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The Impact of Price Advertising on Store Choice and Retail Competition

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ABSTRACT

The Impact of Price Advertising on Store Choice and Retail Competition

Thor Sletten

This dissertation analyzes the role of price advertising in the retail grocery setting, first exploring how consumers use price advertising in their shopping location decisions, and then considering ways in which retailers use price advertising to maximize store traffic and profits, given consumer use of information. Chapter 2 provides a survey of price advertising, and in particular of retailer weekly flyers, or circulars. I examine the retailer's decision process, from the outcomes targeted by retailers to the tactics used to achieve these outcomes. The empirical literature shows that price advertising can affect outcomes such as current period sales, store traffic, and price image. Difficulties relating to data and identification make evaluation of specific tactics difficult, but the theoretical literature has formalized and explored several tactics including deep discounting and maximization of favorable price comparisons. Chapter 3 addresses the impact of price advertising on household shopping location choice. I identify household attributes that I expect to result in greater sensitivity to orange juice price advertising—annual orange juice purchase volume and brand share of household purchases—and find that annual purchase volume is

associated with a greater tendency to visit advertising chains. This provides evidence that week-to-week price advertising measurably changes household shopping location choice. This effect is, however, concentrated on households with high (top 10 percentile) annual orange juice purchases. I find that other households are less likely to choose chains that advertise orange juice. Chapter 4 discusses two alternative price advertising models that lead to opposite predictions regarding strategic complementarity/substitutability (i.e. whether marginal profits from advertising increase/decrease when competitors advertise). To test these predictions, I estimate a complete information game on a sample of four years of orange juice advertising in three major cities. I find that advertising a major brand of orange juice is a strategic substitute, a finding consistent with models in which advertising different products reduces competitive pricing pressure.

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CHAPTER 1

Introduction

This dissertation is an exploration of how consumers use advertisements in their decisions of where to shop, and how retailers use advertised price discounts to affect those decisions. This is a practical application of information economics. Consumers have several sources of potential information about prices. First, they may take advantage of price advertisements. Second, they know prices paid in previous periods, and may also follow prices of goods they do not buy. Third, they may infer pricing behavior of firms based on their knowledge of the strategic interaction between firms. All of these sources of information involve effort and cost: memorization, time, and optimization costs. Because of these costs, the role of price advertising in consumer location choice is unclear. Consumers may or may not read price advertisements. They may or may not have a frame of reference for the advertised discounts (i.e. knowledge of previous prices). And they may or may not make inferences about the prices of unadvertised goods based on the advertised prices.

The dissertation begins with a survey of price advertising, from the advertiser's point of view (Chapter 2). Retailers must, in each week, decide what items to advertise and at what price. However, they face the same difficulties as the researcher in understanding how consumers respond to advertising. For instance, store level data that is easily available to the retailer does not record which consumers choose visit the store, nor which advertisement a consumer might be responding to. Researchers have made some progress in understanding how consumers respond to advertisements; studies indicate that advertising can affect retailers' intermediate goals such as sales and store traffic, and that small changes in prices and in the layout of an advertisement can affect the consumer's overall impression of a store's price level.

Chapter 3 of this dissertation sets out to more directly show the effect of price advertising on store traffic (or at the individual level, store choice) in particular, and makes several interesting findings. I identify household attributes that I expect to result in greater sensitivity to orange juice price advertising—annual orange juice purchase volume and brand share of household purchases—and find that annual purchase volume is associated with a greater tendency to visit advertising chains. This provides evidence that week-to-week price advertising measurably changes household shopping location choice, and that consumers who buy more orange juice are more responsive to orange juice price advertising. A heretofore unasked question is also answered by these results: the effect of advertising is concentrated on households with relatively high (top 10 percentile) annual orange juice purchases. Households outside of this group are less likely to choose chains that advertise orange juice.

This research illustrates the difficulty of empirically analyzing the effectiveness of price advertising in general. Empirically analyzing the effectiveness of specific price advertising tactics is even more difficult. However, theoretical economists have formalized and substantiated some common advertising tactics, described later in Chapter 2. For instance, the intuition behind the practice of deep discounts may be either that of a signal indicating low costs, or a need to commit to low prices to attract customers. Chapter 2 also briefly discusses empirical research into which advertising tactics retailers employ in practice. Retailers tend to advertise products at product-specific demand peaks (for example, beer at the Fourth of July), and tend to advertise brands with higher market share within their categories (for example, Tropicana orange juice vs. other brands of non-frozen orange juice).

Chapter 4 of this dissertation contributes to both the theory and empirical literatures on firm price advertising tactics. First, I suggest a new model of firm advertising competition in which firms use price advertising to differentiate themselves. By appealing to different sets of customers in a particular week (a temporary "niche" strategy), they can reduce consumers' tendency to switch and therefore reduce price competition in general. Second, I test empirically whether price advertising on specific products is a strategic complement or substitute (i.e. whether marginal profits from advertising increase/decrease when competitors advertise). I estimate a complete information game on a sample of four years of orange juice advertising in three major cities, and find that advertising a major brand of orange juice is a strategic substitute, consistent with the differentiation strategy described above.

CHAPTER 2

A Discussion of Price Advertising by Multi-Product Retailers and Survey of Related Literature

2.1. Introduction

Price advertising is the public face of retail pricing. It encompasses Chinese restaurant takeout menus as well as J Crew catalogs, and is a key source of information for consumers in the modern economy. This paper focuses on one of its most important roles–the dissemination of information on current prices (especially temporary discounts) at multi-product retailers. Retail stores carry tens of thousands of products and rely on weekly newspaper flyers to communicate prices and specials to potential customers. As well as encouraging additional consumption, these flyers are a competitive tool for retailers to affect the shopping location decisions of consumers, both in the short run and in the long run. The purpose of this paper is to discuss this common form of price advertising, and focus on the decision process and tactics of the retail advertiser.

The advertising decision process for the retailer is a balance between manufacturer incentives on one hand and intermediate profit-related goals such as sales and store traffic on the other. Empirical research indicates that advertising can affect retailers' intermediate goals such as sales and store traffic. However, the data and identification requirements of some of this research makes quantifying the impact of specific advertising tactics difficult. Thus, the theoretical literature plays a vital role in formalizing and confirming the economic logic of common advertising tactics. Finally, a small literature asks which advertising tactics retailers pursue in practice.

The paper begins by discussing the nature of price advertising and the setting in which retailers make advertising decisions (Section 2.2). Section 2.3 examines how advertising may affect operational objectives of retailers such as current-period sales, store traffic, and price image, including the difficulties involved in measuring the effect of advertising on these goals. Section 2.4 discusses various advertising tactics and their bases in economic theory. Section 2.5 summarizes efforts to measure the use of these advertising tactics by retailers in practice. Section 2.6 concludes.

2.2. The Nature of Price Advertising

2.2.1. What is Price Advertising?

A general definition of price advertising is simply advertising that includes information on prices. Price advertising may include, for example, television ads for cars that include a MSRP (Manufacturer's Suggested Retail Price), radio ads for vacations that mention a package price, or newspaper advertisements with prices for everything from laser eye surgery to peanut butter. While it may be grouped with advertising elements that attempt to persuade consumers or to complement their consumption of goods, price advertising is a form of informative advertising.[1] Its immediate purpose is to inform consumers that a product is available (often through a particular retail outlet) at the announced price.

One of the most intensive forms of price advertising is the weekly newspaper flyer published by grocery chains and other large retailers. These flyers include prices on

[1]See Bagwell (2007) for a survey of economic research into advertising in general, including a discussion of these three views of advertising.

dozens or even hundreds of items offered by a given retailer. Advertisements within these flyers may include product information, alert shoppers to new products, or serve other purposes of the retailer or of product manufacturers. Also, the flyer as a whole serves to remind the consumer of the retailer's presence and general product offerings. However, priority of font and placement in these advertising flyers belongs to prices.

Prices in retail advertising flyers range from the every-day to the deeply discounted. For some retailers, especially supermarkets pursuing an Every-Day Low Price (EDLP) strategy, most of the prices in the flyer are simply the retailer's regular prices. When price discounts are offered, the regular prices are often displayed in small print below the discounted price, as reference prices to emphasize the savings available.[2] Larger discounts are associated with larger and more prominent advertisements. A ads are large picture ads placed in prominent positions on the flyer (front, back, top of interior pages) and drawing attention to large discounts. B ads are smaller ads, often towards the bottom of interior pages. Items are still pictured but may be only slightly discounted.

Advertising and discounting a product incurs two types of costs—the cost of printing and distributing the flyer, and the decreased overall margin on the discounted product. Manufacturers and retailers share these costs through "trade promotions": manufacturers offer a variety of different promotional incentives to encourage retailers to advertise their products, to discount them, and to place them in prominent locations in their stores. The direct cost of circulars, in 2003, was around 5.5 cents per flyer, and a typical grocery store might distribute 15,000 flyers in a week, for a total expense of around $40,000 per year per

[2]Experiments described in Urbany, Bearden, and Weilbaker (1988) indicate that adding reference prices to advertisements raises consumers' perception of value and decreases their tendency to search for better prices.

store.[3] Flyer costs are partially paid using co-operative advertising allowances, which are funds available to the retailer on the condition that manufacturers' products appear in the advertisement. Grocery retailers in particular receive co-operative allowances covering nearly all of their flyer costs (Blattberg and Neslin 1990).

The cost of discounts is more difficult to measure, but one 2005 estimate by the accounting firm KPMG places the amount paid to retailers by manufacturers in the form of trade promotions (thus including both flyers and discounts) at between 12 and 30 percent of supermarket sales (Rittenhouse and Hartley 2005). Manufacturers attempt to induce retailers to discount their products using discounts per wholesale sale ("off invoice") and discounts per retail sale ("scan-backs"), among other deals. The degree to which the wholesale discounts are passed on in the form of lower prices for consumers is, however, at the retailer's discretion. Besanko, Dube, and Gupta (2002) estimated average pass-through rates for 11 grocery categories, and found these rates to vary between 0.22 (toothpaste) and 5.58 (beer).[4] The median pass-through rate for the categories studied was 0.83.

2.2.2. Choosing What to Advertise

Although all retailers may be assumed to be maximizing profits, selecting the profit-maximizing portfolio of advertised goods is a complex problem (even leaving aside the selection of optimal prices on those goods). To reduce optimization costs, retailers rely on

[3] According to Sue Klug, an industry consultant, as quoted in Riell (2003).

[4] A pass-through rate of 0.22 implies that a wholesale discount of $1 would lead to a discount of 22 cents on the retail price. Conversely, a pass-through rate of 5.58 would imply a retail discount of over $5.

planning heuristics, and use advertising (combined with discounts) to meet intermediate goals (Blattberg and Neslin 1990). These intermediate goals include:

- *Store Traffic*: Advertisements are thought to increase the number of shoppers visiting the store in the same week. These additional visits may be extra shopping trips by loyal customers or trips "stolen" from other chains.
- *Current-Period Sales*: Advertisements are known to increase sales of advertised products, and are thought to increase sales of complementary products. The ads increase consumer awareness of products and price discounts on those products.
- *Price Image*: Advertisements may cause consumers to perceive the store as offering better value for money in the long run. Due to limitations in consumers' memory and ability to quickly process price information, consumers likely use heuristics. Using advertisements to update a general impression of a store's price level is one such heuristic.

We can thus frame the effects of price advertising as producing results in one or more of these areas. Table 2.1 is a list of the items chosen for the front page of the flyer from four grocery chains in the Boston area, for the week before Thanksgiving. Turkey or turkey dinner appear on the cover of each advertisement (at one chain turkey and turkey dinner are the only items on the front of the flyer). Other items appear that might be elements of Thanksgiving dinners or substitutes for turkey: butter, chicken breasts, hams, canned and frozen vegetables, and apple pie. Otherwise, the list of items spans the entire grocery store, from branded non-perishable goods to fresh fruits and meats.

Table 2.1. Products Advertised on Cover of Boston Grocery Store Flyers, Week before Thanksgiving

Grocery Chain	Headliners	Cover Advertisements: Other Cover Items	
Shaw's	Turkey Chicken Breast Shoulder Steak	Soda (cans) Butter Orange Juice Blueberries & Blackberries Ice Cream Potato Chips Shrimp	Turkey Breast or Ham (Sliced) Coffee Olive Oil Paper Towels & Bath Tissue Cookies Toaster Pastries
Stop & Shop	Strip Steak Berries Cranberry Juice	Turkey Ice Cream TV Dinners Canned & Frozen Vegetables Ginger Ale (Bottles)	Cereal Salmon Bacon Cake Mix Toothpaste
Market Basket	Turkey Turkey Dinner	(none)	
Foodmaster	Chicken Tenders Ham	Shrimp Chicken Breasts Bottled Water Baby Carrots Muffins Apple Pie Cod Fillets	Oranges Beer Turkey Dinner Frozen Vegetables Flour Cheese Steak

The advertisements in Table 2.1 are clearly trying to attract holiday shoppers, and hoping that discounted turkeys will drive sales of other Thanksgiving dinner items. Increased grocery shopping around the holidays may also be an important opportunity to fix general price impressions in consumers' minds. Also, the wide variety of products advertised may be a tactic to reinforce the idea that the retailer has low prices in all the product categories in the store.

Several criteria were identified by Curhan and Kopp (1986), through a survey of retailers, as being important in the selection of items to promote. First, retailers chose to advertise products of greater importance to consumers more frequently. Second, they considered the "promotion elasticity" of the item—that is, how responsive sales of the items are to temporary discounts (as distinct from price elasticity). A third issue was "promotion wear-out": consumer response to advertisements for products that have recently been included in the flyer will be diminished. This is especially problematic for easily storable products, as households will stockpile goods for future use during sales. Finally, brand support was identified as a consideration. Manufacturers' non-price advertising, coupons, reputation, and overall product quality all contributed to the overall attractiveness of a brand as a potential advertisement.

Additionally, retailers advertise (and discount) products when trade promotions are favorable. Small advertisements with little or no price discount may be used to take advantage of co-op advertising funds contingent on advertising placement (Blattberg and Neslin 1990). Off-invoice and scan-back discounts from manufacturers raise margins for retailers, thus increasing the benefits available from advertising.

2.2.3. Choosing at What Price to Advertise

Price advertising is intimately connected to discounting. For example, in a sample of orange juice sales at grocery stores and other outlets in Chicago,[5] discounts were advertised for 28% of all product-store-weeks, at an average discount of 8.4% from non-advertised product-store-weeks. Together, this activity significantly impacts orange juice sales: in the data, advertised products account for 48% of all sales by volume, and 44% of sales by revenue, despite encompassing only 28% of sample observations.

Retailers begin their advertising selection decision by compiling a list of available manufacturer trade deals. All else equal, higher margin items are more profitable to

[5]This dataset is used in the analysis contained in Chapter Four of this dissertation. The dataset spans 2001 to 2005 and contains weekly observations of orange juice sales, prices, and advertising behavior at a representative sample of retail outlets in Chicago.

advertise, and these trade deals by definition provide higher margins at regular prices. However, there are several reasons why a retailer might want to discount the products it chooses to advertise. First, lower prices may attract customers to the store, both through the provision of additional surplus, and through comparisons with other stores' advertised products. Second, as they are differentiated by location and consumer taste, most retailers have some market power. Because of this market power, the original prices are likely not profit-maximizing for the retailer once the trade deals lower marginal costs. The trade deals thus lead retailers to lower prices (i.e. "pass through" some part of the trade deal) to maximize the value of the promotion. Third, if customers buying the advertised product also increase their purchases of complementary goods, then optimal prices may be even lower than in the single-item scenario.

Theoretically, these motives for discounting might jointly lead retailers to discount away their entire margin. Items priced at or below marginal cost in advertising flyers are famously known as "loss leaders".[6] While it is not clear whether loss leaders literally exist, certain advertised items are sold at steep discounts to their usual prices. Turkeys, as featured in the ads summarized above, are an extreme example of this phenomenon. The vast majority of whole, frozen turkeys (80% in 2003) are sold on holiday specials, and the USDA found that, in 2003, these turkeys were sold at an average price that was two thirds of the price paid by consumers during the rest of the year (Longley 2004). This

[6]"Loss leader" is a poorly defined term even in the academic literature. Another definition, given in Busch and Houston (1985) (as quoted in DeGraba (2006)), is: "Loss leader pricing is the practice of setting prices on selected products at low levels that generates less than the usual profit margins. . . For retailers the objective is to increase store traffic so they can sell other products at traditional profit margins. . . Products that are used as loss leaders are usually well known brands and frequently purchased."

presumably includes specials through which a consumer can spend a certain amount at a store and receive a free turkey.

2.3. Consumer Response to Price Advertising

The most basic practical question relating to price advertising is whether price advertising has any effect on the intermediate goals of retailers: store traffic, current-period sales, and price image. Answering these three questions requires quite different empirical approaches. Measuring advertising's effect on current-period sales is simple, using scanner data available to any retailer. Measuring its effect on store traffic and price image is somewhat more difficult, requiring either consumer surveys, experiments, or the construction of household choice models.

2.3.1. Current-Period Sales

It is well established that advertised discounts increase current-period sales of advertised products at advertising stores. Blattberg, Briesch, and Fox (1995) review this and other empirical generalizations from research on the effects of temporary discounts. The effect on current-period sales can be measured simply by comparing store sales of a product during weeks in which a product is advertised with weeks in which the product is not advertised. A slightly more sophisticated analysis will control for previous weeks' advertising activity, and competitors' advertising activity (e.g. Kumar and Leone 1988). Temporary discounts also affect the sales of complementary and competing products, although the effect varies depending on the products in question (Walters and MacKenzie 1988).

2.3.2. Store Traffic

The evidence of advertising's effect on shopping location choice is somewhat sparse. There are several reasons for this lack of evidence. First, it is difficult to judge whether a consumer traveled to a store in order to take advantage of a sale or whether the consumer took advantage of a sale only because they happened to be at the store. For this reason, and also because of stock-piling and purchase acceleration (discussed in the previous subsection), store-level sales figures make a poor measure of consumers' location decisions. Second, most grocery retailers sell tens of thousands of different products and advertise hundreds every week. This makes identifying the effect of specific advertisements difficult, even with access to store traffic data. Each consumer's current food supplies and preferences determine to which ads that consumer pays attention. Moreover, since the size of an advertising flyer is roughly fixed (especially the high impact areas such as the front cover), each advertisement has an opportunity cost. If orange juice is advertised, some other product such as apple juice or milk is not advertised. This implies that the impact of not advertising any particular product may be minimal for most consumers.

One approach to the question is to find a product for which stockpiling is minimal and consumption occurs at a constant rate. In other words, the researcher requires a product that a given household will purchase at some retailer every week. Assuming that consumers do not change the number of shopping trips made in a given week in response to advertisements, then any shift in sales of the product between competing retailers in a week implies that consumers are changing their shopping location in response to advertisements. Kumar and Leone (1988) take this approach in their study of diaper sales at a set of neighboring stores. They find that diaper sales fall at neighboring stores during weeks in which grocery stores advertise low prices on diapers, implying that consumers are traveling to the advertising stores to buy their diapers rather than to the non-advertising stores. The advantage of this approach is that it only requires store level sales data; however, it also requires the strong assumptions on consumption and consumer shopping behavior described above.

Another approach is to use store sales data in combination with store traffic data. This allows the researcher to relax the assumption that consumers do not stockpile or accelerate purchases, widening the set of products that may be studied. However, it still faces several other difficulties. First, the assumption that consumers do not "cherry pick", or make visits to stores solely to purchase discounted products, is still required. Second, a difficulty is introduced that is not found in Kumar and Leone's study above: overall store traffic statistics are a function of all advertisements, not merely the advertisements of interest. As above, the analysis of advertising on overall store traffic is not ceteris paribus—when a product is advertised some other product is not advertised. Walters and Mackenzie (1988) utilize store sales data in combination with store traffic data at two competing stores. Out of eight categories examined, they found that only one ("rolls/buns") was effective in increasing store traffic.[7] Given the fact that advertising has an opportunity cost, it is not surprising that the effect of a single advertisement on store traffic would not be observable in overall store traffic data.

