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Paying for Shelf Space: An Investigation of Merchandising Allowances in the Grocery Industry*

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Abstract

This research examines the behavior of manufacturers and retailers in the presence of merchandising allowances. Merchandising allowances are fees manufacturers pay retailers to encourage them to allocate certain in-store promotional activities to the manufacturers' brand. According to estimates, retailers collect billions of dollars in these allowance payments annually. Using a three-stage game, I formulate a vertical structural model that endogenously models manufacturer, retailer, and consumer behavior. Manufacturers compete with each other, using merchandising allowance payments, in order to obtain premium shelf space at retail outlets. Retailers, given allowance offers, choose display configurations and then set retail prices. Consumers observe the display and retail prices and determine whether to purchase one or no units of the good. I estimate the model with a method of moments technique using IRI scanner data from the ketchup industry. In addition to estimating consumer tastes parameters, the model yields predictions of the underlying wholesale prices and the merchandising allowances each manufacturer offers. I use the parameter estimates to conduct a counterfactual simulation of how agents might respond when the use of merchandising allowances is no longer permissible. I find that while merchandising allowances increase retail profits, total welfare is lower due to the allowances.

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1 Introduction

The term *merchandising allowance* refers to a fee that manufacturers pay retailers to encourage them to allocate certain in-store promotional activities to the manufacturers' brand(s). These promotional activities include such things as an end-of-aisle display or premium shelf space. The payments for these benefits have a variety of names: slotting allowances, pay-to-stay fees, vendor allowances, display fees, and promotional allowances. Unfortunately, there is a lack of consensus regarding the usage of these terms.[1] To avoid confusion, then, I will simply use *merchandising allowance* to refer to all payments made in order to receive preferential shelving or promotion at retail outlets.

Merchandising allowances are one component of a contract between the manufacturer and the retailer, which typically involves the transaction or invoice price, the magnitude of the allowance, and any other conditions involved in the transaction. The terms of the contract would also include a quantity component. While often discussed in the context of the grocery industry, merchandising allowances are becoming increasingly prevalent in such industries as computer software, tobacco products, and over-the-counter drugs.

In recent years, merchandising allowances, particularly slotting allowances for new products, have become a source of controversy and disagreement.[2] This growing interest in allowances is largely attributable to the amount of money devoted to the practice. A 1983 *Fortune* magazine article on retail trade promotions estimated that spending on merchandising allowances had grown from $1 billion annually in the early 1970's to roughly $8 billion at the time of publication. A 1990 study found that slotting allowance payments, alone, accounted for up to $9 billion in annual grocery industry expenditures (Deloitte & Touche 1990). More recent reports put the current amount spent on slotting allowances at $16 billion per year (Desiraju 2001). In 1999, the tobacco industry, an industry not counted in the

[1] For example, Feighery et al. (1999) use *slotting allowance* to refer to both payments made for new products and payments for premium shelf space for existing products, while Lariviere and Padmanabhan (1997) use *slotting allowance* to reference payments for accepting new products only.

[2] The subject was addressed in a spring 2000 Federal Trade Commission (FTC) workshop. The workshop allowed various participants in the grocery industry to voice their opinions on slotting allowances. A summary of these opinions and conclusions appears in a February 2001 FTC staff report.

Deloitte & Touche figures, spent roughly \$3.5 billion on allowances to retailers (FTC 2001b). Such large dollar amounts make merchandising allowances a major source of revenue for retailers and, conversely, a major financial consideration for manufacturers.

In this paper, I construct an interactive model of behavior in which manufacturers compete for premium shelf space at retail outlets. The structural model is based on models of vertical competition and traditional discrete-choice models of differentiated products. Formally modeling firm and consumer behavior allows us to examine the decisions being made: the retailer's shelf space allocation, the wholesale and retail pricing strategies, and, ultimately, the consumer's choice of which product to purchase.

While there is a growing literature on allowances, few empirical studies have emerged to complement the work that has been started in the theoretical papers. In the FTC staff report on slotting allowances, it was noted that "The few studies that have been undertaken reflect opinion...rather than empirical research," (FTC 2001a). Steiner (1991), writing specifically about merchandising allowances, confirms the FTC's statement by noting that, "A strange property of the entire vertical restraints literature is the absence of empirical investigations of the role of manufacturers' promotional allowances." The lack of rigorous empirical analysis is the largest gap in the allowance literature. This research represents a step towards filling the gap.

