-0.85494 (0.25941)	-0.26339 (0.27417)	-0.30594 (0.27314)
Constant	0.27671 (0.29693)	-2.23170 (0.58714)	-3.83780 (0.60556)	0.22409 (0.29907)	-2.43140 (0.59175)	-4.18620 (0.62472)	-4.03510 (0.62341)
Market Dummy	0.60162 (0.06177)	1.09810 (0.15316)	1.44070 (0.17311)	0.60805 (0.06305)	1.13500 (0.15578)	1.48240 (0.17744)	1.47340 (0.17654)
Income	0.05070 (0.01344)	0.08196 (0.02890)	0.06871 (0.03118)	0.05235 (0.01334)	0.08514 (0.02930)	0.06952 (0.03210)	0.06907 (0.03209)
Family Size	-0.00719 (0.02568)	-0.02093 (0.06293)	-0.06382 (0.06886)	-0.01268 (0.02715)	-0.02150 (0.06415)	-0.06363 (0.07127)	-0.06352 (0.07086)
Presample Yogurt	-	-	-0.01817 (0.01741)	-	-	-0.01823 (0.01787)	-0.01883 (0.01783)
Presample Yogurt^2	-	-	0.00003 (0.00006)	-	-	0.00003 (0.00006)	0.00003 (0.00006)
Presample Yoplait	-	-	0.11815 (0.02472)	-	-	0.12161 (0.02531)	0.12131 (0.02520)
Presample Yoplait^2	-	-	-0.00090 (0.00027)	-	-	-0.00093 (0.00028)	-0.00093 (0.00028)
Presample Lowfat	-	-	0.06506 (0.02219)	-	-	0.06661 (0.02276)	0.06704 (0.02270)
Presample Lowfat^2	-	-	-0.00026 (0.00014)	-	-	-0.00026 (0.00015)	-0.00026 (0.00014)
Rand Effect S.D.	-	1.53920 (0.14655)	1.72610 (0.14227)	-	1.57260 (0.14289)	1.80080 (0.14951)	1.78410 (0.14754)
Log likelihood	-4090.4248	-4000.7550	-3919.6631	-4090.2372	-4000.5729	-3918.8530	-3918.4795