Household-level data enables researchers to more clearly identify sales to new as opposed to existing customers. Grover and Srinivasan (1992) use household spending data

[7]Other categories included baking supplies, paper products, prepared foods, eggs, coffee, carbonated soft drinks, and condiments. This is an interesting example of comparing the impact of advertising and discounting across categories, and would be valuable to repeat with household-level data.

to estimate a segment model of brand and store choice. They find that a store's share of market-wide coffee sales in a given week is increasing with an aggregate measure of coffee promotional activity at the store. This promotion measure is a combination of discounting and advertising, and thus does not isolate the effect of advertising. However, the measure is segment-specific: it places greater weight on promotional activity of each segment's preferred brands. Also, there is no analysis of household trips, only total household spending on coffee.

Household panel data that includes data on shopping trips provides the clearest evidence on consumer store choice decisions. Such data allows direct study of households' frequency of trips to a store, while allowing the researcher to look at households' shopping histories to identify which advertisements a consumer likely focuses on and control for household-store-specific effects. Bell, Ho, and Tang (1998) consider fixed costs vs. variable costs in the consumer's shopping location choice decision. To identify the impact of prices (variable costs), they derive an estimate of the unobserved household shopping list from the observed list of products purchased by the consumer, using historical purchases. They then construct a measure of expected prices from current price advertising and prices previously observed by consumers. They find that variable costs (including advertised prices) play a small but significant role in consumers' shopping location decisions. However, they do not separate the effect of advertising from the effect of other expected discounts.

Chapter 3 of this dissertation also takes advantage of household panel data with data on trips, but focuses on a single product, allowing for more careful isolation of the effect of price advertising. In this chapter, I compare the effect of price advertisements on the store choices of households consuming different levels of orange juice over the sample. I find that high-consumption households are more likely to visit advertising stores, and that low-consumption households are less likely to visit advertising stores (presumably because of the fact that alternative ads are on average more attractive to these consumers). Moreover, I find that only households consuming more orange juice than 90 percent of the remaining population have a positive store choice response to advertising. This suggests that retail managers might be better off advertising "deeply" rather than "widely"; that is, advertising products constituting a larger fraction of individual households' spending rather than products purchased in small quantities by a large number of consumers. It may also be important that orange juice is frequently price advertised, as opposed to other products studied in the past.

2.3.3. Price Image

It is believed that consumers simplify their shopping decision-making, consciously or unconsciously, by forming and maintaining an impression of the general price level of a store (the "price image"). "It is implausible to expect consumers to conduct a controlled experiment across their typical shopping basket, given the number of products, brands, sizes, and formulations in their consideration sets and the apparently low level of effort they exert even in the presence of relatively inexpensive goods (Marmorstein, Grewal, and Rishe 1992[8])." Consumers likely use some limited amount of information to help them infer which store will offer them a greater amount of potential surplus. However, if isolating the effect of advertising on store choice is empirically difficult given shopping

[8]As quoted in Alba et al. (1994).

data, isolating the effect of advertising on price image (which can in turn only be observed through store choice) is nearly impossible. This creates a significant role for experimental and survey approaches to the problem.

In particular, several experimental studies have examined the effect of advertising flyers on consumers' perception of a retailer's overall price level. These studies consider whether changes in advertisements, such as changing the number of advertised discounts or manipulating displayed regular ("reference") prices, can affect this price image. They find, overall, that advertising is successful in changing consumer expectations for non-advertised prices. Reference prices (and the accompanying emphasis of discounts) seem to cause consumers to perceive retailers as offering more value, and for consumer use of heuristics (perceptual shortcuts), based on the number of discounts observed, rather than the magnitude of those discounts.

Urbany et al. (1988) test the effect of reference prices on consumers' perception of stores' price image. They find that adding reference prices to advertisements raises consumers' perception of value and decreases their tendency to search for better prices. This result remains even when reference prices are obviously exaggerated and consumers are skeptical of them. Cox and Cox (1999) test the interaction between reference prices, frequency of purchase, and brand vs. generic products. They find, consistent with Urbany et al., that reference prices posted with sale prices in flyers lowered consumers' perceptions of prices at the store. While reference prices on frequently purchased products and branded products are not more effective than other products, they do find an interaction; reference prices on frequently purchased, branded products are less effective at changing consumers' price image than reference prices on infrequently purchased, branded products.

Alba et al. (1994) study whether consumers use shortcuts in perception ("heuristics") in order to quickly determine what an advertisement implies for the value offered by a store. They test two possible heuristics: they suppose that consumers might perceive the number of advertised discounts to be synonymous with lower overall prices ("frequency" heuristic); alternatively, they suppose that consumers might perceive the depth of discounts to by synonymous with lower overall prices ("magnitude" heuristic). Consumers were found to respond more strongly, in terms of adjusting their price image of the store downwards, when they saw advertisements with many discounted products, than they did when they saw advertisements with deeply discounted products (given the same overall price level in the advertisement).

2.4. Advertising Tactics and Their Relation to Economic Theory

An important role for theoretical research in regards to price advertising is in the formalization of advertising tactics. As the previous section illustrates, the effects of advertising on retailers' store traffic and price image can be difficult to quantify. Despite the difficulties, however, retailers take both price image and expected traffic into account when making advertising decisions, because of their importance to profit. Economic theory cannot prove that particular tactics designed to improve price image, for instance, will be effective. However, modeling consumer choice and strategic interactions between firms can help retailers and researchers understand (under the assumption that direct price comparisons affect consumers' perception of a store's price level) whether varying the advertised price might improve profits. Following are several advertising tactics—the efficacy of which are difficult to test directly—and the theoretical work that supports their economic logic and in some cases extends to novel implications for advertisers.

2.4.1. Maximize favorable head-to-head price comparisons with other retailers (while minimizing unfavorable comparisons)

One concern of retailers is to advertise a "competitive" price.[9] In particular, retailers place importance on having lower (or at least not higher) prices than their close competitors. There are two possible intuitions behind this approach to advertised pricing. The first intuition, found in Varian's (1980) model of random sales and other papers since (Anderson 1999 etc.), is that a store's market share rests on a knife-edge. That is, there is a substantial fraction of customers that will choose to buy from the store that charges the lowest price. Therefore, the marginal value of lowering one's price from one penny more expensive than one's rival to one penny less than that rival is very high. An example of the second intuition is found in Simester (1995). In this model, prices serve as a signal of retailer costs. As a result, viewing advertised prices affects a consumer's belief about the store's costs and his expectations regarding non-advertised prices (note that these expectations could be interpreted as a "price image"). This is true even for consumers who do not intend to purchase advertised products. Together, these intuitions suggest that an advertisement that does not price competitively is a wasted (or even counterproductive) advertisement.[10]

[9] This was a central strategic concern for a retail marketing executive interviewed on the topic of price advertising by the author. Blattberg and Neslin (1990) also cite this sort of competitor price comparison as a major factor in selection of items to promote.

[10] A third intuition is implied by the experimental price image literature above. If consumers are more affected by the number of advertisements in which one store undersells another than by the magnitude of the savings, then demand may have a similar knife-edge quality.

Varian (1980) proposes a model with a large number of stores, each of which has monopoly power over a group of loyal customers. The stores compete on price for another group of customers, who are both uncommitted and informed as to prices. He finds a symmetric equilibrium in mixed strategies: each store advertises a random price in a balance between capturing profit from loyal customers and capturing non-loyal, advertising-sensitive customers. The random price (a mixed strategy with no probability mass below the "monopoly" price) is necessary to avoid being systematically undercut by other stores. In other words, advertising facilitates price discrimination between informed and uninformed consumers (alternatively between loyal and non-loyal consumers). It also generates a pattern of dispersed sale prices, both a high "regular" price and lower "discount" prices. More generally, Varian's paper illustrates the idea of using advertising to improve the effectiveness of discounts. Instead of simply increasing sales to current (or local) customers, advertisers can sell to new (or distant) customers. However, in this model advertising is risky; only the lowest advertised price is of any value, *ex post*.

Bagwell's (1987) model of introductory prices develops the theory of low prices as signals of low cost. His basic model involves a monopolist setting prices in a two stage game. The monopolist has high (low) costs with some probability q (1-q). A consumer decides whether or not to visit the monopolist's store, and then chooses whether or not to buy based on the price they observe. The consumer then repeats these choices in the second period, taking into account the information from the first period. As it turns out, there are two sequential equilibria, one pooling and one separating. When travel costs are low, the pooling equilibrium obtains: both high and low types charge the "low-firm" price in the first period, and extract their respective monopoly rents in the second period.

When travel costs are high, the separating equilibrium obtains: if low-type firms do not communicate their low types with a low introductory price, consumers will not make the second visit.

Simester (1995) develops this model as a single-period, two-good model, in which two retailers compete with each other on either end of a Hotelling line.[11] In this model, the first good must be advertised at a low price in order to convince the consumer of the retailer's low cost type. Because this signal is costlier to the high-cost retailer than to the low-cost retailer, a separating equilibrium may obtain. Simester also develops several other results. First, "identical unadvertised prices is a sufficient but not a necessary condition for identical advertised prices." It is possible, under certain conditions, that a pooling equilibrium may obtain in which high- and low-cost retailers advertise identical prices. Additionally, the differences in advertised prices, in a separating equilibrium, are decreasing in travel costs, and are decreasing in the size of the gap in cost between high- and low-type retailers.

2.4.2. Commit to deep discounts on a few key products

Thanksgiving turkeys provide an example of a product that is heavily discounted (at least relative to its regular price) at a particular time of the year in order to draw customers into the store. The intuition that it is rational for a store to commit to low prices on a few goods, in the hopes of making compensatory profit on other goods, has been formalized in a variety of theoretical papers. The most cited example is Lal and Matutes' (1994)

[11] A Hotelling line (after Hotelling 1929) is a market in which two stores are located on the ends of a line, and consumers are distributed along the line. Consumers pay a travel cost equal to twice the distance from their location to the store(s) they choose to shop at.

model of loss leaders, in which one product is advertised at a price below marginal cost while another, unadvertised product is priced much higher. A variation on this model is proposed by DeGraba (2006), who argues that loss leaders may be made more efficient by selecting products to advertise that tend to be purchased by more profitable customers. Turkeys, being associated with large, home-made meals, are the eponymous example.[12]

The motivation for these models comes from Stiglitz' (1979) "non-existence paradox". In a simple search model with homogenous stores and consumers, imperfect information and travel costs can create a market failure (i.e. no equilibrium exists). Because travel costs are sunk once a consumer reaches a store, each store has an incentive to set price such that the expected value of further search is zero. This results in each store raising its price until each is pricing at the consumer's reservation value.[13] As a result, no consumer expects *ex ante* to receive positive surplus from a shopping trip, and so all consumers remain home. Hence, "non-existence": no equilibrium exists in which consumers shop.

The key insight of Stiglitz' model is that, without any commitment devices (either contemporaneous, through advertising; or dynamic, through retailer reputation) retailers will optimally price at consumers' reservation prices. Lal and Matutes (1994) use this insight to explain why loss leaders might exist. In Lal and Matutes' model, there are two stores, located on either end of a Hotelling line. As in Stiglitz' model, consumers begin without any knowledge of prices, must decide which store (if any) to visit, and may purchase goods once at that store. Also as in Stiglitz' model, the only possible equilibrium price for unadvertised goods is the reservation price. However, in this model

[12]DeGraba, Patrick, "The loss leader is a turkey: Targeted discounts from multi-product competitors," Intenational Journal of Industrial Organization 24 (2006), 613-628.

[13]The reservation price is the maximum price that the consumer will pay to obtain the product.

retailers have the opportunity to advertise one or more products, thereby committing to a price on those products. Providing that transportation and advertising costs are not too low, the equilibrium of the model is such that each store advertises one and the same product at the same price (below marginal cost), and each consumer purchases both the advertised good and the unadvertised good at the closest store.

More generally, Lal and Matutes (1994) is part of a literature in which consumers make shopping decisions by comparing the potential surplus available to them from goods whose prices are advertised, and either do not purchase unadvertised goods or assume their prices to be equal across stores. Several papers extend Lal and Matutes to make the point that products with greater demand are more desirable to advertise. Lal and Narasimhan (1996) show that, if manufacturer advertising can induce consumers to purchase more units of the advertised good, then the price of the advertised good will drop further, creating an inverse relationship between manufacturer non-price advertising and retailer margins. Hosken and Reiffen (2004a) argue that, because firms prefer not to offer goods below cost, advertising goods of higher value to consumers allows a store to attract more shoppers for a given level of advertising spending.

Degraba (2006) uses the basic loss leaders model of Lal and Matutes to focus on consumer heterogeneity. In particular, he suggests that large discounts such as turkeys at Thanksgiving may be an optimal response to the greater per-customer profitability of turkey-buying and non-turkey-buying households, because households buying turkeys are cooking large dinners and are thus buying a variety of other products. Degraba also makes a number of interesting related findings. First, margins should generally be lower on goods that tend to be purchased by more profitable customers. A corollary to this is that widely purchased goods may not be effective loss leader items, because they are not bought chiefly by the profitable segment of a retailer's customers. Finally, overall prices may fall at holidays because consumers are more willing to travel (hence lower prices may attract more customers at holidays than at other times of the year).

Note that, while Degraba does not formally model advertising, in his model non-"targeted" goods are not discounted from their regular prices; thus, it is consistent with a model with both advertising and an information assumption such as in Lal and Matutes (consumers do not know unadvertised prices) or with consumers having some "price image"-like knowledge of non-advertised prices.

2.4.3. Avoid discounting altogether

Many of the above models rely on the assumption that consumers do not remember prices, and so there is no ability for retailers to acquire a reputation for low prices. While this can simplify modeling advertising competition, it has a conceptual cost. If consumers are assumed to have rational expectations, the equilibria in these models all result in non-advertised goods being priced extremely high. This is exactly why deep discounts are profitable in these models. Because consumers, once in the store, are so profitable, retailers are willing to invest heavily in attracting them, either through commitments of surplus (as in Lal and Matutes 1994) or by signaling a low-cost type (as in Simester 1995).

An alternative strategy, assuming that stores can establish and maintain a price image in consumers' minds, is to avoid discounting except for limited reductions tightly tied to manufacturer deals. This is known as the Every-Day Low Price (EDLP) strategy (as opposed to the promotion-driven, or HILO, strategy). The rationale for EDLP vs. HILO is addressed by Bell and coauthors in a series of linked papers (Rhee and Bell 2002; Bell and Lattin 1998; Bell, Ho, and Tang 1998). An EDLP strategy may be profitable because of consumer heterogeneity in fixed costs of shopping. In short, households with higher fixed costs prefer to make fewer shopping trips. When households make fewer trips, they are less able to take advantage of discounts, and therefore prefer stores with smaller week-to-week price variance around a given average price. Thus, discounting frequency may allow for a degree of differentiation between retailers, and increase profitability.

2.5. Advertising Tactics in Practice

What seems clear, after examining the empirical literature on consumer choice in response to price advertising, is that testing the optimality of a given price advertising strategy is difficult. This applies to retailers as well; the difficulties are not merely lack of insider information but problems of identification and difficulty in gathering information. That said, it remains of interest to ask which price advertising tactics retailers use in practice. Two basic empirical results are supported by the existing research. The first regards product selection: advertising is positively associated with a product's share within its category. The second result regards advertising timing: grocery retailers are more likely to advertise goods during product-specific demand peaks.

There is some evidence that category-leading products are advertised more frequently. One early empirical study in the area, Nelson, Siegfried, and Howell (1992) examines ground coffee pricing across markets, and finds that the wholesale price for Maxwell House coffee was higher in markets where it had higher market share. Four theories for this effect are proposed: (1) increasing marginal cost in a market; (2) increased share is correlated with concentration; (3) consumer habit supports higher demand; (4) high market share products make more effective price advertisements (and therefore are discounted in order to advertise, reducing retailer markups). The authors claim to rule out the cost and concentration-based theories by other tests, leaving the possibility that there is either a strong consumer habit effect, or that prominent brands are more attractive for retailers to discount on their own.[14]

The notion that prominent brands are more attractive for retailers to advertise is confirmed by Hosken and Reiffen (2004a, see discussion below). They find, over a dataset of six grocery categories, that products with higher within-category market shares are more likely to be discounted. They also find that the relationship between market share and frequency of discount is non-linear—over six categories, in five (with the exception of tuna) the elasticity of discount frequency with respect to market share was greater than 1.

While these results refer to discounting, they are also consistent with the findings on price advertising reported in Table 4.1 of this dissertation. In each market, the rank of the three brands' of level A advertising and overall advertising in each market is identical to the rank the three brands' sales in that market. Note that, since this is a static comparison and involves no time-series analysis, there is no evidence that market shares are causing the high level of advertising rather than the reverse.

A series of studies studying the timing of discounting finds that advertising increases for products at product-specific seasonal demand peaks. Steiner (1973) finds that general

[14] Nelson et al. also provide several interesting quotes from industry executives. "Let me give you an example. In Philadelphia ... [t]he trade was low balling Maxwell House for their own purposes. This has been going on for years, well before Folgers was ever introduced. It was used as a loss-leading item to build traffic in the major chains...."

merchandise retailers do most of their toy price advertising in the month prior to Christmas. MacDonald (2000) examines a wide range of products in a nationwide store dataset, and finds that almost all products that are ever advertised in grocery flyers are advertised significantly more frequently during seasonal demand peaks.[15] Chevalier, Kashyap, and Rossi (2003) also find that products at (product-specific) seasonal demand peaks are advertised more at a particular grocery chain in Chicago. However, Nevo and Hatzitaskos (2005), using the same data as Chevalier et al., find that advertising is not more effective at increasing product sales during seasonal demand peaks. They also find, for at least one product (tuna), that sales of brands that are aggressively price advertised during the period actually decrease relative to a brand for which advertising stays constant.

Hosken and Reiffen (2004a) do not have data on advertising, but they find a similar result to Chevalier et al. using nationwide pricing data. Hosken and Reiffen point out an interesting result—the price change they observe is primarily due to an increased tendency to put items on sale, rather than any change in the regular price.[16] This is consistent with products being more profitable to advertise during demand peaks. Consistent with Nelson et al. (1992) discussed above, they also find that products with higher within-category market shares are more likely to be discounted.

The two results discussed in this section relate indirectly to the tactics discussed in the previous section. Nelson et al. (1992), among others, suggests the idea that the reason for the increased advertising of popular brands is that these well-known goods serve as focal

[15]It should be noted that MacDonald's demand peaks are defined using sales volume data, and so there is a question of whether demand peaks are caused by advertising. Additionally, many of the peaks are in December.

[16]In a related paper, Hosken and Reiffen (2004b) find evidence that almost all products follow the regular price/low sale price model.

points for consumer price comparisons. In other words, popular brands more effectively signal lower costs in models such as Bagwell (1987) or Simester (1999). Chevalier et al. (2003) argue that their finding (that products are discounted more frequently at product-specific seasonal demand peaks) implies that stores employ a loss-leader strategy, because in some loss leader models products are more effective loss leaders when they are of higher value to consumers. However, their result is also consistent with a more nuanced story of price discrimination as in DeGraba (2006), in which products at seasonal peaks may be discounted to discriminate between less- and more-profitable customers. In a similar vein, also suggested in DeGraba (2006), the overall demand of particular (turkey-buying) consumers may increase around holidays, and those consumers may become more profitable for retailers at that time of year.

2.6. Conclusion

Price advertising and temporary price discounting play an important role in retailers' marketing strategy. However, evaluating their effectiveness is a challenge. This is for two reasons. First, correctly attributing store traffic to price advertisements is difficult. Price advertisements may affect store traffic, either by directly changing the relative surplus of visiting one store over another, or by indirectly changing consumers' perception of overall store price levels. Empirical research has established that some advertisements have an effect on the store choice decisions of some consumers. However, these results may or may not generalize to other consumers and products, and the econometric methods employed in these studies require either rich datasets or strong assumptions on consumption patterns. Effects on price image, including "frequency-heuristic" and reference-price effects, have been shown in experiments, but identifying these effects in store traffic data is an order of magnitude more difficult. Second, many more-specific advertising tactics that may be profitable are difficult to evaluate empirically (often because they are predicated on consumer store choice or price image effects).