The structural model presented below allows for estimates of manufacturer wholesale prices and merchandising allowances. Using the parameter estimates, I conduct a policy simulation to determine how wholesale prices, retail prices, and, ultimately, consumer surplus respond to alternative scenarios. The primary counterfactual involves examining how firms and consumers respond to an alternative state where merchandising allowances are illegal or forbidden. This will help us address allowances' ultimate impact on consumers; the prices they pay.

I find that the presence of merchandising allowances decreases welfare. Using a measure of consumer surplus, I find that, on average, each consumer/household experiences a slight welfare reduction. The individual loss aggregates to a national total of roughly \$10 million.

This result is driven by the fact, in the absence of merchandising allowances, manufacturers are more likely to adjust (downward) their wholesale prices in order to compete for the premium shelf space.

The remainder of the paper is organized as follows: In the next section, I review the relevant literature on vertical restraints, allowances, shelf space allocation, and in-store product marketing. In Section 3, I describe the precise timing or stages of the model and introduce the vertical structural model. To estimate the empirical model, I use data on ketchup sales. For background purposes, Section 4 presents a brief history of the ketchup industry and a summary of the major industry participants. Section 5 contains detailed information regarding the data used in this study. The estimation procedure is detailed in Section 6. Section 7 contains estimation results and analysis of the parameter values and Section 8 concludes.

2 Literature Review

Research on merchandising allowances overlaps the boundaries of several academic disciplines, therefore, a number of relevant literature sources need to be addressed. These are the literature on vertical restraints, slotting allowances, marketing and advertising studies on the impact of shelf space, and literature on structural discrete-choice models.

2.1 Vertical Restraints

There has been considerable work in the economics literature on vertical restraints.[3] Of particular interest to this research is the work that has examined manufacturer behavior when sales of the manufacturer's product depend, in part, on the level of "service" provided by downstream retailers. These "services" are activities designed to increase a brand's sales, such as advertising or in-store display. However, there might be a tendency for a retailer to "under-provide" the service, particularly if it is costly or if there is ample opportunity to free-ride off those retailers that provide the service.

[3] I offer only a brief overview of the literature. For a more thorough discussion, please see Steiner (1991).

Within this context, a number of papers, including Bowman (1955), Telser (1960), Mathewson and Winter (1984), and Winter (1993), have examined optimal manufacturer strategies. The primary question, essentially, is whether a particular vertical restraint, such as resale price maintenance (RPM), promotional allowances, or exclusive territories, would be sufficient to induce the retailer to provide the desired level of service. Both Bowman (1955) and Telser (1960) argue that manufacturers would benefit from using direct payments, as opposed to RPM. Bowman argues that we may not observe this as often, however, because of a concern that these lump-sum allowances violate the Robinson-Patman Act.

As the *Fortune* magazine article clearly demonstrates, the reliance on merchandising allowances has grown substantially since publication of Bowman and Tesler's articles. And yet, as Steiner points out, there remains an absence of empirical work on manufacturers' promotional allowances. This research represents a step towards addressing that concern. In this paper, I assume that manufacturers use merchandising allowances to induce the retailer to provide a promotional service, namely improved shelf space.

2.2 Slotting Allowances

Within economics, there is a small but expanding base of literature on slotting allowances. The first papers on slotting allowances were published in the early 1990s. Economists focused on examining the different roles slotting allowances play in the vertical channel. With these differing models have come conflicting welfare predictions.

Shaffer (1991) compares slotting allowances, resale price maintenance, and standard Nash equilibrium pricing in an effort to determine which practice is more profitable for retailers. Shaffer, using a three-stage pricing game with homogeneous manufacturers and differentiated retailers, shows that, compared to an environment with no slotting allowances, the retailers earn more profit and consumers pay higher retail prices when a lump sum slotting allowance is used. While worse than marginal cost pricing, Shaffer also shows that the use of RPM results in a higher social surplus than lump-sum slotting allowance payments.

Another avenue of research has examined the role slotting allowances may play in signaling the quality of a manufacturer's brand to a retailer. Given the several thousand new grocery products developed each year, all vying for limited shelf space or limited promotion efforts, manufacturers can use a slotting fee to signal (to the retailer) their belief about the quality of their product. Most practitioners (including the studies below) assume manufacturers, because of market research and analysis, have better knowledge than the retailer about consumer demand for their product. Chu (1992) examines two different games: one in which manufacturers signal their quality through advertising expenditures and another in which the retailer screens the manufacturers' quality (to eliminate low quality goods) by requiring slotting allowance payments. While the first case results in higher prices, Chu shows that retail prices will not increase when the retailer uses slotting allowances to screen for manufacturer-type. In Chu's equilibrium, only high-quality goods are willing to pay the allowance, so lower-quality goods disappear from the market and total welfare increases.