Note: Standard Errors in parentheses

Table 6: Additional Estimates

Parameter	Probit	.5 Logit	w/Recent Ads	w/Mean Ads	Ads/ Cal Time	Extra Variables	Random Coeff 1	Random Coeff 2
Advertising* Inexperienced	-	-	-	-	-	-	1.92920 (1.33991)	1.88474 (1.00010)
Advertising* Experienced	-	-	-	-	-	-	0.46744 (1.23330)	0.09722 (1.27440)
T-Stat on Diff	-	-	-	-	-	-	0.96904	1.43886
Advertising	1.54353 (0.60766)	2.10570 (0.85627)	1.99990 (0.84989)	1.73080 (0.82047)	1.51730 (1.27780)	2.40619 (0.89738)	-	-
Advertising* Num Prev Pur	-0.21590 (0.09934)	-0.27106 (0.14411)	-0.35610 (0.10873)	-0.35253 (0.10904)	-0.23703 (0.07343)	-0.39207 (0.11248)	-	-
Recent Ads	-	-	0.04290 (1.08531)	-	-	-	-	-
Mean Ads	-	-	-	2.48400 (2.40050)	-	-	-	-
Random Coef S.D.	-	-	-	-	-	-	1.59770 (2.03510)	1.93240 (1.45230)
On Display	-	-	-	-	-	1.59054 (0.48198)	-	-
On Display* Num Prev Pur	-	-	-	-	-	0.02305 (0.19642)	-	-
In Circular	-	-	-	-	-	1.48767 (0.17613)	-	-
In Circular* Num Prev Pur	-	-	-	-	-	-0.04596 (0.04516)	-	-
Advertising* No Presample Yog.Purchases	-	-	-	-	-	-14.23809 (2.69371)	-	-
Own Price	-4.79234 (0.29839)	-7.21680 (0.43486)	-5.61760 (0.35613)	-5.60710 (0.35583)	-5.55890 (0.35663)	-5.02189 (0.38633)	-5.57670 (0.35143)	-5.59660 (0.35210)
Store Coupon	2.20386 (0.70558)	3.23160 (0.95421)	2.88160 (0.85606)	2.88460 (0.86097)	2.88430 (0.85491)	2.91887 (0.86565)	2.89020 (0.85229)	2.89470 (0.85027)
Competitor Price	0.65377 (0.17218)	1.00150 (0.24940)	0.76818 (0.22139)	0.76963 (0.21953)	0.77910 (0.22006)	0.63461 (0.23211)	0.76262 (0.21782)	0.75828 (0.22031)
Number Prev Purchases	-0.33224 (0.08887)	-0.55373 (0.15038)	-0.27348 (0.09159)	-0.27129 (0.09161)	-0.22153 (0.08142)	-0.27843 (0.09715)	-0.27099 (0.09444)	-0.26959 (0.09677)
Number Prev Purchases^2	0.00106 (0.00093)	0.00019 (0.00124)	0.00124 (0.00099)	0.00119 (0.00099)	0.00082 (0.00095)	0.00130 (0.00106)	0.00087 (0.00096)	0.00082 (0.00103)
Never Purchased	-0.26518 (0.18168)	-0.22113 (0.29160)	-0.64520 (0.21867)	-0.65561 (0.21907)	-0.67253 (0.22325)	-0.59998 (0.22796)	-0.79770 (0.22655)	-0.81772 (0.23021)
Once Purchased	-0.00201 (0.13509)	0.11842 (0.18864)	-0.06829 (0.16101)	-0.07050 (0.16181)	-0.04665 (0.16090)	-0.03513 (0.16683)	-0.07651 (0.16044)	-0.07366 (0.16429)
Prev. Purch/ Time	0.57580 (0.10500)	0.85689 (0.16457)	0.46704 (0.11179)	0.46457 (0.10940)	0.46513 (0.11200)	0.46080 (0.11785)	0.46938 (0.10769)	0.45658 (0.10923)
Purchased Last S. Trip	0.63670 (0.15688)	1.12970 (0.28121)	0.51482 (0.15495)	0.51200 (0.15559)	0.43262 (0.13705)	0.51312 (0.16910)	0.48306 (0.15879)	0.48429 (0.16200)
Days Since Last Purch	-0.00372 (0.00069)	-0.00470 (0.00103)	-0.00504 (0.00092)	-0.00504 (0.00092)	-0.00507 (0.00091)	-0.00552 (0.00096)	-0.00489 (0.00091)	-0.00477 (0.00091)
Time Trend	-0.10565 (0.20370)	-0.19387 (0.30920)	-0.29450 (0.27363)	-0.28784 (0.27332)	-0.38408 (0.28996)	-0.01729 (0.29203)	-0.34474 (0.26948)	-0.35480 (0.26090)
Constant	-3.62905 (0.46957)	-3.05580 (0.72518)	-4.08540 (0.62216)	-4.26380 (0.64286)	-3.94160 (0.61485)	-4.50768 (0.65991)	-3.84760 (0.60839)	-3.74320 (0.62710)
Rand Effect S.D.	1.37419 (0.11292)	1.88010 (0.18230)	1.78680 (0.14829)	1.77310 (0.15277)	1.74520 (0.14943)	1.81363 (0.15305)	1.72300 (0.14234)	1.67460 (0.16554)
Log likelihood	-3908.8654	-3906.0805	-3918.7525	-3918.0326	-3920.9160	-3865.1329	-3919.4955	-3919.3047

Note: Standard Errors in parentheses. Probit estimates multiplied by 1.81 to equalize variances. Mean and variance of advertising variable in column normalized to that of the other columns. Estimates of consumer variables (e.g. income, family size, presample information) are not shown.