Nevertheless, some of these tactics, including deep discounts and avoiding unfavorable price comparisons, have been substantiated through theoretical models. Deep discounts or "loss leaders" are motivated by Stiglitz' (1979) insight that, in the absence of commitment, unadvertised prices are likely to be at reservation (or monopoly) levels. As well as serving as a focus for retailer competition, they may also be used to selectively attract particularly profitable consumers, as in DeGraba (2006). Two different theories may make undercutting (or avoiding) competitors profitable: Varian (1980)-type models, in which many consumers rest "on the knife-edge" and visit the cheapest store regardless of location, or signalling theories (Bagwell 1987 and Simester 1995) in which lower prices signal a lower cost type. Experimental research into price advertising's effect on price image suggests a third motivation: since consumers respond more to the frequency of ads than to the magnitude of savings in forming price images, retailers should pursue a strategy of pricing just under rivals' prices on as many goods as possible. Finally, empirical researchers have attempted to study retailer advertising practices in order to gain insight into which tactics are employed in practice. Increased advertising of popular brands may be a way to more effectively signal low costs. Increased advertising of items at seasonal peaks may be used to discriminate between more- and less- profitable consumers.

CHAPTER 3

Weekly Price Advertisements and Shopping Location Decisions

3.1. Introduction

Price discounts, advertised through newspaper flyers, have been found to stimulate sales of the discounted products (Blattberg and Neslin 1990). In this paper, I investigate whether these price advertisements also factor into a consumer's shopping location decision. Currently, there is no direct finding in the literature that price advertisements affect shopping location decisions. I provide empirical evidence of their impact. Unexpectedly, the positive impact appears limited to a small subset of consumers.

I analyze the impact of price advertising on household location shopping location decisions in the short run. That is, I look for evidence that advertised discounts affect household behavior during the week that a given advertisement is valid. There are two factors that make this analysis somewhat difficult. First, when products are discounted by a retailer, the retailer can not generally distinguish between increased sales volume due to sales to existing customers and due to sales to new customers. I address this problem by using a survey dataset of household shopping trips and purchases that allows me to analyze individual trips and create a shopping history for each household.

Second, the empirical analysis of price advertisements can never be *ceteris paribus*. The front and back pages of a grocery flyer are the most effective advertising areas, and they are by definition limited in space. Grocers must decide between a number of alternatives for this space. Therefore, an important correlated omitted variable in this analysis is the set of price advertisements that might take the place of the advertisements that I observe. In practice, this omitted variable problem makes it difficult to discern the effect of a price advertisement for a single product, because alternative advertisements are similarly effective in stimulating sales and store traffic. My solution to this identification problem is to focus on particular groups of consumers. I identify households who buy high volumes of a product or are loyal to one brand of a product. I then estimate a model of consumer shopping location choices, and compare the impact of advertising on the shopping location choice between the two selected groups of consumers and all other consumers.

I find that households who purchase more orange juice over the course of the sample are more likely, in the short run, to visit chains that advertise price discounts on a leading brand of orange juice. This effect decreases with income. I perform an additional test that indicates that this result is driven by consumers who purchase 25 or more gallons of juice per year; this represents the top 10 percent of the sample. I also find a corollary result: households purchasing less than 25 gallons of juice per year are less likely to visit chains that advertise price discounts on orange juice. Brand loyalty is not found to have significant effect on shopping location choice after a similar test.

This study has two novel implications. First, the results confirm the assumption made by theorists that consumers choose shopping locations taking into account price advertising. However, at least for one product in one market, the effect seems to be confined to households consuming far above average amounts of the product. Only the top ten percent of households, by consumption, were attracted by the advertisements, even though nearly three fourths of the households in the sample purchased orange juice sometime in the sample period. Second, these results are consistent with the hypothesis that price advertising has an opportunity cost: consumers who would have been drawn to a chain by an alternative advertisement take their business elsewhere.

The paper continues as follows: Section 3.2 discusses previous research; Section 3.3 presents the empirical model; Section 3.4 discusses the data used in the analysis; Section 3.5 presents the results, including robustness checks, and Section 3.6 concludes.

3.2. Previous Research

Several empirical studies in the economics and marketing literature address the consumer's choice of where to shop. Smith (2006) examines consumers' valuation of distance, size, and parking, and finds that nearby, moderately sized stores with ample parking are preferred by shoppers in the United Kingdom. In this study I follow Smith's use of "primary shopping location" as the dependent variable of analysis, in place of individual trips. Bell and Lattin (1998) address the role of price format in consumer shopping location decisions. They find that large basket shoppers are more likely to shop at stores with Everyday Low Price (EDLP) pricing formats. They argue that households who make fewer trips are less flexible in their individual product decisions (that is, they will not make extra trips in which better prices could be obtained) and thus prefer less variable prices. In contrast, small basket shoppers prefer promotion-driven (HILO) stores at which they can take full advantage of advertised discounts. Finally, Rhee and Bell (2002) study consumer loyalty to "main stores". They find that relative prices on particular trips do not affect the probability that consumers will change their primary allegiance.

Two marketing studies, taking different approaches, address the effect of price advertising on shopping location choice and contain results consistent with some of the findings of this paper. Kumar and Leone (1988) provide an indirect test of the impact of price advertising on shopping location choice. They show that diaper sales fall at neighboring stores during weeks in which grocery stores advertise low prices on diapers. Kumar and Leone look only at the overall sale of diapers, and have no information on spending by individuals. Because of these data limitations, Kumar and Leone rely on assumptions about household diaper consumption in order to rule out the possibilities that consumers might change stores solely to purchase the advertised product, and that they might stockpile goods in response to sales.

Bell, Ho, and Tang (1998) consider fixed costs vs. variable costs in the consumer's shopping location choice decision. As in this study, they have household-level data and data on grocery retailer price advertising behavior. To study the impact of prices (variable costs), they derive an estimate of the unobserved household shopping list from the observed list of products purchased by the consumer, using historical purchases and differences from prices previously observed by consumers. They find that variable costs play a small but significant role in consumers' shopping location decisions. However, they do not attempt to examine the effect of individual advertisements or explore non-linearities in the relationship between households' spending history and response to price advertisements.

3.3. Empirical Model

3.3.1. Identification

The goal of this paper is to identify the short term impact of price advertising on consumers' shopping location decisions. As discussed above, this short term impact is difficult to identify for several reasons. First, it is difficult to judge whether a consumer traveled to a store in order to take advantage of a sale or whether the consumer took advantage of a sale only because they happened to be at the store. For this reason, and also because of stock-piling (buying for future rather than present consumption) and purchase acceleration (consuming more when products are discounted), store-level sales figures make a poor measure of consumers' location decisions. Second, most grocery retailers sell tens of thousands of different products and advertise hundreds every week. Each consumer's current food supplies and preferences determine to which ads that consumer pays attention. Moreover, since the size of an advertising flyer is roughly fixed (especially the high impact areas such as the front cover), each advertisement has an opportunity cost. If orange juice is advertised, some other product such as apple juice or milk is not advertised. This implies that the impact of not advertising any particular product may be minimal for most consumers.

This paper addresses these two important difficulties in two ways. First, I take advantage of household survey panel data that includes several years of shopping trips and orange juice purchases. This allows me to avoid confusing sales increases with increases in store visits. Second, I use purchase histories gleaned from this panel data to identify groups of consumers who might be particularly receptive to orange juice ads as opposed to other ads that might be run in their place. These two groups are, respectively, high volume orange juice consumers and consumers loyal to a particular brand. Additionally, to facilitate the analysis of brand loyalty and to simplify the presentation of results, the paper studies only advertising of one leading brand.

3.3.2. Choice Model

Formally, households are modeled as choosing between chains. Although consumers in practice may be choosing between stores, advertising decisions tend to be made at the chain level, and advertised prices are usually common between members of a chain in a single market. Thus, for the purpose of measuring response to advertisements, the relevant decision would seem to be chain choice rather than store choice. A choice is defined as the chain at which the household spends the most on groceries in a particular week. Household choice is modeled as a conditional logit model. In the model, households may choose between four different grocery chains in a major metropolitan area, with all other stores aggregated into an outside option. Chains never visited by a given household are eliminated from that household's choice set.

There are two primary empirical specifications considered in the paper. The first is a model considering the difference in advertising response between low and high-volume orange juice consumers. The household's indirect utility is as follows:

$$\begin{aligned} u_{ijt} &= \beta_1 chain\_preference_{ij} + \beta_2 Ad\_A_{jt} \cdot \log\_annual\_oj_i \\ &+ \beta_3 Ad\_B_{jt} \cdot \log\_annual\_oj_i + \beta_4 Ad\_A_{jt} \cdot \pi_i + \beta_5 Ad\_B_{jt} \cdot \pi_i \\ &+ \beta_6 Ad\_A_{jt} \cdot \log\_annual\_oj_i \cdot \pi_i + \beta_7 Ad\_B_{jt} \cdot \log\_annual\_oj_i \cdot \pi_i \end{aligned}$$

Where:

Ad_A_{jt} and Ad_B_{jt} are indicator variables taking the value of one if chain j advertised Tropicana in week t at advertisement size A or B respectively.

$chain\_preference_{ij}$ is calculated as $\text{Log}(s_{ij}/s_{i0})$, where s_{ij} is the fraction of weeks in the sample in which chain j was household i's choice of chain, and s_{i0} is the fraction of weeks in which the outside option was household i's choice.

$log\_annual\_OJ_i$ is calculated as the log of the annual OJ consumption of household i, in gallons.

π_i is a vector of demographic variables: Household Size[1] and Annual Income (in \$1,000s)[2]

The second model considers the difference in advertising response between consumers who buy Tropicana almost exclusively and other, non-loyal consumers. The household's indirect utility is as follows:

[1] This variable is truncated at 6 in the data.

[2] In the data, income is given in ranges. I assign the median of the range to each household as a value for annual income.

$$
\begin{aligned}
u_{ijt} &= \beta_1 chain\_preference_{ij} + \beta_2 Ad\_A_{jt} \cdot share\_TP_i \\
&+ \beta_3 Ad\_B_{jt} \cdot share\_TP_i + \beta_4 Ad\_A_{jt} \cdot \pi_i + \beta_5 Ad\_B_{jt} \cdot \pi_i \\
&+ \beta_6 Ad\_A_{jt} \cdot share\_TP_i \cdot \pi_i + \beta_7 Ad\_B_{jt} \cdot share\_TP_i \cdot \pi_i
\end{aligned}
$$

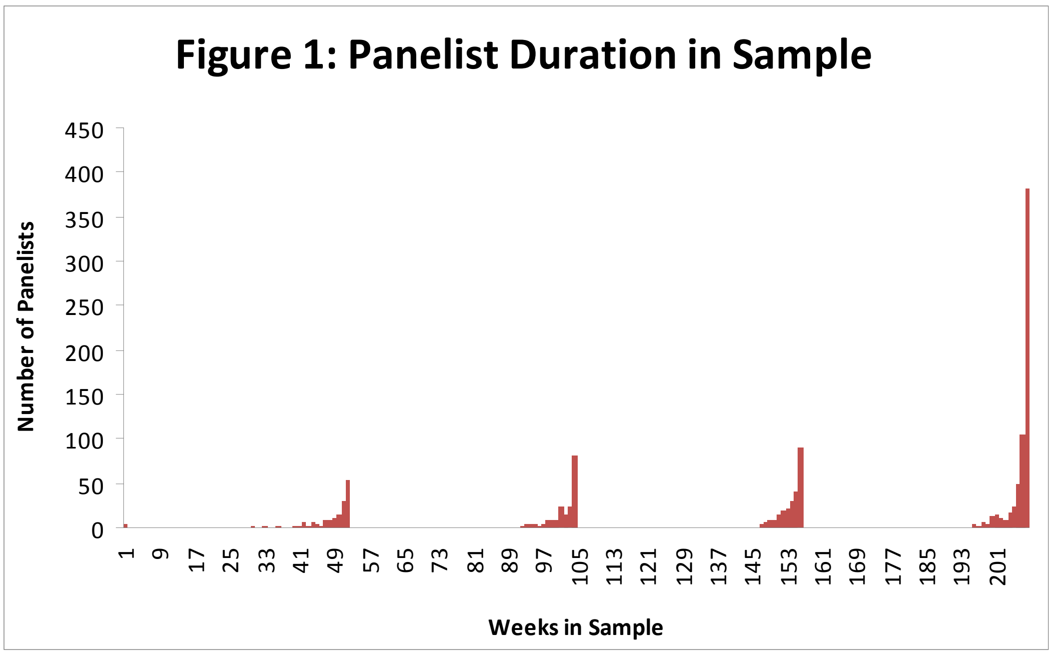
Where:

$share\_TP_i$ is the fraction of household i's refrigerated orange juice purchases which are of Tropicana Pure Premium orange juice.

All other variables are as stated above.

3.4. Data

The data in this paper was collected by Information Resources Inc. (IRI) and consists of two parts. The first is a scanner dataset of store-level sales, prices and other promotional activity for the non-frozen orange juice category. The data consist of weekly observations over four years (Q4 2001-Q3 2005) for a representative sample of grocery retailers in the Boston, MA, area. The second dataset is a scanner panel dataset (household-level), which covers grocery shopping trips made by a panel of 1715 consumers in the Boston area. The panel spans the same four years as the store-level dataset, but is unbalanced; most panelists stay in the panel at least one year, and most enter and exit at year-ends; Figure 3.4 shows the amount of time panelists are active in the panel and when the panelists tend to exit. Data is self-reported and includes trips, total spending per trip, and details of orange juice purchases; Table 3.1 reports summary statistics for the variables relevant to the analysis. Note that the household panel is part of a larger survey and includes 461 households that do not purchase orange juice during the sample period. These households are included in the analysis, except in regressions including the variable "Tropicana Share of Household Orange Juice Purchases". Additionally, the data includes trips both with and without orange juice purchase (the majority of trips do not include orange juice purchases).



Along with the shopping histories of individual households, the key variable of interest in this study is the Feature (advertising) variable. Feature advertisements are the flyers distributed to consumers either through home newspaper delivery or through direct delivery via post. They are a primary means by which grocery retailers communicate information about price discounts and other specials to consumers, and are essentially the only way to communicate prices to consumers not yet at the store. While retailers are responsible for the decisions of what to include in the feature advertisements (henceforth "to feature"), manufacturers often foot the bill: not only do manufacturers refund at least

Table 3.1. Summary Statistics

Variable	Number of Obs.	Median	Mean	Standard Deviation
Annual OJ Purchases (Gallons)	1715	4.56	9.05	12.10
(conditional on purchase ? 1)	1254	8.58	12.38	12.61
Log Annual OJ Purchases	1715	1.71	1.62	1.25
(conditional on purchase ? 1)	1254	2.26	2.21	0.90
Tropicana Share of HH OJ Purchases	1254	0.33	0.39	0.28
Income	1715	50.00	57.28	32.90
Log Income	1715	3.93	3.85	0.76
Family Size	1715	3.00	2.87	1.42

Note: 461 households did not record a purchase of orange juice during the sample period.

a portion of the price discounts through lower wholesale prices and other inducements, but they also pay for nearly all of the feature advertisement itself. This happens through the use of advertising allowances, funds available to the retailer on the condition that manufacturers' products appear in the advertisement (Blattberg and Neslin 1990).

The data distinguishes three main types of feature advertisements: A, B, and C level ads. A ads are large picture ads placed in prominent positions on the flyer (front, back, top of interior pages) and drawing attention to large discounts. B ads are smaller ads, often towards the bottom of interior pages. Items are still pictured but may only be slightly discounted. C ads are relatively rare in the data; they are smaller than B ads, often lacking pictures and discounts. Data on the use of these feature levels in the sample is

Table 3.2. Frequency of Feature Advertising, by level

Brand	Feature Level			Market Share (by volume)
	A	B/C	None	
Florida's Natural	20.4%	19.5%	60.1%	16.9%
Minute Maid	9.6%	10.2%	80.3%	10.0%
Tropicana Pure Premium	46.0%	18.5%	35.2%	73.1%

presented in Table 3.2, for the most common brands in the most popular size (64 ounces). Because of the infrequency of C-level ads, they are included in the analysis jointly with B-level ads.

As is clear from the table, retailers feature these juices heavily; non-frozen orange juice is a popular item for featuring because it is purchased by a large fraction of the population (high penetration) and is relatively difficult to store for more than a week or two (low storability). Figure 2 displays a histogram of log (base 10) annual orange juice consumption in the sample.

For households purchasing orange juice at some point during their time in the panel, the distribution of annual orange juice purchase is centered around 8.6 gallons per year, or approximately one half-gallon carton every three weeks.[3] Table 3.3 describes the frequency of single and multiple purchase in the data. When buying orange juice, consumers purchase one container of juice approximately two thirds of the time, and two containers

[3]Five households with orange juce consumption between 100-1000 gallons per year were eliminated from the sample as outliers. Inclusion of these values did not substantially affect the results, however.

Table 3.3. Orange Juice Purchase Quantities

Units Purchased	Frequency	Percent
1	42,626	66.1%
2	16,061	24.9%
3	3,194	5.0%
4	1,712	2.7%
5 or more	924	1.4%

a further one fourth of the time. That is, they do not buy additional units to store for later consumption.

Feature advertising, because of the fixed costs of layout and design and the mass-market nature of distribution (through newspapers), tends to be determined at the chain-market level. Thus, the models estimated in the next section assume that chains make one advertising decision per week per product. For simplicity, I use only advertisements relating to the most common size, 64 ounces. Table 3.4 gives a summary of the chains and their shares of orange juice sales, as well as their featuring behavior. The chains displayed in Table 3.4 are also the chains used for the analysis; they are the four chains in the Boston area with more than 10% market share. The other chains have been folded into an outside option.

Panelists' shopping histories are used to create three variables. First, in order to control for unobserved location and price variables, I create a chain-preference variable for each consumer-chain combination. I model chain preference as the log of the ratio

Table 3.4. Chain Market Shares and Featuring Behavior

	Share of OJ Sales by Volume	A-Level Featuring, % of Possible Weeks		
		Florida's Natural	Minute Maid	Tropicana
Market Basket	28.1%	17.3%	0.5%	13.0%
Shaw's	14.7%	27.4%	14.4%	67.3%
Stop & Shop	27.0%	10.6%	9.7%	37.5%
Star Market	18.7%	26.4%	13.7%	65.4%

of weeks a given chain was a consumer's chosen shopping location to the weeks that the consumer chose the outside option (a location other than the four chains studied). The chain preference for the outside option is set to 0.

Panelist taste for orange juice in general is measured by constructing a second variable, log annual orange juice. I sum up each household's total orange juice consumption, by volume, and divide by the total number of weeks during which the household participated in the sample. This number is then converted to gallons and to years, and the log of the result is used for estimation. A third variable measures taste for Tropicana brand orange juice in particular. This variable is derived by dividing each household's total purchases of Tropicana orange juice by its overall orange juice purchases.

In reviewing the data we are interested in understanding which consumers can be affected by advertised price discounts. Table 3.5 shows the results of the regression of a household-level Herfindahl index of brand purchase on a household-level Herfindahl index of chain spending and several demographic variables. The data suggests that, first of all,

Table 3.5. Regression of Brand Loyalty on Chain Loyalty and Demographic Variables

Dependent Variable: Brand Loyalty (Herfindahl index)

Independent Variables:

Chain Loyalty (Herfindahl index)	0.133	***
	0.019	
Income	-0.002	***
	0.000	
Income^2	0.000	*
	0.000	
# of Family Members	-0.027	**
	0.012	
# of Family Members^2	0.004	**
	0.002	
Constant	0.670	***
	0.020	

legend: * p<0.10; ** p<0.05; *** p<0.01

households that spend their money at fewer chains are more likely to purchase a narrower set of goods. Second, households of at least 3 people buy narrower sets of goods as family size increases. (The set of products purchased by households widens when the household size goes from 1 to 2) Third, the set of products purchased by households widens as income rises, at income levels below $50,000, and narrows as income rises, at income levels above $50,000.