Lariviere and Padmanabhan (1997), while also examining the role allowances can play in signaling quality, alter the game presented in Chu by allowing manufacturers to offer slotting allowances to the retailer. These allowance offers are intended to signal product quality as well as reimburse the retailer for a portion of the cost associated with stocking the product. Lariviere and Padmanabhan, in specifying a separating equilibrium, show that the optimal behavior for a high demand manufacturer is to offer a positive slotting allowance and a lower wholesale price.

While most papers on slotting allowances examine the role slotting allowances play in the vertical channel and its effect on profits and retail prices, Desiraju (2001) is one of the few papers to focus on comparing the strategies retailers may use to set the magnitude of slotting allowance payments. Desiraju compares two different methods a retailer might plausibly use to set slotting allowances: one in which allowances are determined "brand-by-brand" (i.e. each manufacturer pays a different slotting allowance) and another in which all products pay a uniform allowance. Desiraju, following the convention used in Chu and Lariviere and Padmanabhan, classifies new products as being a product for which consumers have either a high or low attraction. Desiraju solves for the optimal retailer-manufacturer contract under a number of different scenarios (ex. asymmetric information regarding the market attractiveness of the new product, and exogenous wholesale prices) and finds that brand-by-brand allowances are preferable regardless of whether there is symmetric or asymmetric information about a product's attractiveness, but actual slotting allowance payments are larger in magnitude in the uniform allowance case. Desiraju's model also makes a prediction about retail margins that my empirical model can address. Desiraju predicts that retail margins and slotting allowances should be negatively correlated.

At the heart of these slotting allowance models is the notion that the retailer takes on risk when agreeing to carry a manufacturer's brand. Retailers incur several costs when agreeing to accept a new product: e.g. stocking costs, computer costs, opportunity cost. Some products will ultimately fail or sell below expectations and an allowance can be thought of as a means of transferring some costs back to the manufacturer. Sullivan (1997) models the use of slotting allowances in the context of product failure and shows that allowances may be affective tools in risk-sharing and are consistent with a situation wherein the supply of goods far outpaces sales growth. Additionally, Sullivan offers historical data on the number of products introduced by manufacturers, retail prices, margins, and retail profit to anecdotally contradict Shaffer's claims that slotting allowances have negative welfare implications. Sullivan shows that in 1970, there were roughly 1,800 new products introduced. By 1990 this number had grown to around 16,000 products annually. According to the logic presented in the theoretical model, if new product introductions have increased substantially (i.e. if the supply of products has increased), then slotting allowances may, in fact, be an efficiency enhancing mechanism that both decreases the tendency of manufacturers to develop new products and increases the number of products a retailer would be willing to carry.

While there has been greater understanding of the roles allowances play, the studies above illustrate that there is no clear consensus with regard to welfare implications.[4] Are allowances an efficiency-enhancing mechanism, as Sullivan might argue, or are they welfare-reducing, as Shaffer might argue? In an effort to answer this question, Bloom, Gundlach, and Cannon

[4] Azzam (2001) addresses this by proposing an empirical model which can be used to test the effect slotting allowances have on price-cost margins.

(2000) conduct a survey of participants in the grocery industry (both manufacturers and retailers).[5] The respondents were asked about their level of agreement or disagreement with a number of statements regarding slotting allowances, such as "Retailer product assortments are often based on slotting fees" or "Slotting fees have come about as a result of greater retailer influence." The respondents were also asked a set of questions regarding the effect slotting allowances have had on the industry, such as "What effect have slotting fees had on the prices charged by retailers?" Not surprisingly, Bloom, Gundlach, and Cannon find mixed reviews: manufacturers tend to see slotting allowances as symptomatic of retail-power, while retailers tend to view slotting allowances as fair or efficient.[6]

2.3 Marketing and Advertising Literature

Relevant literature in the marketing and advertising fields focuses primarily on two specific areas: how retailers allocate shelf space and the impact that shelf space has on retail sales.

The work devoted to examining how retailers determine shelf space allocation typically involves developing a mathematical algorithm in which a retailer compares his expected profits under all possible shelving combinations. Whether these models are static (Borin, Farris, and Freeland 1994) or dynamic (Corstjens and Doyle 1983), the main idea is that the retailer has limited space to store goods and must, then, determine which mix of products earns him the greatest profit.