Chart 1 - Density of Purchase Frequencies

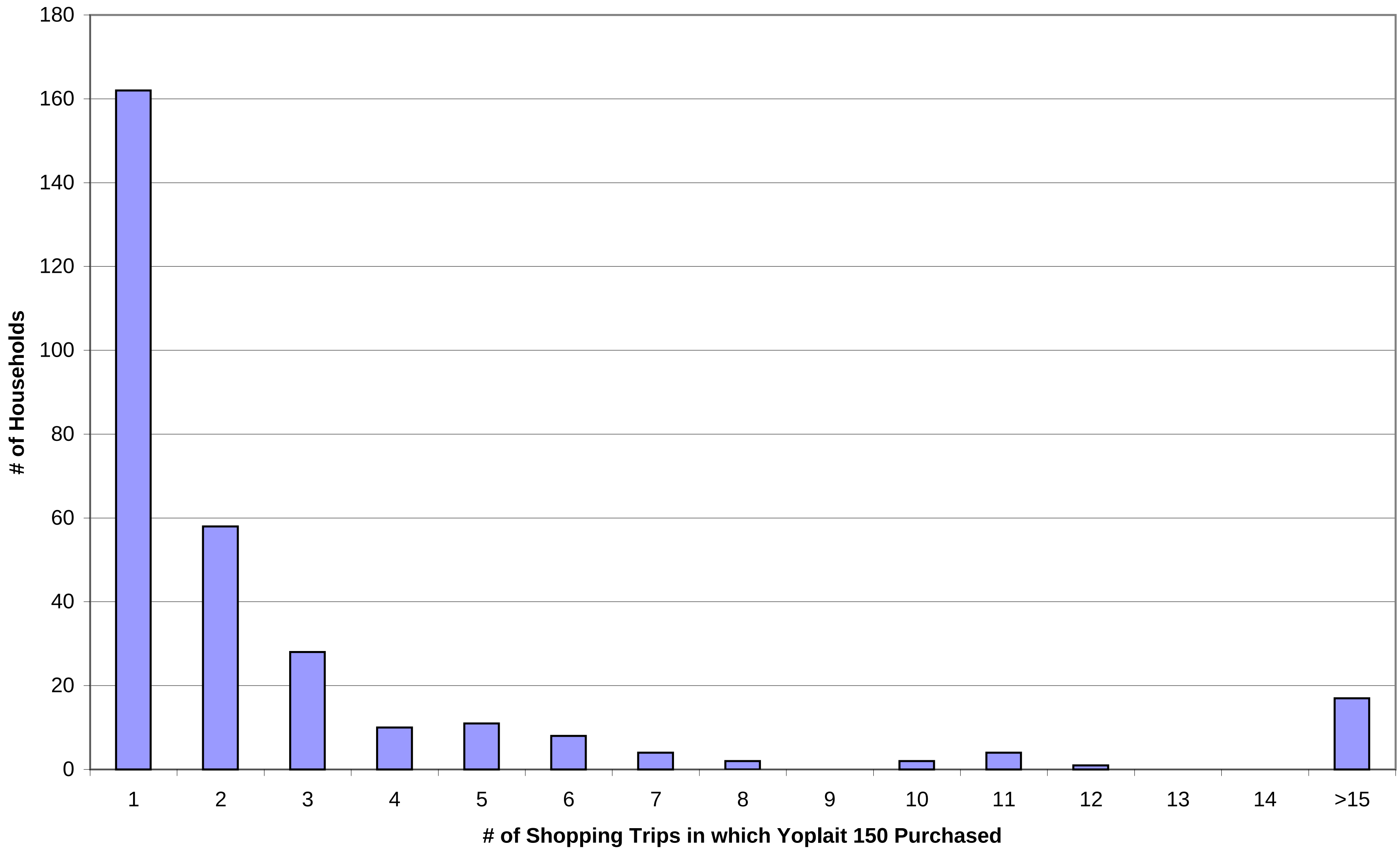


Chart 2

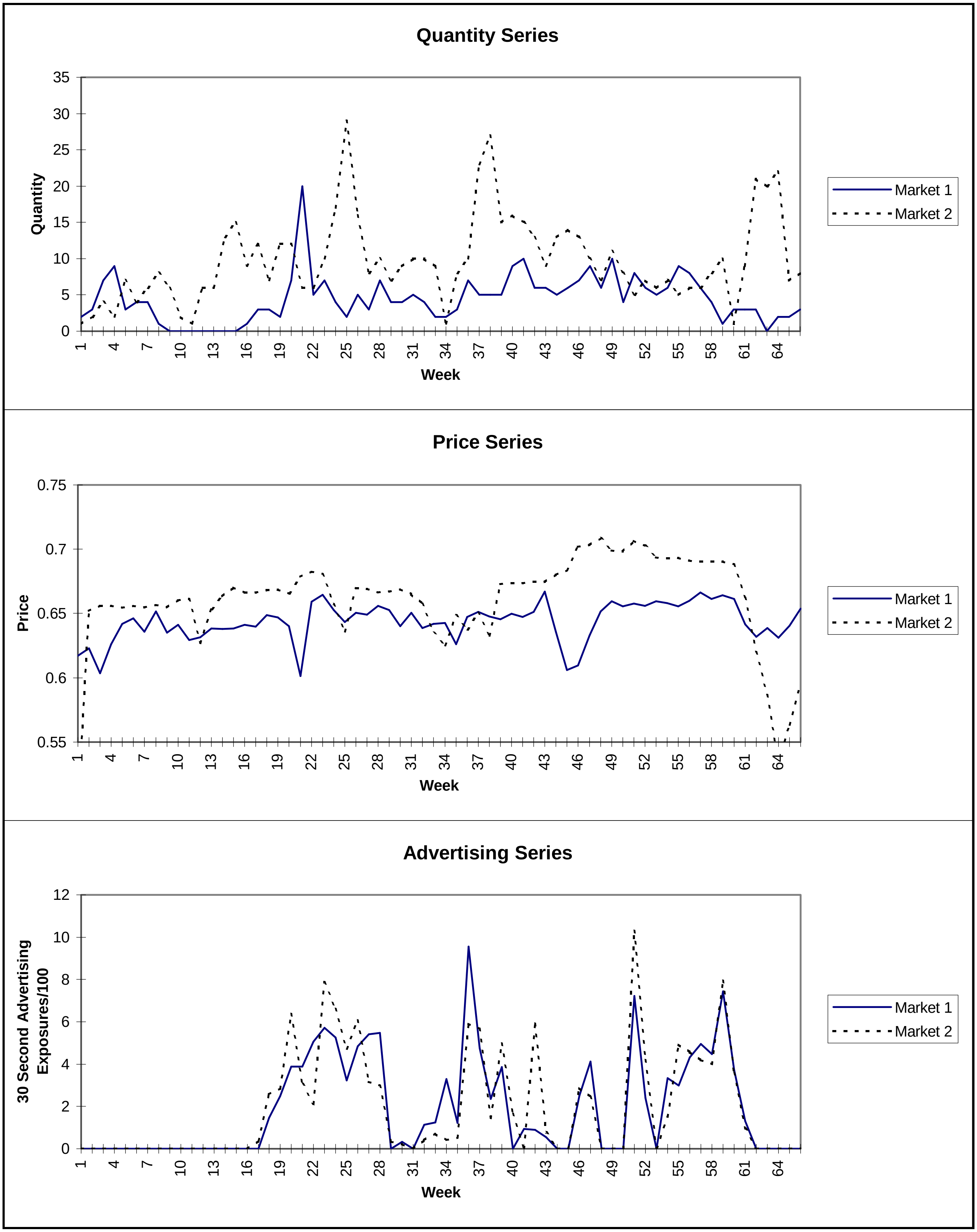
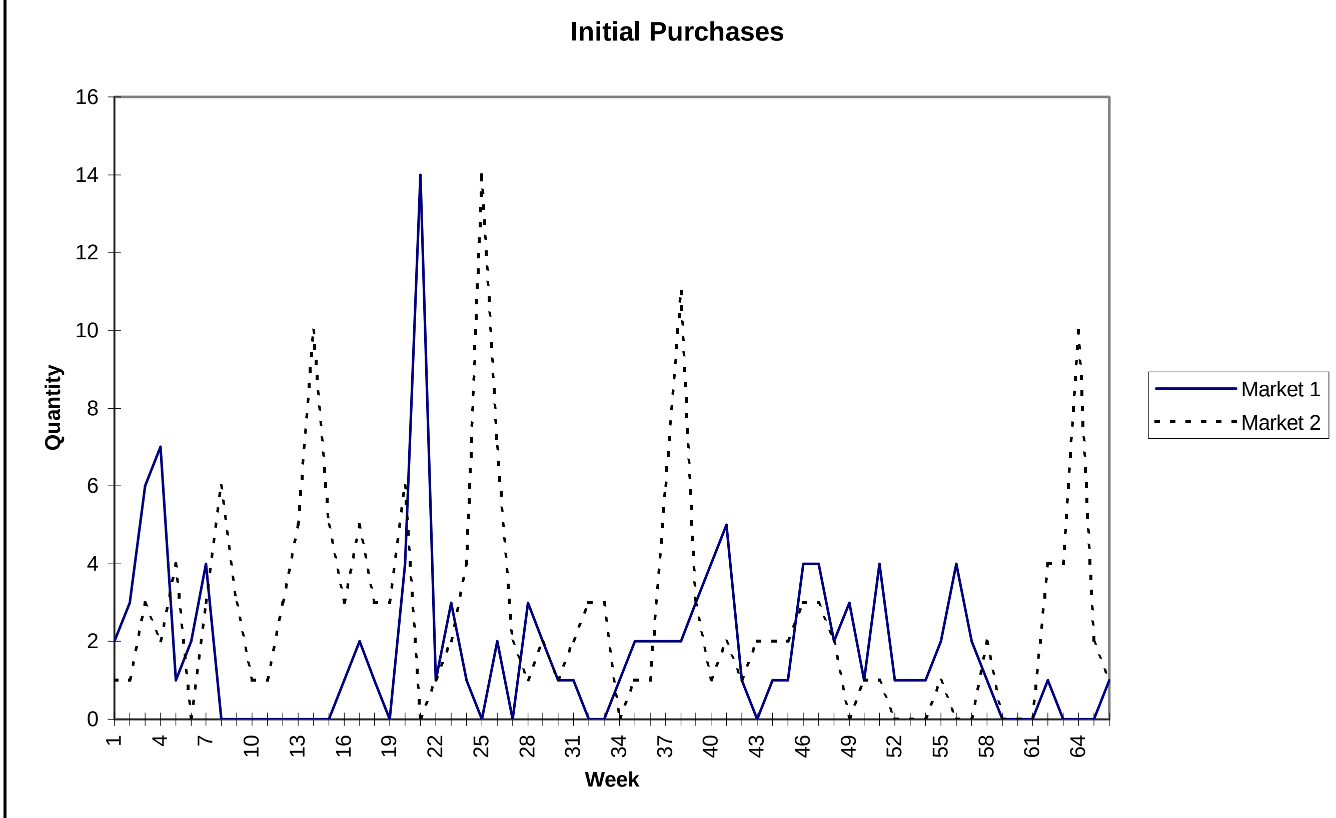