3.5. Results

The results of the logit chain choice model are presented in Tables 3.6, 3.7, and 3.8. Table 3.6 describes the impact of household orange juice consumption interacted with various parameters on households' shopping location decisions. First, notice that the variable "Level A Feature" has a negative and significant impact on likelihood of chain

Table 3.6. Impact of Household OJ Consumption on Household Shopping Location Decision

Variable: / Model:	A	B	C	D
Level A Feature	-0.0180 **	-0.0444 ***	-0.0130	-0.0573 *
	(0.0076)	(0.0134)	(0.0200)	(0.0309)
Level B Feature	0.0174	0.0017	0.0526 *	-0.0080
	(0.0114)	(0.0198)	(0.0302)	(0.0458)
Chain Preference	0.8566 ***	0.8563 ***	0.8567 ***	0.8569 ***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
A Feature x Log Annual OJ Purchases		0.0149 **	0.0196 ***	0.0459 ***
		(0.0062)	(0.0064)	(0.0155)
B Feature x Log Annual OJ Purchases		0.0091	0.0164 *	0.0543 **
		(0.0093)	(0.0097)	(0.0236)
A Feature x Family Size			-0.0184 ***	-0.0173 *
			(0.0057)	(0.0104)
B Feature x Family Size			-0.0270 ***	-0.0177
			(0.0088)	(0.0156)
A Feature x Income			0.0002	0.0010 ***
			(0.0002)	(0.0004)
B Feature x Income			0.0002	0.0009
			(0.0004)	(0.0007)
A Feature x Log Annual OJ x Family Size				-0.0006
				(0.0047)
B Feature x Log Annual OJ x Family Size				-0.0053
				(0.0070)
A Feature x Log Annual OJ x Income				-0.0005 ***
				(0.0002)
B Feature x Log Annual OJ x Income				-0.0004
				(0.0003)

*, **, and *** represent P-values less than 0.1, 0.05, and 0.01 respectively.

choice in all but one specification of the model (specification C). This result reflects the opportunity cost of an advertisement. Level A Feature describes the impact of advertising of Tropicana orange juice for people who do not buy any orange juice over the course of the sample: when a grocery chain advertises orange juice, it is not advertising some other potentially attractive product, and people who never buy orange juice will be less likely to visit that chain.

The variable of interest is "A Feature x Log Annual OJ Purchases", the interaction of the Level A Feature dummy variable with the log of the household's average annual orange juice purchases. The estimated coefficient is statistically significant and positive in all three models in which it appears. In other words, households that buy more orange juice are more likely to visit chains that advertise orange juice. Additionally, the interaction of level A advertising, annual orange juice purchases, and income is statistically significant and negative. This implies that as income rises, high-orange juice-consuming households become less responsive to advertising. Overall, this is consistent with the idea that consumers are more likely to travel for a low price on orange juice when orange juice takes up a larger share of their household budget.

The coefficients on Level B Feature and associated interaction terms are of similar signs to the coefficients on Level A Feature, but are generally less significant.

Table 3.7 describes the impact of household brand loyalty interacted with various parameters on households' shopping location decisions. The main variable of interest in these regressions is Level A Feature interacted with the fraction of each household's orange juice purchases that are Tropicana products. This variable indicates whether households that are highly loyal to Tropicana are more likely to change their shopping location decision in response to a Tropicana advertisement. The estimated coefficient on this variable is positive and statistically significant in all three models in which it appears. This is parallel to the result from Table 3.6, suggesting that both brand loyalty and overall orange juice consumption increase consumers' response to advertisements in their shopping location decisions.

However, other results in this table suggest that brand loyalty has a different effect on consumers' advertising response than did household orange juice consumption. All other coefficients on Level A Feature and its interactions are statistically insignificant.

Table 3.7. Impact of Brand Loyalty on Household Shopping Location Decisions, All Households

Variable: / Model:	A	E	F	G
Level A Feature	-0.0180 **	-0.0412 ***	-0.0159	-0.0471
	(0.0076)	(0.0145)	(0.0249)	(0.0382)
Level B Feature	0.0174	0.0360 *	0.1041 ***	0.1247 **
	(0.0114)	(0.0214)	(0.0387)	(0.0578)
Chain Preference	0.8566 ***	0.8580 ***	0.8585 ***	0.8586 ***
	(0.0033)	(0.0038)	(0.0038)	(0.0038)
A Feature x Tropicana Share of HH OJ purchases		0.0714 **	0.0677 **	0.1453 *
		(0.0291)	(0.0294)	(0.0775)
B Feature x Tropicana Share of HH OJ purchases		-0.0547	-0.0729	-0.1371
		(0.0463)	(0.0467)	(0.1234)
A Feature x Family Size			-0.0093	-0.0022
			(0.0063)	(0.0107)
B Feature x Family Size			-0.0304 ***	-0.0593 ***
			(0.0097)	(0.0157)
A Feature x Income			0.0001	0.0002
			(0.0003)	(0.0005)
B Feature x Income			0.0005	0.0016 **
			(0.0004)	(0.0007)
A Feature x Tropicana Share x Family Size				-0.0189
				(0.0227)
B Feature x Tropicana Share x Family Size				0.0848 **
				(0.0359)
A Feature x Tropicana Share x Income				-0.0004
				(0.0009)
B Feature x Tropicana Share x Income				-0.0029
				(0.0015)

*, **, and *** represent P-values less than 0.1, 0.05, and 0.01 respectively.

Additionally, the interaction between Level B Feature, Tropicana Share, and Family Size is positive and significant. This indicates that larger families who are loyal to Tropicana products are more likely to shop at chains that advertise Tropicana at the B level. It is not clear why this should occur only at the B level but not at the A level.

Because household brand loyalty is measured as the ratio of Tropicana purchases to total orange juice purchases, the brand loyalty estimator may be measured with greater error for households that consume low levels of orange juice over the sample period. Table

Table 3.8. Impact of Brand Loyalty on Household Shopping Location Decision, High-OJ Volume

Variable: Model:	H	I	J	K
Level A Feature	0.0042	0.0237	0.1249 ***	0.0375
	(0.0121)	(0.0214)	(0.0375)	(0.0588)
Level B Feature	0.0398 **	0.0924 ***	0.2397 ***	0.1847 **
	(0.0185)	(0.0305)	(0.0575)	(0.0860)
Chain Preference	0.8568 ***	0.8572 ***	0.8589 ***	0.8588 ***
	(0.0053)	(0.0053)	(0.0053)	(0.0053)
A Feature x Tropicana Share of HH OJ purchases		-0.0445	-0.0501	0.1287
		(0.0401)	(0.0405)	(0.1055)
B Feature x Tropicana Share of HH OJ purchases		-0.1335 **	-0.1463 **	-0.0554
		(0.0621)	(0.0626)	(0.1633)
A Feature x Family Size			-0.0237 ***	-0.0253 *
			(0.0088)	(0.0149)
B Feature x Family Size			-0.0309 **	-0.0631 ***
			(0.0134)	(0.0211)
A Feature x Income			-0.0004	0.0012 *
			(0.0004)	(0.0007)
B Feature x Income			-0.0007	0.0019 *
			(0.0006)	(0.0010)
A Feature x Tropicana Share x Family Size				0.0079
				(0.0300)
B Feature x Tropicana Share x Family Size				0.1035 **
				(0.0475)
A Feature x Tropicana Share x Income				-0.0034 ***
				(0.0013)
B Feature x Tropicana Share x Income				-0.0067 ***
				(0.0020)

*, **, and *** represent P-values less than 0.1, 0.05, and 0.01 respectively.

3.8 presents the results obtained when the models used in Table 3.7 are estimated using only households with high annual orange juice purchase volume (at least 1 quart of orange juice per week, on average). In model K, where all variables are included, neither Level A nor Level B Feature interacted with the Tropicana loyalty variable are statistically significant. However, the coefficients on Level A and Level B Feature interacted with Tropicana Share and Income are both negative and statistically significant. This indicates that (at least among high-volume consumers), as income rises, Tropicana-loyal buyers are less likely to change shopping locations in response to advertisements.

Overall, these estimates clearly indicate that consumers that purchase more orange juice also take more account of orange juice advertisements when making shopping location decisions. The results also show that consumers who buy more Tropicana as a fraction of their overall orange juice purchases are more likely to factor Tropicana advertisements into their location decisions. However, the result is not robust to a more restrictive definition of brand loyalty.

3.5.1. Non-Linear Analysis of Advertising Impact

The previous regressions treated household annual juice consumption as a (log) linear variable. In this section I follow up by analyzing several strata of the consumption distribution separately. One concern about this annual juice consumption variable is that 27 percent of households in the sample do not purchase any orange juice during the sample period. Table 3.9 compares the means of these households' demographic and history variables with households who purchase orange juice at least once during the sample period. All variables are higher for the orange juice-buying households by between 10 and 20 percent; however, these differences are not statistically significant, and larger household size could be responsible for much of the increase in the other variables.

Table 3.10 presents results of model A from the main analysis, estimated on various strata of the juice consumption distribution. The coefficient on Level A Feature is significant and negative for all households except for those at the 90th percentile and above, for whom it is significant and positive. This indicates that the earlier results were driven

Table 3.9. Comparison of Demographic and History Variables for Orange Juice- and Non Orange Juice-Buying Households

Households Purchasing No Orange Juice During Sample Period

	Observations	Median	Mean	St. Dev.
Annual Income (1000's of $)	461	40	48.2	31.1
Household Size	461	2	2.6	1.5
Total Spending, All Products	461	$ 7,075.64	$ 9,455.48	$ 8,231.41
Total Trips	461	301.0	463.4	627.6

Households Purchasing At Least One Unit of Orange Juice

	Observations	Median	Mean	St. Dev.
Annual Income (1000's of $)	1254	60	60.6	32.9
Household Size	1254	3	3.0	1.4
Total Spending, All Products	1254	$ 11,969.14	$ 13,510.96	$ 9,163.50
Total Trips	1254	433.5	563.8	492.2

Table 3.10. Results of Choice Model, by Annual Household Orange Juice Consumption

Consumption:	**None**	**0 to 13 gal.**	**13 to 24 gal.**	**24 to 100 gal.**
Variable:	< 27th Percentile	27th to 75th Percentile	75th to 90th Percentile	> 90th Percentile
Level A Feature	-0.0409 **	-0.0208 **	-0.0343 *	0.0679 ***
	(0.0171)	(0.0104)	(0.0183)	(0.0233)
Level B Feature	0.0222	0.0168	-0.0185	0.0769 **
	(0.0241)	(0.0160)	(0.0278)	(0.0365)
Chain Preference	0.8505 ***	0.8591 ***	0.8673 ***	0.8424 ***
	(0.0068)	(0.0048)	(0.0081)	(0.0095)

(*,**,***) represent P-values less than (0.1, 0.05, 0.01) respectively.

by extremely high-volume households. In the terms of opportunity cost, one could say that an orange juice advertisement is not more effective than an alternative advertisement except for households purchasing an economically important amount. In this case, economically important corresponds to approximately one half-gallon carton per week.

The coefficient on Level B Feature is not significantly different from zero, except for consumers at the 90th percentile and above, for whom it is significant and positive. Unlike the A-level advertisements, B-level advertisements do not appear to have a significant opportunity cost. This is consistent with the fact that the space allotted to B-level feature advertisements is less constrained. However, B-level advertisements appear to have a significant effect only on the location choice of households consuming more than 1 half-gallon carton per week.

I also repeat the analysis of advertising and brand loyalty using different strata of the juice consumption distribution. As I discuss above, it is possible that the Tropicana share of total purchases is a poor measure of taste for brands for households who purchase few units of orange juice. Table 3.11 presents the results of model E from the main analysis estimated on various strata of the juice consumption distribution, in order to test this concern. The results confirm the doubts raised by Table 3.8; the coefficient on Level A Feature x Tropicana Share of HH OJ purchases is significant and positive for households consuming less than 13 gallons per year (one half-gallon carton every two weeks). The coefficient is insignificant for the other groups and for Level B Feature x Tropicana Share. If brand share were affecting consumer choice, I would expect the coefficients to be greater for households who are more likely to purchase orange juice in any given week.

Table 3.11. Results of Choice Model, by Annual Household Orange Juice Consumption

Consumption:	**0 to 13 gal.**	**13 to 24 gal.**	**24 to 100 gal.**
	27th to 75th Percentile	75th to 90th Percentile	> 90th Percentile
Variable:			
Level A Feature	-0.0638 ***	-0.0075	0.0261
	(0.0179)	(0.0314)	(0.0420)
Level B Feature	0.0339	0.0454	0.0381
	(0.0269)	(0.0444)	(0.0607)
Chain Preference	0.8589 ***	0.8675 ***	0.8421 ***
	(0.0048)	(0.0081)	(0.0096)
A Feature x Tropicana Share of HH OJ purchases	0.1131 ***	-0.0633	0.0884
	(0.0381)	(0.0584)	(0.0740)
B Feature x Tropicana Share of HH OJ purchases	-0.0509	-0.1679	0.0923
	(0.0606)	(0.0918)	(0.1162)

(*,**,***) represent P-values less than (0.1, 0.05, 0.01) respectively.

3.5.2. Other Robustness Tests

While the above functional form is useful in capturing consumer choice among various shopping options, it does not allow for estimation of household-chain fixed effects. An alternative analysis that allows me to control for household-chain effects is to compare the propensity for each household in the sample to visit each store in weeks when that store is advertising vs. in weeks when that store is not advertising. Table 3.12 displays a summary of this propensity comparison as a binary variable: 1 if a given household has a higher propensity to visit a given store during advertising weeks.

In contrast to the main analysis, these results indicate that orange juice advertising has a positive effect on the propensity to visit a store, on average. Even households that never purchase orange juice turn out to visit advertising stores more frequently.[4] The effect of advertising on the propensity to visit a store increases between households that

[4]This would be consistent, for example, with advertising serving as a signal of low costs.

Table 3.12. Household Propensity to Visit Chains When Advertising, by Annual Household Orange Juice Consumption

Consumption:	None	0 to 13 gal.	13 to 24 gal.	24 to 100 gal.
Variable:	< 27th Percentile	27th to 75th Percentile	75th to 90th Percentile	> 90th Percentile
Households with Propensity Lower	227 44.9%	406 42.1%	143 40.6%	104 43.5%
Households with Propensity Higher	279 55.1%	558 57.9%	209 59.4%	135 56.5%

Results analytically weighted by total number of household visits to the chain.

do not purchase orange juice and those who do, although the effect is not relatively as strong on the highest-consumption households as it is in the main analysis.

One final concern is whether the results are potentially affected by non-representative sampling. Sampling weights are included in the data, balancing the sample for several demographic variables: income, race, age, and household size. Tables .6, .7, and .8 (in the Appendix) repeat the analysis of Tables 3.6, 3.7, and 3.8 respectively, but correcting using the sampling weights. A few minor changes in level of significance occur, but the analysis of the main variables of interest remains the same.

Additionally, several estimations were performed but are not included in the paper. I estimated the primary model on A-level and B-level advertisements separately. There was no substantive change in the results from the joint model. I estimated the primary model excluding consumers who did not purchase orange juice during the sample. There was no substantive change in the results from the joint model. Estimation of the model with outliers included also did not have a significant effect on results. I also considered

Table 3.13. Relative Timing of Advertising (Feature) vs. In-Store Display

Feature:	Display: None	Small	Large	Total
None	295	0	0	295
	100%	0%	0%	100%
C-Level	2	0	0	2
	100%	0%	0%	100%
B-Level	136	2	16	154
	88%	1%	10%	100%
A-Level	320	5	56	381
	84%	1%	15%	100%
Total	753	7	72	832
	91%	1%	9%	100%

estimating the model on in-store displays in place of feature advertisements, as a check on this analysis; however, as table 3.13 describes, in this category products are only displayed in connection with feature advertisements, and in-store displays are rare overall (chains use in-store displays for Tropicana in 10 percent of sample periods, as opposed to feature advertising in 65 percent of sample periods).

3.6. Conclusion

This paper addresses the impact of price advertising on consumer shopping location choice. I identify consumer attributes that I expect to result in greater sensitivity to price advertising of orange juice–annual orange juice purchase volume and brand share of household purchases–and find that annual purchase volume is associated with more frequent trips to advertising chains. This provides evidence that week-to-week price advertising measurably changes household shopping location choice. Because households tend to shop where products they more frequently purchase are advertised, these results are also consistent with location choice theories in which consumers choose stores at which they expect their chosen basket of goods to cost the least.

This tendency to visit grocery chains in response to price advertisements is, however, limited to the top 10 percentile of households in terms of orange juice purchase. Households outside of the top 10 percentile are less likely to visit a chain when it advertises a discount on orange juice. This negative effect is a novel result, although it is a natural implication of the opportunity cost created by space limitations for prominent advertising locations in the newspaper flyer. If a consumer never or rarely purchases orange juice, then they may prefer a chain that advertises an alternative product. For the retail manager, this result implies that a product's penetration (the percentage of consumers who purchase a product at least occasionally) may be less important in driving store traffic than the number of heavy users of the product.

Additionally, it appears that consumers respond to advertisements in a non-linear fashion; that is, the response to discounts is not directly proportional to the amount of household spending on orange juice. Data on a larger basket of goods for each household would allow one to test the possibility that consumers place greater weight certain items when considering the cost of shopping at each location, or even that they use a lexicographic decision process.

CHAPTER 4

The Strategic Timing of Price Advertisements

4.1. Introduction

Temporary price reductions advertised to consumers through newspaper inserts and mailings ("feature ads") are a prominent aspect of grocery retail pricing. For example, in my sample of orange juice sales in Chicago, discounts were advertised for 28% of all product-store-weeks, at an average discount of 8.4% from non-advertised product-store-weeks. This activity significantly impacts orange juice sales: in the data, advertised products account for 48% of all sales by volume, and 44% of sales by revenue, despite encompassing only 28% of sample observations.

Despite their importance, there is little empirical research into the strategic aspect of these advertisements; that is, how are firms' profits from advertising affected by other firms' decision to advertise? This paper aims to fill this gap. I first examine two models of advertising, developing predictions as to whether advertising a particular product ought to be a strategic complement or a strategic substitute (i.e. are retailers' marginal profits from advertising higher or lower, respectively, when competitors also advertise). I then test the predictions by estimating a complete information advertising game.

In this paper I make two contributions to the literature. First, I suggest a new intuition for how firms might use price advertising—to segment consumers by advertising distinct sets of goods, resulting in lower pricing pressure on non-advertised goods. Second, I provide evidence on the strategic timing of price advertisements in an important industry, finding that advertising particular products tends to be a strategic substitute. This evidence is consistent with the above intuition.

The strategic timing of advertising is important for two reasons. First, price advertising may have a significant impact on store choice. Kumar and Leone (1988) and others find evidence to this effect, and Blattberg and Neslin (1990) confirm that retailers consider this an important reason to advertise. This implies that useful models of advertising should take into account retailers' effect on competitors' sales volumes and sets of customers as well as on their own. The strategic interactions in these models should in turn be consistent with the timing observed here in the data. Additionally, strategic complementarity vs. substitutability may be useful in understanding retailer-manufacturer interactions. For instance, if advertising were a strategic complement (and thus retailers advertise the same product), then manufacturers might be inclined to compete for the privilege of having the advertised good. This would be an otherwise unobserved benefit of having a market-leading product.

In this paper, I derive predictions from two models of advertising competition. The first model is Lal and Matutes (1994), which explains the existence of "loss leaders" as discounts that induce customers to shop at stores they would otherwise not visit. Loss leaders alone do not lead to a prediction about strategic complementarity; however, Lal and Matutes allow consumers to visit both stores, which leads firms to advertise the same product in order to reduce the cost of the discount; that is, the model predicts advertising to be a strategic complement. In contrast, consumers may have different tastes for different brands. In such a model, advertising different products segments consumers; thus, it is more difficult to induce consumers to switch stores, a result which decreases competition and raises equilibrium prices on other goods. In the next section, I put forth an example of a model illustrating this intuition, and find that this segmentation model predicts that advertising will exhibit strategic substitutability.

To discriminate between these two competing models of retailers' strategic interactions, I estimate a complete information simultaneous advertising game. Each firm's profits from advertising are modeled as a latent variable dependent on the other firm's action as well as market and firm specific factors and a firm-period-specific error term. The probability of drawing error terms that imply the observed advertising choices, in equilibrium, is calculated from this model. By combining the probabilities I am thus able to estimate the parameters of the model by maximum likelihood. I estimate the model using four years of orange juice advertising data from three different markets: Boston, Chicago, and Dallas. The sample (after minimum market share restrictions) constitutes 8 firms and a total of 10 binary competitive relations within the three markets.