Chen et al. (1999) models the retailer optimizing his shelf space allocation (across all product categories) in order to attract the most consumers, by increasing the probability that a consumer will be able to find his or her preferred brands. The assumption is that the more shelf space (as measured in linear feet) category j has at retailer i, the more likely it is that the consumer will be able to find his or her preferred brand (in category j) at i's store.

The models of this type overlook some important decision variables, however. The most

[5] Bloom, Gundlach, and Cannon also provide a thorough summary of the numerous pro- and anti-competitve arguments on slotting allowances.

[6] Smaller manufacturers are particularly upset about slotting allowances. As MacAvoy (1987) shows, large manufacturers may actually wish to use slotting allowances to raise the price of shelf space in order to foreclose rivals from the market.

glaring omission is their failure to incorporate merchandising/slotting allowances or other types of incentives. In addition, a number of the important decisions, such as the retail margins or mark-ups, are exogenous to the retailer. Finally, the models in this particular vein of the literature ignore the decision of where the chosen products should be placed on the shelf.[7] It makes no difference whether a product is displayed on the top, bottom, or middle shelf; at the checkout counter or in the store's back corner.

Since shelf space allocation models do not address the importance of positioning, the natural question to ask is whether shelf space location actually matters to sales. According to the literature, the answer is yes. Several studies have used reduced form models to estimate the impact of shelf space on price elasticity (often referred to as "space elasticity"). These studies conclude that shelf space does matter, but its magnitude may not be that large compared to other variables, such as price (Frank and Massy 1970, Curhan 1972, and Bommer and Walters 1996)). A cross-category study by Chiang and Wilcox (1997) also finds a strong correlation between dollar sales and the shelf space allocation.

Drèze et al. (1994) is one of the few papers that draws a clear distinction between shelf space, measured as the number of facings or store-keeping units (SKUs), and the position of the product on the shelf. After conducting a series of field experiments at sixty Dominick's Finer Foods stores in the Chicago area, they conclude that the position on the shelf is far more important, in determining sales, than the number of facings.[8] While this result is promising, the majority of work has largely overlooked the role that positioning can play in retail sales. Areni, Duhan, and Kiecker (1999) use field and laboratory experiments to test whether point-of-purchase displays increase sales of the featured brand. Their paper does not attempt to model consumer behavior explicitly, however, so it is difficult to generalize from their findings.

[7] Instead, the focus is on choosing the optimal number of facings for each brand.

[8] Drèze et al., in fact, state that "A couple of facings at *eye level* did more for a product than five facings on the *bottom shelf*."

2.4 Discrete-Choice Structural Models

The modeling technique used in this paper is based on discrete-choice structural models of differentiated products. The majority of recent papers in this research area, such as Chintagunta, Dube, and Singh (2003), Manuszak (2000), and Nevo (2001), can trace their roots to Berry (1994) and Berry, Levinsohn, Pakes (1995, henceforth BLP). The modeling technique pioneered by Berry and BLP has changed demand estimation for two principle reasons: the random coefficients approach adopted to model consumer heterogeneity alleviates the independence of irrelevant alternatives (IIA) problem that has plagued logit models and provides a solution to the problem of endogenous prices. As a result, models in the likeness of Berry and BLP produce more accurate price elasticities and unbiased coefficient estimates.

The majority of these empirical discrete-choice models fail to differentiate between manufacturer and retailer behavior, however. Retailers are included only to the extent that they place a fixed mark-up on the wholesale price. For example, BLP focuses on price-setting behavior at the manufacturer level in their paper on automobile prices. Similarly, Nevo models the manufacturers of ready-to-eat cereal, but does not model the supermarkets. Given the nature of merchandising allowances, it is essential to model the behavior of both manufacturers and retailers, separately, for they both make decisions critical to understanding the role slotting allowances play. A few papers, however, such as Besanko, Gupta, and Jain (1998), Besanko, Dube, and Gupta (2000), and Chintagunta, Dube, and Singh (2003) have formally modeled both the upstream and downstream firms in the vertical channel. In these models, manufacturers set a wholesale price for the product and retailers, taking the wholesale price as given, set the retail price as some mark-up over the wholesale price.