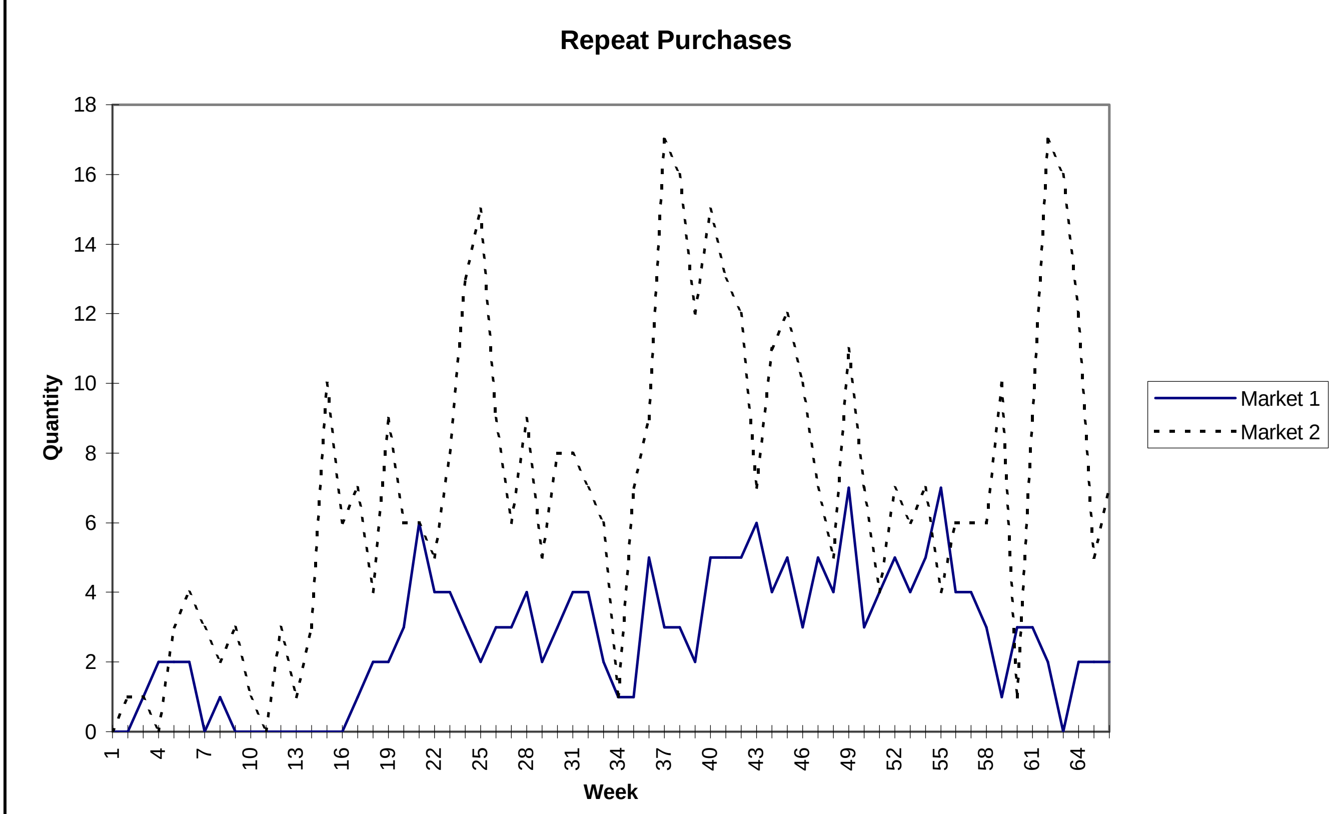

Quantity Series
Quantity
Week
Market 1
Market 2
Price Series
Price
Week
Market 1
Market 2
Advertising Series
30 Second Advertising Exposures/100
Week
Market 1
Market 2

Chart 3


Initial Purchases
Quantity
16
14
12
10
8
6
4
2
0
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
46
49
52
55
58
61
64
Week
Market 1
Market 2


Repeat Purchases
Quantity
18
16
14
12
10
8
6
4
2
0
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
46
49
52
55
58
61
64
Week
Market 1
Market 2

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