Overall, my estimates indicate that advertising orange juice is a strategic substitute—advertising is more profitable for firms when their competitors do not advertise identical brands. This effect is more statistically significant in Boston than the rest of the country, but the estimates are still consistently negative across various competitive pairs. This result (strategic substitutability) is consistent with the segmentation model developed in this paper, and not consistent with loss leader models such as Lal and Matutes (1994). Interestingly, the only significant exception to this rule is in Boston, in the strategic interaction between two firms with common ownership, which is also consistent with the prediction of the segmentation model; commonly owned firms would presumably have little need to take actions (such as advertising) to reduce competitive pricing pressure.

Existing research considers why firms might offer price discounts, and when. Some of the theories put forward are: (1) intertemporal discrimination between patient and impatient consumers (Sobel 1984 or Pesendorfer 2002) and (2) discrimination between consumers with heterogeneous information acquisition costs (Varian 1980). Empirically, Warner and Barsky (1995) and Chevalier, Kashyap, and Rossi (2003) find increased frequency and depth of price discounts around holidays and product-specific demand peaks, while Nevo and Hatzitaskos (2005) reassess the latter study's data and find somewhat different results.

Previous research into the advertising of these periodic discounts has naturally been more focused on competition between stores[1]. Because advertised prices are able to provide information to consumers at an earlier stage than do prices posted in stores, they are more likely to have an impact on consumers' store choices (see empirical evidence in Kumar and Leone 1988). Varian (1980) puts forth a model of advertising and store choice; in the model retailers advertise randomly drawn prices to consumers, in order to discriminate between consumers with low and high information acquisition costs. Bester and Petrakis' (1995) model follows similar lines, but their result allows for a more realistic single high regular price with periodic randomly drawn price reductions. Simester (1995) shows how retailers could use price advertising to signal their marginal cost type. Note that the above models, while modeling advertising as a strategic decision, do not specifically address the decision of which product to advertise at what time. If anything,

[1]See Bagwell (2005) for a survey of the theoretical and empirical literature on advertising.

Varian (1980) and Bester and Petrakis (1995) imply that the advertising behavior of each retailer should be random and unrelated to the advertising behavior of the other retailer.

A few theoretical models do address the question of the strategic timing of price advertisements. The first is Lal and Matutes (1994), which will be described in detail in the following section. This is an example of a loss leader model, in which retailers advertise products at a large discount to attract consumers into the store, where they will pay high prices for other, non-advertised goods. The equilibrium found by the authors is one in which firms choose to advertise the same products at the same time. Anderson (2000) develops a framework similar to the intertemporal discrimination models described above (such as Pesendorfer (2002)), which allows for advertising by firms and store-switching behavior by consumers, thereby creating a strategic link between the retailers. The model supports both an equilibrium in which advertising is a strategic substitute and one in which it is a strategic complement. However, it is somewhat unsatisfactory for the purpose of this paper, since the type of equilibrium depends on the size of the set of store-switching consumers. Anderson also motivates his paper with a simple data exercise that finds empirical results similar to those in this study.

Methodologically, a number of previous articles are relevant to this paper. The segmentation model in the next section is inspired by frameworks such as D'Aspremont et al.'s (1979) adaptation of Hotelling (1950), where firms have an incentive to locate farther apart in spaceto reduce pricing pressure (with greater distance, fewer consumers are willing to switch stores in response to a given price reduction). Borenstein and Netz (1999) and Sweeting (2005) examine similar "timing as location" questions empirically. The empirical model follows the tradition of complete information, simultaneous, static entry game models in the spirit of Bresnahan and Reiss (1990) and Berry (1992), and more recently Ciliberto and Tamer (2004) and Sweeting (2005), among others.

The paper proceeds as follows. Section 4.1 introduces the topic and research question, and outlines the relevant literature. Section 4.2 presents the models of advertising competition. Section 4.3 discusses feature advertising in general and explores the data used in the study. Section 4.4 presents the empirical model and results. Section 4.5 concludes.

4.2. Models of Retail Competition With Advertising

I now consider two models of retail competition with advertising.

4.2.1. Loss Leaders and Cherry Picking (Lal and Matutes 1994)

The intuition underlying the "loss leader" concept is that retailers offer large discounts on one set of products in order to make high margins on other products. The Lal and Matutes (1994) model begins with the assumption that consumers do not observe unadvertised prices before visiting the store. With positive transportation costs (which are sunk, upon arrival at a store), a store can set a price equal to the consumer's reservation price for each good, and the consumer will still purchase the goods. Expecting this, however, the consumer will not shop at the store, because their utility from the trip will be negative (zero surplus received at store, minus transportation costs). Price advertising overcomes this reluctance to travel: by advertising discounts, firms are able to commit to a price and guarantee positive utility to consumers for a shopping trip, even though consumers correctly infer that the store will charge their reservation price for non-advertised goods[2]. And, if advertising is costly, given a particular amount of surplus that a retailer needs to

[2]Consumers are assumed to be identical except for their physical location.

offer to a potential customer, it will be efficient to advertise only one product at a deeper discount instead of two products at a shallower discount. Thus, the retailer ends up with one product at a discounted price and one product at a high (reservation) price.

The loss leader concept alone, as described above, does not generate a prediction as to strategic complementarity. If firms are located far enough from each other such that they do not compete for customers, their advertising should be independent (no strategic complementarity or substitutability). However, in the model as Lal and Matutes (1994) develop it, consumers are choosing between two stores, and moreover they can visit more than one store. In this setting Lal and Matutes find that there is only one equilibrium in which each firm advertises only one of the goods, and that is the equilibrium in which each firm advertises the same good. This occurs because advertising different goods induces consumers to "cherry-pick" (that is, to visit both stores and buy the advertised good). Cherry-picking ruins the profitability of the stores' strategies; each could now profitably deviate by advertising to match the other store.

Alternatively, we may consider the approach taken by Chevalier et al. (2003). Their interpretation of the loss leader concept focuses on the choice of product to advertise. In the loss leader setup, since only one product is being advertised, that product is wholly responsible for guaranteeing the surplus to the potential customer, as well as bearing any price discounts associated with competition between retailers. Since prices are restricted to be non-negative, in general firms will choose to advertise the product with the higher reservation price. For our purposes, since each firm is choosing the product with higher demand, then firms' choices of products to advertise will be positively correlated. This is not strictly strategic complementarity, but in the case that there are product demand characteristics observable to the firms but not to the econometrician, the empirical model will generate a coefficient consistent with strategic complementarity.

In summary, in the Lal and Matutes (1994) model, advertising is either independent or is a strategic complement.

4.2.2. Segmenting Consumers by Brand

This model supposes a different role for advertising; instead of inducing consumers to shop, advertising serves to create differentiation between retailers (just as non-price advertising does in other contexts). By advertising different brands, stores offer different incentives to customers with different tastes. Customers who anticipate a discount on a much-favored brand will require a commensurately larger discount on other goods in order to switch to another store not offering that discount. In other words, selective advertising in one set of goods ("loss leaders") can reduce the incentive to lower prices on other goods (and possibly lead to higher profits) even in a non-cooperative game.

Consider a two-stage game. The first stage is a simultaneous move advertising game. The result of this game is a pair of advertisements, which together with consumer preferences determine the parameters for the second stage, a pricing game.

Suppose there are two stores, $i = 1, 2$, in the same physical location, each selling brands $k = A, B$ and an aggregate good C. All costs for the firms are set to zero. There are measure 1 of consumers, each having valuation v_A and v_B respectively for the two brands, where $v_A > 0$, $v_B > 0$, and where $v_A - v_B$ is distributed uniformly on $\left(-\frac{1}{2}, \frac{1}{2}\right)$. In other words, there is a distribution of preferences for one brand over another. Once at a store i and presented with prices p_k^i (set by the firms), the consumer will choose the brand offering the larger surplus $v_k - p_k^i$, choosing each with probability $\frac{1}{2}$ if the surpluses are equal. Each consumer values the aggregate good at V_C, where V_C is an arbitrarily high constant. Consumers demand exactly one good of brand A or B, and one unit of the aggregate good C.

The actions are as follows. In the first stage, each store simultaneously chooses either brand A or B to advertise at a price of $p_k^i = 0$. The other (not-advertised) product is sold at some positive price $p_{-k}^i = P_{Non-Sale}$. For later convenience, I assume $P_{Non-Sale} > \frac{1}{2}$. In the second stage, each store i simultaneously sets a price p_C^i for the aggregate good C. Consumers choose exactly one store to shop at, by comparing the surplus offered at each store:

$$\begin{aligned}
\text{Consumer Surplus at store } i \text{ if } A \text{ advertised} &= \max[v_A, v_B - P_{Non-Sale}] + V_C - p_C^i \\
\text{Consumer Surplus at store } i \text{ if } B \text{ advertised} &= \max[v_A - P_{Non-Sale}, v_B] + V_C - p_C^i
\end{aligned}$$

They choose the store offering the greatest surplus, choosing each with probability $\frac{1}{2}$ if the surpluses offered are equal. Stores then collect profits. Stores and consumers are fully informed of the advertising and pricing decisions once they are made.

The strategies for each firm consist of an advertising decision (advertise A or B) for stage 1 and a pricing decision for stage 2 (set price p_C^i). Stage 2's pricing decision is contingent on the advertising observed in Stage 1. The solution concept is subgame perfect Nash equilibrium.

I solve for the equilibrium using backward induction. Since brands A and B are essentially equivalent, I will take as given store 1's strategy to advertise brand A, and consider store 2's two possible strategies: advertising brand A, or advertising brand B.

If store 2 chooses to match store 1's strategy, by advertising brand A, each consumer then considers the surplus available to him. From above, we know that the surplus available at each store is $\max[v_A, v_B - P_{Non-Sale}] + V_C - p_C^i$. Since, for all consumers, $|v_A - v_B| < \frac{1}{2}$, our assumption $P_{Non-Sale} > \frac{1}{2}$ means that $|v_A - v_B| < P_{Non-Sale}$, or $v_A > v_B - P_{Non-Sale}$. Therefore $\max[v_A, v_B - P_{Non-Sale}] = v_A$ for all consumers, and so everyone will purchase good A, as even the most B-loyal consumers still find v_A to be greater than $v_B - P_{Non-Sale}$. As both stores are offering the discount, the surplus offered by each store is thus $v_A + V_C - p_C^i$; thus, consumers will choose whichever store offers lower p_C^i (or choose randomly with probability $\frac{1}{2}$ if $p_C^1 = p_C^2$). This corresponds to the classic Bertrand setup, and the equilibrium of the subgame will be that both firms will choose p_C^i to equal marginal cost, in this case 0. Since all consumers choose brand A, and the profit per unit on brand A is 0, both firms earn profit of 0 in equilibrium.

Now let us consider the situation when store 2 chooses to advertise brand B. Our assumption $P_{Non-Sale} > \frac{1}{2}$ again simplifies the consumer's decision. As in the previous case, all consumers visiting store 1 will will choose brand A, since $v_A > v_B - P_{Non-Sale}$, or $v_A - v_B > -P_{Non-Sale}$. The same argument holds for store 2 and brand B: all consumers choosing store 2 will also choose brand B. Consumer surplus is therefore given by:

$$\begin{aligned}
\text{Consumer Surplus at store 1 } (A \text{ advertised}) &= v_A + V_C - p_C^1 \\
\text{Consumer Surplus at store 2 } (B \text{ advertised}) &= v_B + V_C - p_C^2
\end{aligned}$$

Thus, a consumer will choose store 1 if $v_A + V_C - p_C^1 > v_B + V_C - p_C^2$ or when $v_A - v_B > p_C^1 - p_C^2$. Let $N^i(p_C^i - p_C^{-i})$ be the fraction of consumers choosing each store i (noting that each consumer's decision is a function not of prices but of the difference in prices). Since $v_A - v_B$ is distributed uniformly on $\left(-\frac{1}{2}, \frac{1}{2}\right)$, the number of consumers choosing each store is given by:

$$N^i\left(p_C^i - p_C^{-i}\right) = \frac{1}{2} - \left(p_C^i - p_C^{-i}\right) = \frac{1}{2} - p_C^i + p_C^{-i}$$

for $p_C^i - p_C^{-i}$ in the interval $\left(-\frac{1}{2}, \frac{1}{2}\right)$, and 0 and 1 above and below the interval respectively.

The profit Π of firm i is therefore (keeping in mind that marginal cost is 0):

$$\Pi^i = p_C^i \cdot N^i\left(p_C^i - p_C^{-i}\right) = p_C^i \cdot \left(\frac{1}{2} - p_C^i + p_C^{-i}\right)$$

for $p_C^i - p_C^{-i}$ in the interval $\left(-\frac{1}{2}, \frac{1}{2}\right)$. For $p_C^i - p_C^{-i}$ above the interval, $\Pi^i = 0$; below the interval, $\Pi^i = p_C^i$.

Taking the first order condition, we find the best response function:

$$b^i\left(p_C^{-i}\right) = \frac{1}{4} + \frac{p_C^{-i}}{2}$$

for the interval $\left(-\frac{1}{2}, \frac{1}{2}\right)$.

We can see from this pair of best response functions that a symmetric equilibrium to the subgame exists, in which each firm sets a price on the aggregate good of $p_C^i = \frac{1}{2}$. Consumers see prices and choose stores by maximizing their surplus; since the prices set on the aggregate good are equal, consumers who prefer brand A (measure $\frac{1}{2}$) visit store 1 and buy brand A and consumers who prefer brand B (measure $\frac{1}{2}$) visit store 2 and buy brand B. By substituting these prices and quantities into the profit equation above, we find the profits collected by each firm to be $\frac{1}{4}$.

Given the equilibria of these two subgames, and the remaining two subgames (the analysis of which proceeds similarly), we may construct the following table of payoffs for the reduced form of the first stage game:

		Store 2's Advertisement	
		A	B
Store 1's Advertisement	A	$0, 0$	$\frac{1}{4}, \frac{1}{4}$
	B	$\frac{1}{4}, \frac{1}{4}$	$0, 0$

This simultaneous move game is a kind of coordination game, and there are two pure strategy equilibria: store 1 advertises A and store 2 advertises B, or vice versa. Thus, I have shown two pure strategy sequential Nash equilibria to the game: [i] stores $(1, 2)$ advertise (A, B) in the first stage and in the second stage set a price of $\frac{1}{2}$ following an advertising history of (A, B) or (B, A), and a price of 0 following an advertising history of (A, A) or (B, B), and [ii] stores advertise (B, A) in the first stage and in the second stage set a price of $\frac{1}{2}$ following an advertising history of (A, B) or (B, A), and a price of 0 following an advertising history of (A, A) or (B, B). The equilibrium outcome of this game is that each store advertises a different good and earns a profit of $\frac{1}{4}$.

Thus, we see in this simple setting how advertising different goods leads to higher prices and profits than does advertising the same goods. In summary, therefore, the segmentation model prediction is that advertising is a strategic substitute.

Two assumptions should be addressed here. First note that I assume that consumers choose only one store to visit, as in Anderson (2000). Second, the assumption $P_{Non-Sale} > \frac{1}{2}$: while this is not an innocuous assumption, I choose to make it because it delimits the scope of the model in a way that I think is justified. A quick examination of the data reveals that prices for goods in weeks when the product appears in a feature advertisement are much lower than in weeks when the product does not appear in a feature advertisement. This has the obvious result that most consumers buy a product that is on sale–just as in the model, once the consumer has chosen a store, the discount overwhelms the difference in preferences. This kind of pricing behavior is common to many grocery retailers, including the retailers this study focuses on. An alternative strategy exists, in which stores have "everyday low prices" and feature advertisements merely report regular prices and offer a few small additional discounts. However, modeling the choice between these two strategies is beyond the scope of this paper. For more on this topic see for example Bell and Lattin (1998).

4.3. Data and Institutional Background

The data in this paper was collected by Information Resources Inc. (IRI), and consists of two parts. The first is a scanner dataset of store-level sales, prices, and other promotional activity for the non-frozen orange juice category. The data consist of weekly observations over four years (Q4 2001-Q3 2005) for a representative sample of grocery retailers in three markets: Chicago, Boston, and Dallas. The second dataset is a scanner panel dataset (household-level), which covers all trips made by a panel of 5702 consumers distributed between these markets, and spans the same four years as the store-level dataset. The trips are recorded by consumers after the fact, and include when the trip was made and the total amount spent on each trip, as well as the quantities and prices paid for any items in the non-frozen orange juice category.

4.3.1. Feature Advertisements

The key variable of interest in this study is the Feature variable. Feature advertisements are the flyers distributed to consumers either through home newspaper delivery or through direct delivery via post. They are a primary means by which grocery retailers communicate information about price discounts and other specials to consumers, and are essentially the only means of reaching consumers not yet at the store. While retailers are responsible for the decisions of what to include in the feature advertisements (henceforth "to feature"), manufacturers often foot the bill: not only do manufacturers cover at least part of the price discounts through lower wholesale prices and other inducements, but they usually pay for nearly all of the feature ad itself. This happens through the use of advertising allowances, funds available to the retailer on the condition that manufacturers' products appear in the advertisement (Blattberg and Neslin 1990).

The data distinguishes three main types of feature advertisements: A, B, and C level ads[3]. A ads are large picture ads placed in prominent positions on the flyer (front, back, top of interior pages) and drawing attention to large discounts. B ads are smaller ads, often towards the bottom of interior pages. Items are still pictured but may be only slightly discounted. C ads are relatively rare in the data; they are smaller than B ads, often lacking pictures and discounts. Data on the use of these feature levels in the data is presented in Table 4.1, for the most common brands in the most popular size (64 ounces). As is clear from the table, retailers feature these juices heavily; non-frozen orange juice is a popular item for featuring because it is purchased by a large slice of the population

[3]The data also distinguishes A+ ads; these are A ads which also include a coupon. A+ ads are very rare in the data and seem to be unique to certain retailers. They are treated as A level ads for the purpose of this study.

Table 4.1. Advertising by Featue Level, All Chains (64 ounces)

Boston

Brand	Feature Type			Market Share
	A/A+	B/C	None	(by volume)
Florida's Natural	20.4%	19.5%	60.1%	16.9%
Minute Maid	9.6%	10.2%	80.3%	10.0%
Tropicana Pure Premium	46.0%	18.5%	35.2%	73.1%

Chicago

Brand	Feature Type			Market Share
	A/A+	B/C	None	(by volume)
Florida's Natural	14.9%	16.4%	68.8%	13.7%
Minute Maid	27.9%	22.1%	50.0%	31.9%
Tropicana Pure Premium	29.6%	21.9%	48.6%	54.4%

Dallas

Brand	Feature Type			Market Share
	A/A+	B/C	None	(by volume)
Florida's Natural	11.6%	14.8%	73.7%	11.4%
Minute Maid	18.8%	16.1%	65.2%	37.8%
Tropicana Pure Premium	21.5%	15.5%	63.0%	50.8%

Market shares are calculated based on sales of the sample brands (not including other brands, store brands, etc.)

(high penetration) and is relatively difficult to store for more than a week or two (low storability)[4].

Since A ads are the largest and the most critical for affecting customer behavior and price perception, this paper focuses on them when considering firms' price advertising strategies. Henceforth, a firm's decision to feature will be defined as their decision to

[4]Penetration and storability are considered to be important criteria for price discounting, because together they imply that many people will be looking to buy the product in any given week. This increases the efficacy of the advertisement.

advertise a product at the A level. Moreover, in the estimation to follow, I will look specifically at the decision to feature the 64 ounce varieties of each of the top three brands: Florida's Natural, Minute Maid, and Tropicana Pure Premium.

4.3.2. Markets and Stores

While many diverse stores appear in the data as selling orange juice, I only consider grocery chains with at least a 10% share of orange juice sales by volume in their market[5]. This cutoff leaves us with two grocery retail chains in Chicago, three in Dallas, and four in the Boston market. Feature advertising, because of the fixed costs of layout and design and the mass-market nature of distribution (i.e. newspapers), tends to be set at the chain-market level. Thus, the models estimated in the next section assume that chains make one advertising decision per week per product[6]. Table 4.2 gives a summary of the chains and their shares of orange juice sales, as well as their featuring behavior.

One interesting feature of the Boston market is that the chains Shaw's and Star Market are owned by the same company (Albertson's during the sample, more recently purchased by Supervalu) although they are operated as separate brands and distribute separate feature advertisements every week. This may provide some insight as to whether common ownership affects strategic substitutability.

[5]Walmart is not included in the sample; however, other discounters such as Target are present but do not pass the 10% test.

[6]In the rare case that the feature variable differs between stores in a given chain during a week, I treat the mode of the feature variable as the chain's decision.

Table 4.2. Chain Share of Orange Juice by Volume, Chain Featuring Activity

	Share of OJ Sales by Volume	A-Level Featuring %		
		Florida's Natural	Minute Maid	Tropicana
Boston				
Market Basket	28.1%	17.3%	0.5%	13.0%
Shaw's	14.7%	27.4%	14.4%	67.3%
Stop & Shop	27.0%	10.6%	9.7%	37.5%
Star Market	18.7%	26.4%	13.7%	65.4%
Chicago				
Dominick's	22.5%	12.5%	23.6%	24.5%
Jewel	53.4%	17.3%	32.2%	34.6%
Dallas				
Albertson's	19.8%	17.6%	20.8%	24.0%
Kroger	27.0%	10.6%	22.6%	23.6%
Tom Thumb	24.8%	2.6%	13.0%	16.8%

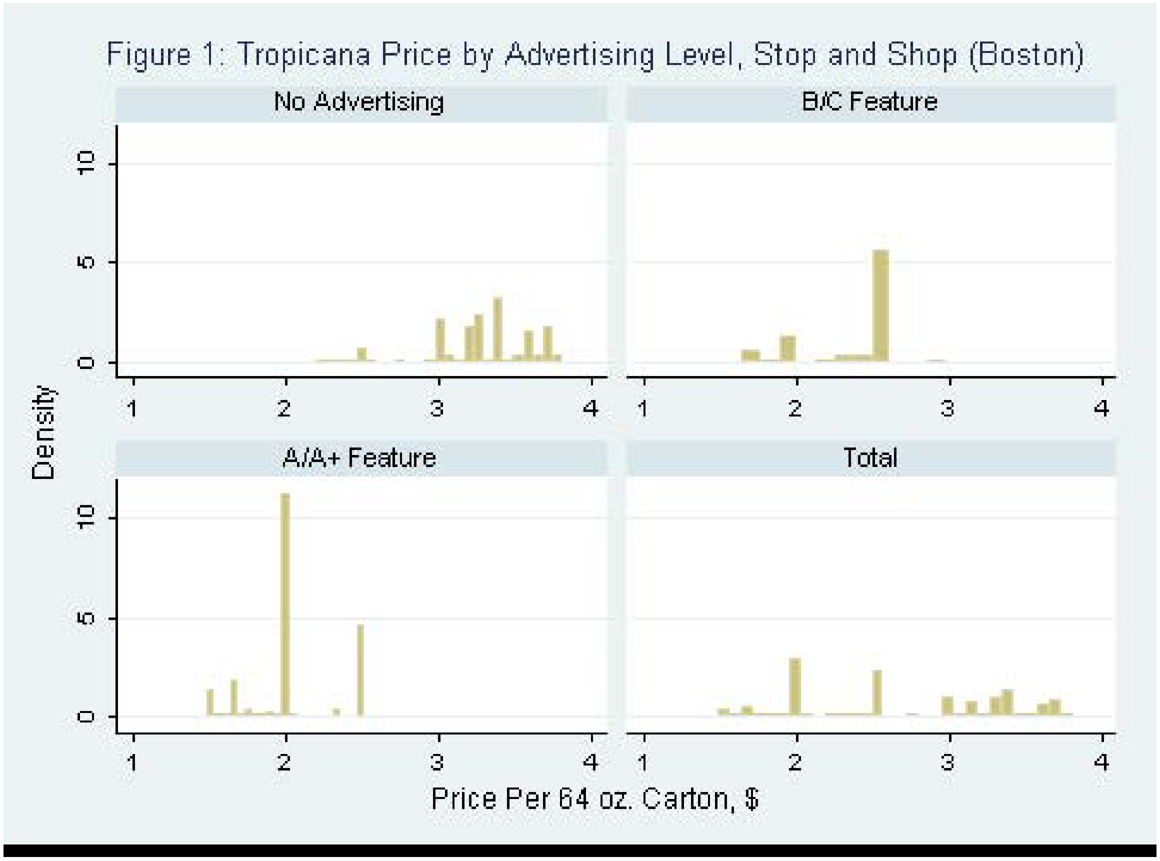
4.3.3. Descriptive Analysis

4.3.3.1. Feature Frequency. Tables 4.1 and 4.2 describe retailers' featuring of orange juice, by brand and retail chain. Table 4.1 (on page 80) shows relative levels of featuring by brand in each market. The amount of featuring in the sample varies widely between brands. In each market, the most heavily featured brand at the A/A+ level and overall is Tropicana Pure Premium. It is not, however, the most advertised product at the B/C level in any market. Note that, in each market, the market share ordering is identical to the advertising frequency ordering (overall and A/A+). Determining the causality behind this correlation is beyond the scope of this paper. However, this observation is consistent with a retailer preference for advertising products with greater penetration (market share).

Market shares and advertising levels also vary somewhat between markets. Chicago and Dallas are roughly similar, with Tropicana enjoying a slight advantage in advertising and a larger advantage in market share, with Minute Maid as a fairly close competitor. Advertising levels are slightly higher in Chicago than in Dallas. However, in Boston, Minute Maid is a distant third in both market share and advertising, and Tropicana is the clear market leader in both sales and advertising. Again, advertising seems to be related to market share.

Table 4.2 (page 82) shows relative levels of featuring by chain in each market. First, it can be seen that the differences between markets observed in the previous table seem to persist even when disaggregated to the chain level. In Boston, Tropicana is heavily advertised compared with the other two brands at each chain (with the exception of Market Basket), and at each chain Minute Maid is the least advertised brand. In Dallas and Chicago, Tropicana is advertised slightly more frequently than Minute Maid at each chain, and Florida's Natural takes third place in each case.

However, this table does reveal large differences in orange juice featuring activity between chains. Market Basket and Tom Thumb, for instance, almost never (<3% of the sample) advertise Minute Maid and Florida's Natural, respectively. However, Shaw's and Star Market advertise Tropicana at the A/A+ level in more than 65% of weeks. It can also be observed here that Shaw's and Star Market's advertising behavior is extremely similar, despite the fact that they maintain distinct identities and publish different advertisements.



This issue will be revisited in the discussion of results. Finally, orange juice market share does not seem to be strongly associated with featuring behavior.

4.3.3.2. Features and Prices. Figure 4.3.3.2 shows a set of weekly price histograms for Tropicana Pure Premium (64 oz), by the feature advertisement choice of the retailer, in this case Stop & Shop in Boston. Prices at all Stop & Shop stores in the sample are included. When the retailer opts not to feature, prices are generally between \$3 and \$4[7]. Choosing to feature at the B level is associated with a drop in price, most frequently to

[7]Some of this variation is due to the fact that non-advertised prices are generally not identical across stores (as opposed to advertised prices, because of the use of common newspaper features).

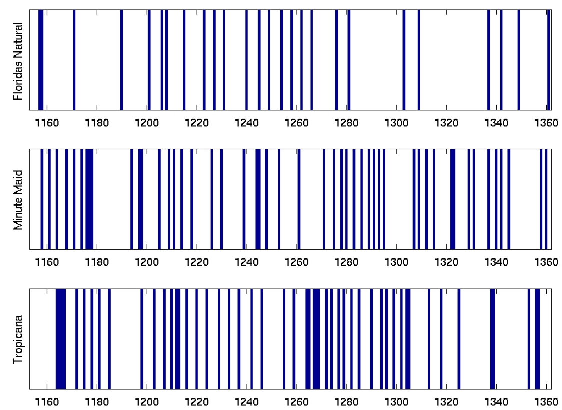
around \$2.50. Choosing to feature at the A level is associated with a further drop to \$2 or less (about 75% of A-level weeks).

There are two important facts visible in this figure. First, almost all prices below a certain threshold (in this case \$3) are advertised. Conversely, almost all advertisements include a price below this same \$3 threshold. In other words, Stop & Shop is generally not attempting to match competitors' low advertised prices using unadvertised in-store specials. Second, advertised prices are heavily concentrated around a small number of "round" prices: \$2.50, \$2, \$1.67 (i.e. "Three for \$5"), and \$1.50, with particular peaks around \$2.50 for the B-level features and \$2 for the A-level features. Previous research has noted the existence of such round numbered prices, and has explained them as being easier for the consumer to remember (Jones 1896). In this case, it suggests that modeling firms' advertising strategies empirically and taking the associated prices as given may not be throwing away so much information, as the greatest share of price variation seems to occur between different feature levels rather than within them.

4.3.3.3. Featuring, by Retailer. Figure 4.1 describes the behavior of individual stores (the two Chicago chains). Panel A consists of three diagrams describing the featuring behavior of Dominick's. Each graph represents Dominick's' A-level feature advertisements for a brand, with dark bars representing advertisements and white space representing no advertisements. Panel B contains the same diagrams describing Jewel's featuring behavior. The first thing to notice is that most advertisements run only for one week at a time. This varies somewhat by firm and brand; for example Dominick's advertises Florida's Natural two weeks in a row only once, while Jewel advertises Tropicana more than one week in a row over 10 times during the sample. Another feature visible here is

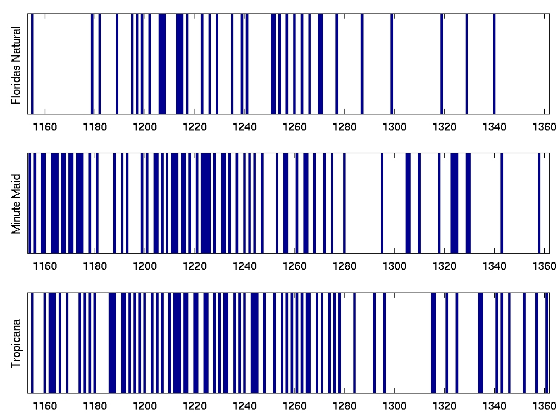
Figure 4.1. Advertising by Brand, for Chicago Retailers

Dominick's



Number of Brands Featured at A-Level	Number of Weeks
0	91
1	108
2	9
3	0

Jewel



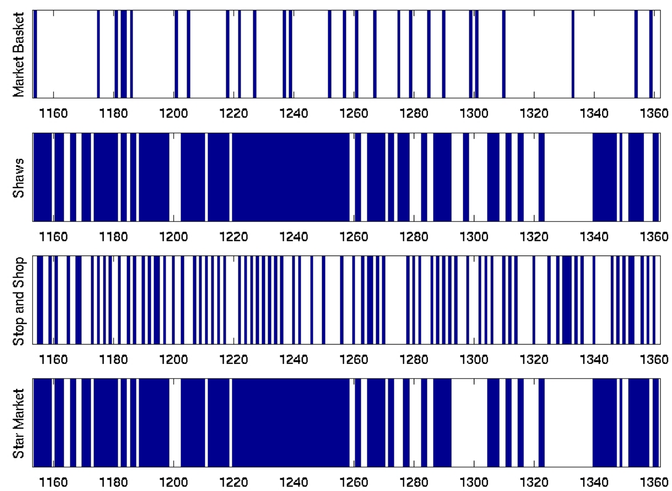
Number of Brands Featured at A-Level	Number of Weeks
0	72
1	100
2	33
3	3

that advertising is mostly irregular. While advertising in back to back weeks is relatively rare, it is also rare to see a regular pattern of on and off weeks persist for more than a few months. There are some holiday peaks visible here. For instance, Christmas appears at about week 1164 in the data (and subsequently in week 1217, 1269, etc.), and Dominick's can be seen to advertise Tropicana for four weeks straight around week 1164[8]. Finally, it should be noted that firms generally don't advertise different brands during the same weeks. Dominick's clearly tries to advertise brands at different times (more than one brand is advertised during only nine weeks, and never more than two brands at once). Jewel's advertising does not seem to exhibit the same deliberate avoidance, but neither does it seem to exhibit positive coordination among brands.

4.3.3.4. Featuring, by Market. Figures 4.2, .3, and .4 compare the behavior of firms within markets, using each firm's A-level featuring of Tropicana Pure Premium (64 oz.). Figure 4.2 describes the behavior of the Boston retailers. The first observation that is clear from this figure is that Star Market and Shaw's (the co-owned firms), despite being operated as separate chains and sending out separate feature advertisements, are advertising at very similar times. With this exception, however, it is clear that retailers in this market pursue quite different strategies. Shaw's and Star Market feature Tropicana during two thirds of the sample, almost always for more than one week at a time, and on one occasion for nearly 40 straight weeks (also not featuring for nearly 20 weeks at one point). Stop & Shop features Tropicana in less than 40% of the sample weeks, but almost never features more than one week in a row. Conversely, Stop & Shop also never goes more than six weeks without a feature. Finally, Market Basket features Tropicana in less than 15% of sample weeks, rarely featuring more than one week in a row and frequently going long periods without featuring. The tables accompanying the figure give the frequency of advertising conditional on the advertising of another firm (the same pairs

[8]Chicago has a winter peak in orange juice sales that is only present to a lesser degree in Boston and not at all in Dallas; my own theory from experience living in Chicago is that consumers think the vitamin C in the juice will protect them from colds during the winter.

Figure 4.2. Advertising of Tropicana Pure Premium (64 oz.), Boston



Market Basket	Shaw's 0	Shaw's 1	Total
0	60	121	181
1	8	19	27
Total	68	140	208

Market Basket	Stop & Shop 0	Stop & Shop 1	Total
0	107	74	181
1	23	4	27
Total	130	78	208

Market Basket	Star Market 0	Star Market 1	Total
0	61	120	181
1	9	18	27
Total	70	138	208

Shaw's	Stop & Shop 0	Stop & Shop 1	Total
0	39	29	68
1	91	49	140
Total	130	78	208

Shaw's	Star Market 0	Star Market 1	Total
0	41	89	130
1	29	49	78
Total	70	138	208

Stop & Shop	Star Market 0	Star Market 1	Total
0	66	2	68
1	4	136	140
Total	70	138	208

that will later be used for estimation). Most of the tables report numbers not far from what would be expected if advertising were unrelated; the exception is the table showing the joint featuring of Shaw's and Star Market, in which (0,0) and (1,1) are clearly of disproportionately large frequency. Figure .3 (in the Appendix) shows featuring behavior in the Dallas market; at first glance, this picture seems to indicate mild coordination. For example, Tom Thumb and Albertsons have quite similar featuring patterns in the first year or so of the sample. The tables also indicate some positive correlation; (0,0) and (1,1) are slightly more likely than random chance would indicate for each pair of retailers. In

Chicago (Figure .4, in the Appendix) no obvious pattern emerges from the figure; again, the table indicates some positive correlation.

Overall, the raw data would seem to indicate, for Dallas and Chicago at the least, that firms have a mild tendency to advertise Tropicana at the same time. However, the model below will help determine whether this is a function of strategic complementarity or of common unobservable shocks to the profitability of advertising, such as manufacturer promotional activity.

4.4. An Empirical Model of Feature Advertising

4.4.1. Setup

This section tests the main question of the paper: do stores profit from advertising the same products at the same time? Following the theoretical model above, my empirical model will be a two-player, static, simultaneous move entry game[9]. In each week, I model the decision of each retailer to feature a given product or not in a week (i.e., to "enter" the advertising market for that item). Retailers make their featuring decisions by comparing the expected weekly profits after each action.

The key feature of the model is the joint determination of advertising decisions. In this model, a firm's profits from featuring depend on firm- and week-specific demand and supply factors, but also depend on the competition's actions. Moreover, the competition's actions are endogenously determined, so that profits are dependent not only directly on the firm's own idiosyncratic payoff shocks, but indirectly on the idiosyncratic payoff shocks of competing firms, through the rival's advertising decision. The resulting coefficient on

[9]Behavior may well be history-dependent, but the paucity of store- and week- specific cost and demand data makes a fully dynamic model of advertising impractical.

the competitor's featuring behavior provides us with an estimate of the effect of other firms' feature advertisements on the profitability of advertising; that is, whether featuring a particular product is a strategic substitute.

Formally, in each week $t = 1, 2, ..., 206$ two firms $i = 1, 2$ decide whether or not to feature a product. For simplicity, firms are assumed to make independent choices from week to week, and are myopic in the sense that they do not take into account the effect of this week's decision on next week's, even though past featuring is included in the regression. Each firm's featuring decision is denoted by f_{it}, where $f_{it} = 1$ if firm i features the product at the A level in the weekly advertisement, and $f_{it} = 0$ otherwise.

Firm i's profits in week t for featuring decision $f \in 0, 1$ are given by the following reduced form:

$$\begin{aligned} \Pi_{it,f=1} &= \alpha f_{-it} + \beta f_{it-1} + \gamma 1\left[i = 1\right] + \Xi_t + \varepsilon_{it} \quad \text{(advertising)} \\ \Pi_{it,f=0} &= 0 \quad \text{(not advertising)} \end{aligned}$$

The first two terms in the upper equation are featuring decisions: the first is the opponent's decision whether or not to feature in the current week, and the second is the firm's own featuring decision in the previous week. γ is a firm-level characteristic. The Ξ_t term is a calendar-week characteristic[10]; this is included in the model specifically because there are important seasonal effects that are unobservable to the econometrician. The foremost concern is the promotional activity of manufacturers and wholesalers. Manufacturers offer discounts, advertising support, and other incentives that make a very large difference in

[10] By calendar-week characteristic I mean that there is a set of 51 dummy variables, the first taking the value of 1 from the first saturday of the year to the next friday, and so on until the end of the calendar year.

the profitability of advertising, but the promotional schedules and related contract information are not generally available. However, some of this activity may be consistent from year to year, and this variable is intended to capture it if possible[11]. Finally, ε_{it} is the idiosyncratic firm- and week-specific component of profits; it is independently normally distributed with mean of 0 and standard deviation of 1. In the model, the specific realization of ε_{it} is assumed to be common knowledge to the participants, but unobservable to the econometrician.

4.4.2. Equilibria

This two-player, simultaneous move game may have one of four different equilibria in pure strategies, depending on the value of the ε_{it}'s, where the strategies are denoted (f_1, f_2) : $(0,0); (0,1); (1,0)$; and $(1,1)$–in other words, no firm advertises, one firm advertises, or both firms advertise. Using the above profit equations, we can see that firm i will advertise if $\alpha f_{-it} + \beta f_{it-1} + \gamma 1\left[i=1\right] + \Xi_t + \varepsilon_{it} > 0$. Since the ε_{it}'s are assumed to be indepent and distributed normally with mean 0 and standard deviation 1, then the probability of obtaining the equilibrium (0,0) is given by:

$$
\begin{aligned}
P(f_{1t} &= 0, f_{2t} = 0|\Xi_t, \varepsilon_{it}) = P(f_{1t} = 0|\Xi_t, \varepsilon_{it})P(f_{2t} = 0|\Xi_t, \varepsilon_{it}) \\
&= P(\alpha f_{2t} + \beta f_{1t-1} + \gamma + \Xi_t + \varepsilon_{1t} > 0|\Xi_t, \varepsilon_{it})P(\alpha f_{1t} + \beta f_{2t-1} + \Xi_t + \varepsilon_{2t} > 0|\Xi_t, \varepsilon_{it}) \\
&= P(-\beta f_{1t-1} - \gamma - \Xi_t < \varepsilon_{1t}|\Xi_t, \varepsilon_{it})P(-\beta f_{2t-1} - \Xi_t < \varepsilon_{2t}|\Xi_t, \varepsilon_{it}) \\
&= \Phi(-\beta f_{1t-1} - \gamma - \Xi_t)\Phi(-\beta f_{2t-1} - \Xi_t)
\end{aligned}
$$

[11] One concern with such a variable is that it may capture more than intended—even biasing the main coefficient of interest (α) if, for instance, firms were somehow using dates to coordinate (e.g. we both feature at Christmas, neither features at Thanksgiving). I have not come across any evidence or mention of anything so systematic, but the concern remains valid.

Similarly,

$$P(f_{1t} = 0, f_{2t} = 1|\Xi_t, \varepsilon_{it}) = \Phi(-\alpha - \beta f_{1t-1} - \gamma - \Xi_t)\Phi(\beta f_{2t-1} + \Xi_t)$$

$$P(f_{1t} = 1, f_{2t} = 0|\Xi_t, \varepsilon_{it}) = \Phi(\beta f_{1t-1} + \gamma + \Xi_t)\Phi(-\alpha - \beta f_{2t-1} - \Xi_t)$$

$$P(f_{1t} = 1, f_{2t} = 1|\Xi_t, \varepsilon_{it}) = \Phi(\alpha + \beta f_{1t-1} + \gamma + \Xi_t)\Phi(\alpha + \beta f_{2t-1} + \Xi_t)$$

However, this ignores the fact that some of these equilibria are counted twice. For $\alpha > 0$, or strategic complementarity, there exists a region in which neither firm finds it profitable to advertise when the other firm doesn't advertise, but does find it profitable when the other firm does choose to advertise. That is, the probability regions calculated above for $(0, 0)$ and $(1, 1)$ are overlapping. For $\alpha < 0$, the same issue occurs with $(0, 1)$ and $(1, 0)$. I deal with this problem by dividing the overlapping region in half, and reducing the probabilities for each equilibrium downward accordingly. Alternatively, one might assume that the equilibrium is selected by a different process. I test this assumption by estimating the model assuming that one firm is a stackelberg leader; that is, that the leading firm decides whether or not to advertise first, and then the following firm decides whether or not to advertise. This has the result that when $\alpha > 0$, $(1, 1)$ always obtains, and when $\alpha < 0$, $(1, 0)$ always obtains, where the strategies are given as (leader, follower).

Estimation proceeds by maximum likelihood.

4.4.3. Results

4.4.3.1. Main Results. Tables 4.3, 4.4, and 4.5 present the main results in three parts, one brand per panel. Table 4.3 displays the estimated parameters for the above model,

Table 4.3. Results of Pairwise Entry Model, Tropicana

	Chicago		Dallas		
Variable	Jewel and Dominick's		Albertson's and Tom Thumb	Albertson's and Kroger	Tom Thumb and Kroger
Opponent Feature	-0.166		-0.241	0.038	-0.252
	-		(0.154)	(0.136)	(0.173)
Own Feature (t-1)	-0.386		0.517 **	0.731 ***	0.054
	-		(0.207)	(0.212)	(0.233)
Own Feature (t-2)	-0.060		-0.421 **	-0.513 **	-1.038 ***
	-		(0.211)	(0.238)	(0.300)
Own Feature (t-3)	0.152		0.107	0.401 *	0.008
	-		(0.206)	(0.211)	(0.239)
Store Intercept	-0.347		-0.043	0.184	0.282 *
	-		(0.151)	(0.157)	(0.167)

	Boston					
Variable	Market Basket and Shaw's	Market Basket and Stop & Shop	Market Basket and Star Market	Shaw's and Stop & Shop	Shaw's and Star Market	Stop & Shop and Star Market
Opponent Feature	-0.233	-0.857	-0.299 *	-0.409 ***	2.012	-0.3599 ***
	(0.167)	-	(0.172)	(0.126)	-	(0.125)
Own Feature (t-1)	0.933 ***	-1.494	0.935 ***	0.037	1.942	0.049292
	(0.196)	-	(0.198)	(0.152)	-	(0.152)
Own Feature (t-2)	0.073	0.302	0.089	0.645 ***	-0.961	0.70401 ***
	(0.211)	-	(0.214)	(0.149)	-	(0.147)
Own Feature (t-3)	0.394 **	-0.364	0.556 ***	-0.029	0.919	0.11096
	(0.200)	-	(0.201)	(0.154)	-	(0.152)
Store Intercept	-0.994 ***	-1.138	-0.890 ***	0.549 ***	0.002	-0.53328 ***
	(0.215)	-	(0.212)	(0.152)	-	(0.146)

using Tropicana Pure Premium (64 oz.), the top-selling product in the sample. Each possible pair of stores in a market is estimated pair-wise, thus producing one set of estimates for the Chicago market, three sets of estimates for the Dallas market, and six sets of estimates for the Boston market. Tropicana is presented first since, as the most popular (and most featured) product, it should be the most important brand for the purpose of strategic interaction between retailers. The primary result is the coefficient on opponent feature (α in the model). It is negative but insignificant in three out of four cases in Chicago and Dallas (positive and insignificant in one case). However, it is negative and significant in three out of six cases in Boston, with two more being negative but insignificant. The notable exception is the opponent feature coefficient for Shaw's vs. Star Market. This coefficient is positive, and while I did not obtain standard errors because of the near non-singularity of the information matrix, the coefficient is much higher in magnitude than the other coefficients, and this finding is consistent with the visual evidence from Figure 4.2, that Shaw's and Star Market feature Tropicana Pure Premium during almost exactly the same time periods (recall that they are commonly owned, and thus likely face different incentives in competing with each other than with other firms). Overall, then, these estimated coefficients are consistent with price advertising being a strategic substitute, especially in the case of Boston.

The estimates of the other coefficients are less consistent between markets. Firms in Dallas are significantly more likely to advertise Tropicana if they advertised in the previous week, but less likely to advertise if they advertised two weeks ago. The results in Boston are more mixed; several of the pair-wise coefficients on own featuring in periods (t-1) and (t-2) are significant and positive, but several are negative and insignificant. Finally, many of the firm intercept estimates are significantly different from zero, reflecting the fact that in many of the pairs advertising is generally more profitable for one firm than the other.

Tables 4.4 and 4.5 present the results with respect to Minute Maid and Florida's Natural. There are two interesting features of the Minute Maid results. First, the coefficients on opponent feature (α) that were negative but insignificant in the Dallas market become significant. This may reflect the fact that Minute Maid has a larger market share in Dallas and plays a more important part in the competition between firms. Second,

Table 4.4. Results of Pairwise Entry Model, Minute Maid

	Chicago		Dallas		
Variable	Jewel and Dominick's		Albertson's and Tom Thumb	Albertson's and Kroger	Tom Thumb and Kroger
Opponent Feature	-0.106		-0.362 **	-0.001	-0.389 **
	(0.125)		(0.165)	-	(0.185)
Own Feature (t-1)	-0.328 *		0.553 ***	1.073	-0.388
	(0.175)		(0.202)	-	(0.243)
Own Feature (t-2)	-0.048		0.653 ***	0.266	-0.138
	(0.176)		(0.210)	-	(0.255)
Own Feature (t-3)	0.474 ***		-0.080	0.079	-0.115
	(0.166)		(0.214)	-	(0.238)
Store Intercept	-0.223		-0.120	0.169	0.464 ***
	(0.144)		(0.157)	-	(0.170)

	Boston					
Variable	Market Basket and Shaw's	Market Basket and Stop & Shop	Market Basket and Star Market	Shaw's and Stop & Shop	Shaw's and Star Market	Stop & Shop and Star Market
Opponent Feature	-2.350	-19.455	-2.408	-0.149	2.250	-0.11109
	-	-	-	-	-	-
Own Feature (t-1)	4.068	-31.243	4.059	1.644	33.855	1.6676
	-	-	-	-	-	-
Own Feature (t-2)	-2.746	-37.390	-2.801	-0.642	-32.485	-0.89668
	-	-	-	-	-	-
Own Feature (t-3)	2.139	-1.498	2.127	0.363	31.641	0.3906
	-	-	-	-	-	-
Store Intercept	-1.367	-2.326	-1.362	-0.001	-0.258	-0.15609
	-	-	-	-	-	-

while the signs of the Boston results remain the same as for Tropicana, the standard errors become undefined (again due to the near non-singularity of the information matrix). This is probably due to Minute Maid's extremely small market share in Boston (and the extremely low degree to which it is featured). The Florida's Natural coefficient estimates describe a similar picture to the Tropicana results, with negative but insignificant estimates for the effect of opponent featuring in Chicago and Dallas, and some negative and

Table 4.5. Results of Pairwise Entry Model, Florida's Natura

	Chicago		Dallas		
Variable	Jewel and Dominick's		Albertson's and Tom Thumb	Albertson's and Kroger	Tom Thumb and Kroger
Opponent Feature	-0.206		-0.128	-0.004	-1.552
	(0.180)		(0.186)	-	-
Own Feature (t-1)	-0.136		1.233 ***	2.020	1.260
	(0.290)		(0.280)	-	-
Own Feature (t-2)	-0.220		-0.176	-0.978	0.416
	(0.275)		(0.309)	-	-
Own Feature (t-3)	0.144		0.036	0.498	-0.543
	(0.270)		(0.292)	-	-
Store Intercept	-0.249		0.227	0.991	0.748
	(0.175)		(0.191)	-	-

	Boston					
Variable	Market Basket and Shaw's	Market Basket and Stop & Shop	Market Basket and Star Market	Shaw's and Stop & Shop	Shaw's and Star Market	Stop & Shop and Star Market
Opponent Feature	-0.403 **	-0.568	-0.400 **	-0.157	2.001	-0.18526
	(0.164)	-	(0.167)	(0.164)	-	-
Own Feature (t-1)	0.845 ***	-0.634	0.834 ***	0.987 ***	2.656	0.98643
	(0.192)	-	(0.195)	(0.215)	-	-
Own Feature (t-2)	-0.201	-0.007	-0.083	-0.412 *	-1.818	-0.33101
	(0.216)	-	(0.218)	(0.247)	-	-
Own Feature (t-3)	-0.029	-0.290	0.003	0.349	1.304	0.36832
	(0.202)	-	(0.208)	(0.228)	-	-
Store Intercept	-0.354 **	0.306	-0.314 **	0.440 **	-0.096	-0.53864
	(0.155)	-	(0.155)	(0.174)	-	-

significant results in Boston (with the exception of Shaw's and Star Market, the co-owned firms). Together, these two sets of estimates confirm the inference from the Tropicana Pure Premium results—that feature advertising is a strategic substitute.

4.4.3.2. Robustness to Alternative Equilibrium Assumptions. Tables .9 and .10 (in the Appendix) present the results of a change in how multiple equilibria contribute to the likelihood of the model. As discussed above, for a certain set of ε's (unobserved variables) in each market and time period multiple equilibria may obtain. For instance, if advertising is a strategic substitute, then for a certain set of ε's both (0,1) and (1,0) are possible equilibria. For the main result, I made the assumption that each possible equilibrium (in this model there are never more than two) obtains with probability = 0.5. Tables .9 and .10 present the results of the estimates using Tropicana Pure Premium data, with two alternative assumptions; first, that the first firm operates as a Stackelberg leader, and second, that the second firm operates as a Stackelberg leader. In practice, this means that in the areas of potential multiple equilibrium, the equilibrium in which the leading firm enters is always selected.

The results in tables .9 and .10 make clear that the estimates on the primary coefficient of interest, α, are remarkably insensitive to these changes in the equilibrium selection mechanism. In no cases do the signs of the estimates change, and in no cases are the changes in the estimates even as large as the standard errors on the coefficients. Estimates of other coefficients are similarly insensitive to these mechanism changes.

4.5. Conclusion

This paper has addressed the issue of strategic advertising timing by grocery retailers. First, I discussed the implications of an existing set of "loss leader" models typified by Lal and Matutes (1994)—that firms might be offering discounts on one set of products in order to make their money back on other products, and would in consequence advertise the same products as other firms in order to reduce the cost of these discounts[12]. I then presented an alternative model, similar to a location competition model such as that in

[12]Alternatively, as in Chevalier et al. (2003) or MacDonald (2000), different products are advertised because products with greatest demand make the most effective loss leaders.

D'Aspremont et al. (1979), in which firms choose to advertise different products in order to segment consumers (akin to locating far apart in physical space). This increased spacing of consumers reduces the incentive for firms to reduce prices, resulting in higher equilibrium prices. To test the predictions of these models (strategic complementarity vs. strategic substitutability), I used data on orange juice feature advertising. Simple data analysis shows positive correlation between firms' advertising timing. However, estimating the effect of other firms' behavior on the profitability of advertising via a complete information static game (a la Bresnahan and Reiss 1990 or Berry 1992) allows me to control for common shocks and previous behavior, and yields the opposite result, that firms find it less profitable to advertise a product when other firms advertise the same product. That is, I find price advertising to be a strategic substitute. The result is found across a number of markets and brands, and is robust to an alternative set of equilibrium selection assumptions within the model.

Further research in this area might progress along several lines. First, the importance of store choice in these models suggests a role for household-level panel data. Panel data would allow for further testing of the implications of the models above; in particular, investigation of consumers' store switching behavior would indicate whether appealing to differences in tastes can have an economically significant impact on prices and profits. Second, the role of manufacturers is a very interesting aspect of retail advertising, which this paper has not investigated fully due to the difficulty of obtaining data. Finally, there is scope for further investigation into this question using more sophisticated methods to account for multiple equilibria, as in Ciliberto and Tamer (2003) who offer a relatively simple estimator that yields a set of possible coeffiecients without making assumptions on the equilibrium selection mechanism. However, I am not optimistic that these methods will yield narrow enough predictions to comfirm or refute the results presented here.

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APPENDIX

Appendix

1. A Dataset of Household Shopping Trips

1.1. Introduction

Household shopping location choice and price advertising are best studied with data on consumer trips over time. Data on individual trips allows the researcher to make inferences regarding households' shopping location decisions without the assumptions required with store-level data. For example, to attribute increases in store-level sales to advertising might involve assuming consumers do not stockpile goods for future consumption, and that they consume goods at a constant rate regardless of the amount purchased in a week. Unfortunately, even if these assumptions are occasionally applicable, the majority of products are both stockpiled and consumed at variable rates. Household-level data also allows the researcher to demonstrate advertising-attracted consumers' spending on other goods than the advertised goods. Additionally, there are many unobserved factors affecting shopping location choice, such as geographical and taste factors, that the researcher could never hope to capture perfectly; hence, a previous shopping location history is very useful as a control. Past purchase data is also useful, as seen in Chapter 3 of this dissertation.

Table .1. Summary Statistics (Demographics)

Variable	Number of Obs.	Median	Mean	Standard Deviation
Income	1715	50.00	57.28	32.90
At Least One Head of Household Stay-at-Home	1715	1.00	0.65	0.48
Family Size	1715	3.00	2.87	1.42

1.2. Panelists

The dataset described here was collected by Information Resources Inc. (IRI). The dataset is a household-level panel dataset, which covers grocery shopping trips made by a panel of 1715 consumers in the Boston area.[1] The panel spans four years (Q4 2001 to Q3 2005), but is unbalanced. Most panelists stay in the panel at least one year, and most enter and exit at year-ends. Figure .2 shows the amount of time panelists are active in the panel and when the panelists tend to exit. The left axis represents the week in which panelists first record a trip in the sample, and the right axis represents the week in which they last record a trip. Points closer to the 45 degree line represent shorter life-spans in the sample. Table .1 reports summary statistics for some demographic variables relevant to the analysis. Many other variables are available, including pet ownership, ages of household members, and credit card ownership.

[1] A companion dataset exists and is used in the analysis in Chapters 3 and 4 of this dissertation. It is a scanner dataset of store-level sales, prices and other promotional activity for the non-frozen orange juice category. The data consist of weekly observations over four years (Q4 2001-Q3 2005) for a representative sample of grocery retailers in the Boston, Ma., Chicago, Il., and Dallas, Tx. metropolitan areas. The shopping trip panel also extends to these cities, but only the portion of the dataset covering Boston is described here.

Figure .1. Panelist Entry and Exit Weeks

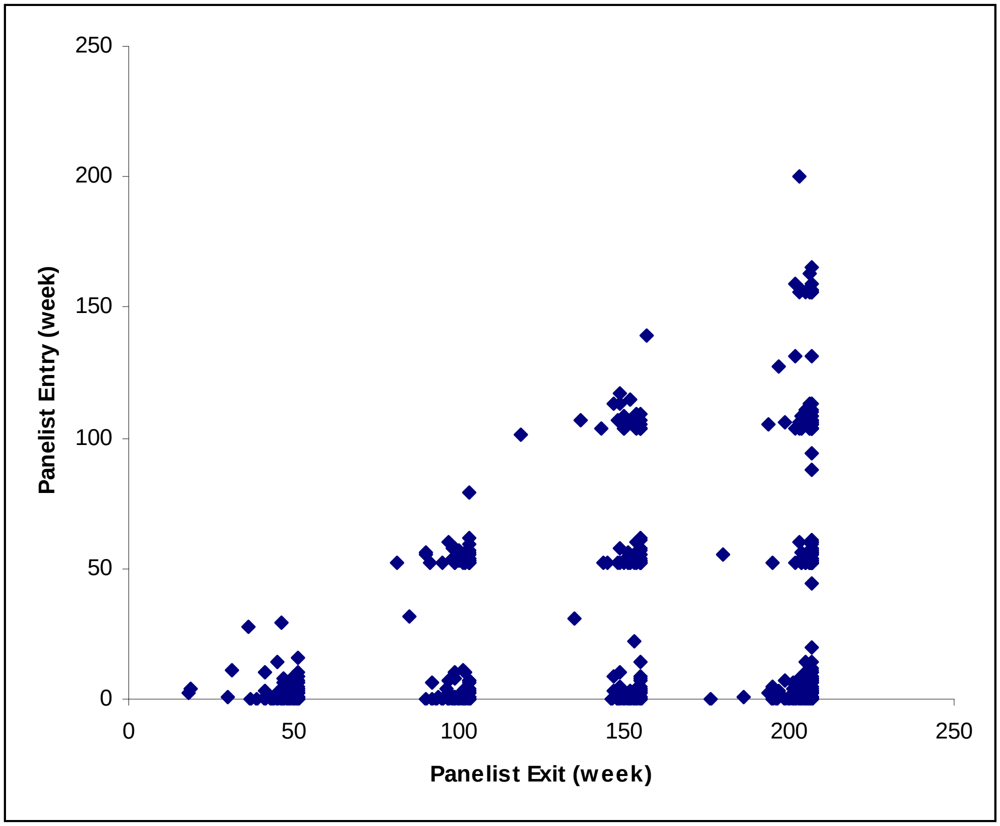


Figure .2.

Data is self-reported and includes trips and total spending per trip. For each trip, panelists scan their purchases of food and other consumer packaged goods (CPGs) such as health and beauty products, and record their total spending for the trip. There are approximately 631,000 trips described in the data. It is difficult to identify exactly how many panelist-weeks the dataset covers, because no explicit data exists on the entry and exit times for panelists. By defining a panelist's time in the sample as the weeks between their first and last trips, I estimate that there are over 260,000 household-weeks in the sample. The resulting mean number of trips per week is about 2.4.

1.3. Retail Outlets

The data records trips to six types of retail outlets: grocery stores (e.g. Stop & Shop), warehouse club stores (e.g. Costco), convenience stores (e.g. Texaco), department stores, drug stores (e.g. CVS), and mass merchandisers (e.g. Wal-Mart).[2] Table .2 reports trips taken, dollars spent, and dollars per trip for each retail category. The largest group of household chain visits recorded in the data, both by frequency (43 percent) and by spending total (48 percent), is to grocery stores, where households' mean expenditure per chain visit is around $26 dollars. Mass merchandisers are also a common destination, representing 23 percent of chain visits and 26 percent of spending. Spending per mass merchandiser visit is similar to grocery stores, perhaps indicating that Walmart and Target supercenters have begun to replace traditional grocery store visits. Total spending at warehouse club stores (13 percent) is lower than at grocery stores or mass merchandisers, but spending per chain visit is much higher (over $63). Convenience stores, drug stores, and department stores are visited frequently (29 percent of visits) but are relatively unimportant to total spending (only 14 percent). Overall, grocery stores are visited approximately once per household-week, drug stores and mass merchandisers approximately once every two household-weeks, and the other retail outlets approximately once every 6-8 weeks on average.

Shopping locations are recorded in the data with varying degrees of precision. The data includes store name, chain, outlet type, and address where available. Some shopping trips are linked to a particular store in IRI's database. Other stores are linked to a

[2] Two more outlet types (Unknown and Specialty) are of minimal relevance to the analysis and are not included in the descriptive statistics here.

Table .2. Household Spending and Trips by Outlet Type

Outlet Type	Total Spending	% of total	No. of Trips	% of total	dollars per trip	trips per hh-week
Grocery Stores	719.4	48%	268847	43%	$ 26.76	1.03
Warehouse Clubs	197.1	13%	31175	5%	$ 63.22	0.12
Mass Merchandisers	392.2	26%	145921	23%	$ 26.88	0.56
Department Stores	33.6	2%	38895	6%	$ 8.64	0.15
Drug Stores	144.2	10%	103025	16%	$ 14.00	0.40
Convenience Stores	23.9	2%	42958	7%	$ 5.56	0.17
Total	1510.4		630821		$ 23.94	

catch-all chain code; thus, in the data a trip may be to the Shaw's supermarket in Porter Square, Cambridge, MA, or it may be to an unidentified Shaw's. The majority of trips are recorded as being to these unidentified outlets of a chain, making it impractical to study household choice of store rather than of chain. A small minority of trips are coded as "Grocery Store" or "Drug Store", etc. If the researcher were interested in shopping behavior at the outlet level, these observations would be useful. Other studies may have to treat these observations as noise. Table .3 shows the extent of this aggregation effect.

In a few cases, several store names are coded as part of the same chain. IRI's nomenclature usually refers to a store's ownership rather than its banner; thus further investigation was required to determine whether these represent name changes over time, operational mergers, or simply common ownership with separate operations. As a result of my investigation of chain merger and acquisition histories, for purposes of displaying and analyzing data "Shop and Save" and "Hannaford" stores are treated as one chain and "Demoula's"

Table .3. Extent of Chain Aggregation in Data

Outlet Type	Spending, Named Chains (millions)	Spending, Catch-all (millions)	Trips, Named Chains	Trips, Catch-all
Grocery Stores	634.7	84.7	225107	43740
Warehouse Clubs	197.1	0.0	31175	0
Mass Merchandisers	340.4	51.8	102906	43015
Department Stores	0.0	33.6	0	38895
Drug Stores	137.7	6.5	98243	4782
Convenience Stores	11.2	12.7	25363	17595
Total	1321.2	189.3	482794	148027

and "Market Basket" are treated as one chain, but "Bread and Circus" and "Stop and Shop" are treated as different chains, as are "Star Market" and "Shaw's".

1.4. Distribution of Individual Household Activity

This section discusses individual household shopping activity. Table .4 shows the distribution of trips per household-week, contingent on at least one trip in the week. A significant percentage of household-weeks include more than one trip, including 2.8 percent with at least 10 trips.

Table .5 reports the distribution of trips per chain per week, contingent on at least one trip to a chain. Over 75 percent of trips are unique in a week, and most of the remainder are double or triple trips. The average number of chains visited is 3.2, contingent on at least one chain visited in the week.

Table .4. Histogram of Trips per Household-Week

No. of Trips in a week	Household-Weeks	% of Total	Cumulative % of Total
1	55,126	28.0%	28.0%
2	44,898	22.8%	50.8%
3	32,484	16.5%	67.4%
4	21,951	11.2%	78.5%
5	14,451	7.4%	85.9%
6	9,621	4.9%	90.8%
7	6,124	3.1%	93.9%
8	3,867	2.0%	95.8%
9	2,621	1.3%	97.2%
10+	5,596	2.8%	100.0%

Table .5. Histogram of Number of Visits Per Chain Per Household-Week

No. of Trips	Chains Visited	% of Total	Cumulative % of Total
1	351,665	0.7612	0.7612
2	77,532	0.1678	0.929
3	20,313	0.044	0.973
4	6,774	0.0147	0.9876
5	2,643	0.0057	0.9933
6	1,305	0.0028	0.9962
7	798	0.0017	0.9979
8	404	0.0009	0.9988
9	194	0.0004	0.9992
10+	375	8.0%	100.0%

1.5. Conclusion

A simple examination of this dataset provides interesting results on how consumers shop. Households in the data make multiple shopping trips per week, an average of 2.4. Spending is spread around a number of different types of retail outlets. Grocery stores receive

Table .6. Impact of Household OJ Consumption on Household Shopping Location Decision, Weighted by Demographics

Variable: / Model:	A	B	C	D
Level A Feature	-0.0203 **	-0.0500 ***	-0.0402 *	-0.0884 ***
	(0.0081)	(0.0143)	(0.0212)	(0.0328)
Level B Feature	0.0187	-0.0062	0.0318	-0.0265
	(0.0121)	(0.0209)	(0.0316)	(0.0476)
Chain Preference	0.8564 ***	0.8562 ***	0.8564 ***	0.8567 ***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
A Feature x Log Annual OJ Purchases		0.0172 ***	0.0197 ***	0.0488 ***
		(0.0066)	(0.0069)	(0.0165)
B Feature x Log Annual OJ Purchases		0.0149	0.0211 **	0.0579 **
		(0.0099)	(0.0103)	(0.0247)
A Feature x Family Size			-0.0129 **	-0.0114 *
			(0.0060)	(0.0109)
B Feature x Family Size			-0.0231 **	-0.0129
			(0.0091)	(0.0163)
A Feature x Income			0.0004	0.0014 ***
			(0.0002)	(0.0004)
B Feature x Income			0.0002	0.0010
			(0.0004)	(0.0007)
A Feature x Log Annual OJ x Family Size				-0.0007
				(0.0049)
B Feature x Log Annual OJ x Family Size				-0.0056
				(0.0073)
A Feature x Log Annual OJ x Income				-0.0006 ***
				(0.0002)
B Feature x Log Annual OJ x Income				-0.0005
				(0.0003)

*, **, and *** represent P-values less than 0.1, 0.05, and 0.01 respectively.

nearly half of dollars and trips; however, a significant portion of spending is done at mass merchandisers, wholesale clubs, and drug stores. Trips to mass merchandisers resemble trips to grocery stores, and as expected convenience stores receive many small trips, and wholesale clubs few large trips. Most chains are only visited once during a week, although repeat trips do happen. Some data limitations exist in the form of trip location aggregation, but on the whole are acceptable given the potential of the data for research.

2. Additional Tables and Figures

Table .7. Impact of Brand Loyalty on Household Shopping Location Decision, All Households, Weighted by Demographics

Variable:	Model: A	E	F	G
Level A Feature	-0.0203 **	-0.0496 ***	-0.0500 *	-0.0539
	(0.0081)	(0.0154)	(0.0266)	(0.0406)
Level B Feature	0.0187	0.0265	0.0787 *	0.1100 *
	(0.0121)	(0.0227)	(0.0407)	(0.0606)
Chain Preference	0.8564 ***	0.8561 ***	0.8564 ***	0.8565 ***
	(0.0035)	(0.0040)	(0.0040)	(0.0040)
A Feature x Tropicana Share of HH OJ purchases		0.0824 ***	0.0798 **	0.0911
		(0.0311)	(0.0315)	(0.0827)
B Feature x Tropicana Share of HH OJ purchases		-0.0250	-0.0397	-0.1296
		(0.0491)	(0.0497)	(0.1305)
A Feature x Family Size			-0.0028	0.0034
			(0.0067)	(0.0113)
B Feature x Family Size			-0.0261 **	-0.0505 ***
			(0.0101)	(0.0164)
A Feature x Income			0.0002	-0.0001
			(0.0003)	(0.0005)
B Feature x Income			0.0005	0.0011
			(0.0004)	(0.0008)
A Feature x Tropicana Share x Family Size				-0.0162
				(0.0240)
B Feature x Tropicana Share x Family Size				0.0713 *
				(0.0374)
A Feature x Tropicana Share x Income				0.0006
				(0.0010)
B Feature x Tropicana Share x Income				-0.0018
				(0.0016)

*, **, and *** represent P-values less than 0.1, 0.05, and 0.01 respectively.

Table .8. Impact of Brand Loyalty on Household Shopping Location Decision, High-OJ Volume Households, Weighted by Demographics

Variable:	Model: H	I	J	K
Level A Feature	0.0104	0.0223	0.1205 ***	0.0885
	(0.0129)	(0.0226)	(0.0398)	(0.0620)
Level B Feature	0.0541 ***	0.0942 ***	0.2359 ***	0.2212 **
	(0.0195)	(0.0321)	(0.0603)	(0.0897)
Chain Preference	0.8561 ***	0.8564 ***	0.8582 ***	0.8581 ***
	(0.0055)	(0.0055)	(0.0056)	(0.0056)
A Feature x Tropicana Share of HH OJ purchases		-0.0266	-0.0355	0.0233
		(0.0430)	(0.0435)	(0.1124)
B Feature x Tropicana Share of HH OJ purchases		-0.0984	-0.1159 *	-0.1177
		(0.0662)	(0.0667)	(0.1724)
A Feature x Family Size			-0.0237 **	-0.0317 **
			(0.0093)	(0.0157)
B Feature x Family Size			-0.0273 **	-0.0614 ***
			(0.0139)	(0.0218)
A Feature x Income			-0.0004	0.0006
			(0.0004)	(0.0007)
B Feature x Income			-0.0010	0.0012
			(0.0006)	(0.0011)
A Feature x Tropicana Share x Family Size				0.0221
				(0.0318)
B Feature x Tropicana Share x Family Size				0.1037 **
				(0.0492)
A Feature x Tropicana Share x Income				-0.0023 *
				(0.0013)
B Feature x Tropicana Share x Income				-0.0054 **
				(0.0021)

*, **, and *** represent P-values less than 0.1, 0.05, and 0.01 respectively.

Table .9. Testing the Impact of Alternative Equilibrium Assumptions (Tropicana in Chicago, Dallas)

Dominick's vs. Jewel

	Estimates		
	Model 1	Model 2	Model 3
Opponent Feature	-0.1660	-0.1603	-0.1844
	-	0.1211	0.1288
Own Feature, t-1	-0.3858	-0.3851	-0.3846
	-	0.1873	0.1872
Own Feature, t-2	-0.0600	-0.0609	-0.0748
	-	0.1673	0.1695
Own Feature, t-3	0.1523	0.1510	0.1557
	-	0.0000	0.1768
Store Intercept	-0.3470	-0.3556	0.3120
	-	0.1454	0.1488

Model 1: Probability 0.5
Model 2: Dominick's as Stackelberg Leader
Model 3: Jewel as Stackelberg Leader

Albertson's vs. Tom Thumb

	Estimates		
	Model 1	Model 2	Model 3
Opponent Feature	-0.2407	-0.2381	-0.2627
	0.1540	0.1533	0.1584
Own Feature, t-1	0.5171	0.5163	0.5146
	0.2069	0.2149	0.2024
Own Feature, t-2	-0.4211	-0.4199	-0.4366
	0.2113	0.2124	0.1900
Own Feature, t-3	0.1071	0.1065	0.0941
	0.2055	0.2102	0.2086
Store Intercept	-0.0429	-0.0578	-0.1122
	0.1509	0.1566	0.1545

Model 1: Probability 0.5
Model 2: Albertson's as Stackelberg Leader
Model 3: Tom Thumb as Stackelberg Leader

Albertson's vs. Kroger

	Estimates		
	Model 1	Model 2	Model 3
Opponent Feature	0.0378	0.0362	0.0471
	0.1361	0.1339	-
Own Feature, t-1	0.7310	0.7311	0.7196
	0.2119	0.2120	-
Own Feature, t-2	-0.5132	-0.5133	-0.5252
	0.2378	0.2410	-
Own Feature, t-3	0.4007	0.4008	0.4020
	0.2105	0.2111	-
	0.1836	0.1835	-0.3037
	0.1568	0.1609	-

Model 1: Probability 0.5
Model 2: Albertson's as Stackelberg Leader
Model 3: Kroger as Stackelberg Leader

Tom Thumb vs. Kroger

	Estimates		
	Model 1	Model 2	Model 3
Opponent Feature	-0.2519	-0.2695	-0.2366
	0.1726	-	-
Own Feature, t-1	0.0543	0.0540	0.0464
	0.2329	-	-
Own Feature, t-2	-1.0384	-1.0376	-1.0283
	0.2999	-	-
Own Feature, t-3	0.0083	0.0093	0.0162
	0.2395	-	-
	0.2824	0.2644	-0.3802
	0.1670	-	-

Model 1: Probability 0.5
Model 2: Tom Thumb as Stackelberg Leader
Model 3: Kroger as Stackelberg Leader

Table .10. Testing the Impact of Alternative Equilibrium Assumptions (Tropicana in Boston)

Market Basket vs. Shaw's

	Estimates Model 1	Model 2	Model 3
Opponent Feature	-0.2335	-0.2316	-0.2978
	0.1675	0.1579	0.1793
Own Feature, t-1	0.9329	0.9341	0.8875
	0.1965	0.1965	0.1996
Own Feature, t-2	0.0732	0.0718	0.0278
	0.2114	0.2114	0.2139
Own Feature, t-3	0.3943	0.3964	0.3650
	0.1997	0.1999	0.2014
Store Intercept	-0.9945	-1.0073	1.0154
	0.2155	0.2087	0.2334

Model 1: Probability 0.5
Model 2: Market Basket as Stackelberg Leader
Model 3: Shaw's as Stackelberg Leader

Market Basket vs. Stop & Shop

	Estimates Model 1	Model 2	Model 3
Opponent Feature	-0.8573	-0.7609	-0.9544
	-	-	0.2608
Own Feature, t-1	-1.4939	-1.4708	-1.5282
	-	-	0.2844
Own Feature, t-2	0.3020	0.3125	0.2168
	-	-	0.2263
Own Feature, t-3	-0.3641	-0.3546	-0.4215
	-	-	0.2416
Store Intercept	-1.1381	-1.2348	1.0041
	-	-	0.2166

Model 1: Probability 0.5
Model 2: Market Basket as Stackelberg Leader
Model 3: Stop & Shop as Stackelberg Leader

Market Basket vs. Star Market

	Estimates Model 1	Model 2	Model 3
Opponent Feature	-0.2992	-0.2978	-0.3594
	0.1722	0.1793	0.1830
Own Feature, t-1	0.9349	0.8875	0.8988
	0.1978	0.1996	0.2004
Own Feature, t-2	0.0893	0.0278	0.0501
	0.2138	0.2139	0.2165
Own Feature, t-3	0.5560	0.3650	0.5274
	0.2009	0.2014	0.2030
Store Intercept	-0.8899	1.0154	0.8906
	0.2115	0.2334	0.2302

Model 1: Probability 0.5
Model 2: Market Basket as Stackelberg Leader
Model 3: Star Market as Stackelberg Leader

Shaw's vs. Stop & Shop

	Estimates Model 1	Model 2	Model 3
Opponent Feature	-0.4088	-0.4232	-0.3820
	0.1260	0.1322	0.1204
Own Feature, t-1	0.0375	0.0398	0.0563
	0.1524	0.1524	0.1511
Own Feature, t-2	0.6446	0.6417	0.6573
	0.1487	0.1485	0.1477
Own Feature, t-3	-0.0289	-0.0280	-0.0217
	0.1536	0.1535	0.1533
Store Intercept	0.5487	0.4951	-0.6312
	0.1518	0.1589	0.1456

Model 1: Probability 0.5
Model 2: Shaw's as Stackelberg Leader
Model 3: Stop & Shop as Stackelberg Leader

Shaw's vs. Star Market

	Estimates Model 1	Model 2	Model 3
Opponent Feature	2.0123	1.9035	1.9693
	-	-	-
Own Feature, t-1	1.9416	1.5886	1.5972
	-	-	-
Own Feature, t-2	-0.9606	-0.7909	-0.7974
	-	-	-
Own Feature, t-3	0.9194	0.7919	0.8036
	-	-	-
Store Intercept	0.0024	-0.0386	-0.3332
	-	-	-

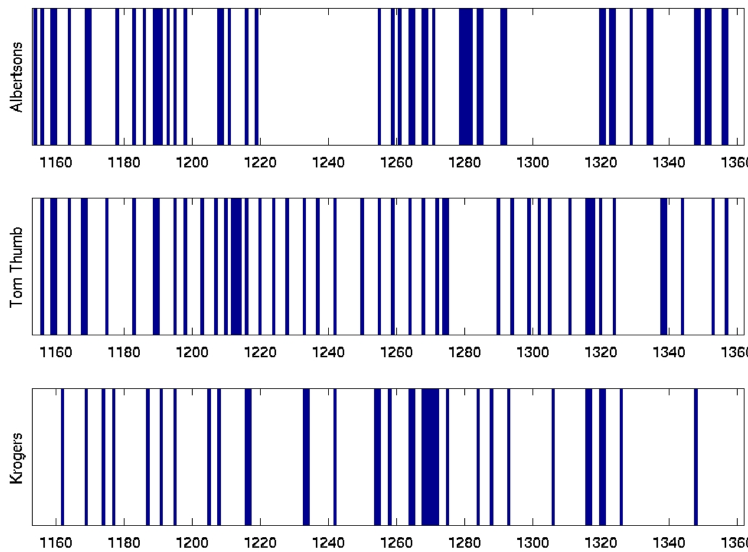
Model 1: Probability 0.5
Model 2: Shaw's as Stackelberg Leader
Model 3: Star Market as Stackelberg Leader

Stop & Shop vs. Star Market

	Estimates Model 1	Model 2	Model 3
Opponent Feature	-0.3599	-0.3564	-0.3897
	0.1247	0.1196	0.1297
Own Feature, t-1	0.0493	0.0489	0.0404
	0.1517	0.1516	0.1527
Own Feature, t-2	0.7040	0.7072	0.6965
	0.1466	0.1467	0.1473
Own Feature, t-3	0.1110	0.1128	0.1009
	0.1521	0.1522	0.1525
Store Intercept	-0.5333	-0.5691	0.4363
	0.1465	0.1437	0.1569

Model 1: Probability 0.5
Model 2: Stop & Shop as Stackelberg Leader
Model 3: Star Market as Stackelberg Leader

Figure .3. Advertising of Tropicana Pure Premium (64 oz.), Dallas

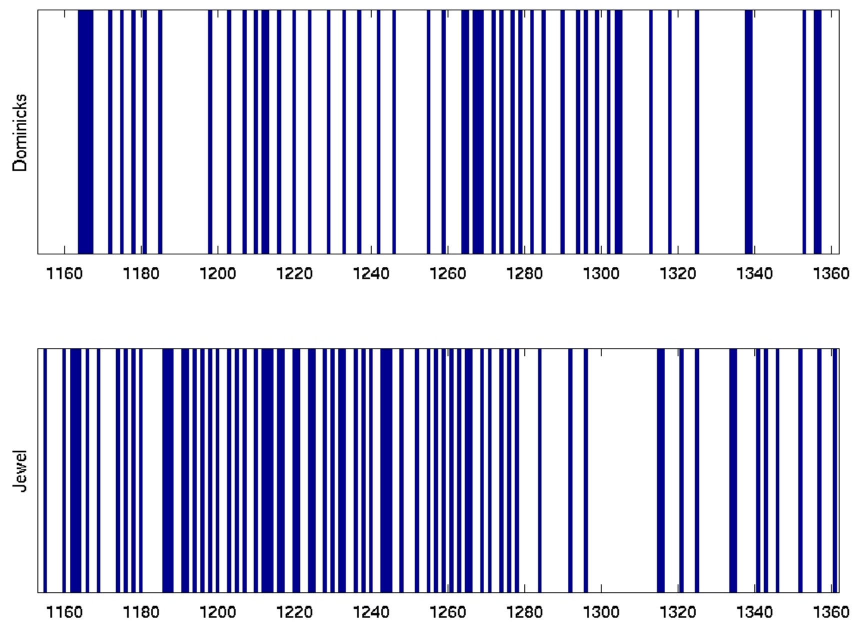


	Tom Thumb		
Albertson's	**0**	**1**	**Total**
0	127	31	158
1	32	18	50
Total	159	49	208

	Kroger		
Albertson's	**0**	**1**	**Total**
0	138	20	158
1	35	15	50
Total	173	35	208

	Kroger		
Tom Thumb	**0**	**1**	**Total**
0	137	22	159
1	36	13	49
Total	173	35	208

Figure .4. Advertising of Tropicana Pure Premium (64 oz.), Chicago



	Jewel		
Dominicl	**0**	**1**	**Total**
0	106	51	157
1	30	21	51
Total	136	72	208