3 The Model

3.1 The Game

Manufacturers compete with each other over premium shelf space at retail outlets. Each manufacturer offers a merchandising allowance to the retailer in exchange for an agreement to devote premium shelf space for the manufacturer's brand. Retailers are assumed to be "local monopolists" and have enough shelf space to stock each brand.[9] However, each retailer can devote premium shelf space (an eye-level shelf allocation or end-of-aisle display, for example) to only one brand.[10]

The interaction between manufacturers and retailers is modeled as a three-stage game. In the first stage of the game, each manufacturer j makes their offer to the retailer. Each offer is comprised of three elements: a merchandising allowance (A_j) and two conditional wholesale prices (w_j^j, w_j^0). The first wholesale price (w_j^j) is the per-unit wholesale price manufacturer j receives if the retailer selects brand j for the premium shelf space. The second wholesale price (w_j^0) is the per-unit wholesale price manufacturer j receives for its product if another brand, instead, receives the premium space. In the second stage, the retailer receives the offers from all J manufacturers, evaluates expected profit under each display configuration, and decides which brand to position in the premium space. In the third stage, the retailer sets a retail price (p_j) for each of the J brands.

Figure 1 illustrates a simple duopoly version of this game in which two manufacturers compete for premium shelf space at a monopolist retailer. I now discuss the full structural model, beginning in the game's final stage (consumer choice) and working backwards to the manufacturer's behavior.

3.2 Utility and Demand

A consumer $i = 1, ..., I$ visits a retail store in market $m = 1, ..., M$ and chooses either to purchase one of the J brands in a given product category or chooses not to purchase any of the brands. Each brand j has two attributes: (x_j, p_j), where x_j is a vector of K visible attributes, and p_j is the price. The indirect utility consumer i in market m obtains from purchasing product j is given by:

[9] Allowing for competition downstream might produce interesting results as downstream competition could potentially dampen the relative power of the retailer. However, Slade (1995) finds that over 90 percent of households do not engage in comparison shopping between grocery stores in order to find the lowest price. Therefore, the assumption of a local monopoly does not seem inappropriate.

[10] The inherent idea present in this model can be easily summarized by what one marketer familiar with the grocery industry told me: "the days of supermarkets doing things, without being paid, are long gone."

$$u_{ijm} = x_j\beta_i - \alpha_i p_{jm} + \varepsilon_{ijm} \tag{1}$$

The coefficients (α_i, β_i) capture consumer i's tastes for attributes x and price p. The term ε_{ijm} is a mean-zero stochastic term capturing consumer i's idiosyncratic utility from product j and is assumed to be distributed type II extreme value.

Consumers also have the ability to by-pass purchasing any of the offered brands. This is referred to as purchasing the "outside good" or the "no purchase" option. For identification purposes, I normalize the indirect utility from the outside option to be:

$$u_{i0m} = \varepsilon_{i0m} \tag{2}$$

The multinomial logit model displays the well-known independence of irrelevant alternatives (IIA) problem. The IIA problem refers to the restrictive (unrealistic) substitution patterns imposed by the logit model. Several econometric techniques have emerged to correct the IIA problem, such as the nested logit model. I choose to adopt a random coefficients framework to model individual variations from mean preferences.[11] More formally, I model:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \nu_i,\ \ \nu_i \sim N(0,1)$$

where (α, β) are the mean preferences for price and observable characteristics, D_i is a $d \times 1$ vector of observed consumer characteristics, Π is a $(K+1) \times d$ matrix of coefficients that illustrate how tastes for product characteristics vary with consumer attributes, and ν_i represents additional characteristics of consumer i which are not captured through demographic information and are unobservable to the econometrician. Inclusion of ν_i accounts for the possibility that individuals with identical demographic characteristics may still have different tastes for price and observable characteristics. The ν_i are assumed to be independent from D_i and are distributed *iid* standard normal.

[11] Nevo (2000) presents a useful overview of the intricacies of the random coefficients logit model. This paper has benefited greatly from Nevo's work.

The consumer is assumed to purchase one unit of the good which provides the highest expected utility from all of the goods in his choice set. In other words, consumer i will purchase brand j if:

$$U\left(D_i, x_{jm}, p_{jm}, \varepsilon_{ijm}, \nu_i\right) \geq U\left(D_i, x_{km}, p_{km}, \varepsilon_{kjm}, \nu_i\right) \ \forall k \neq j$$

This specification ignores an important component in the demand for products: the shelf space allocation. To accurately address the question why manufacturers would be willing to pay for premium shelf space, we must try to understand how premium space affects sales. To model the way in which shelf space affects the consumer's discrete product choice decision, consider the factors that enter a consumer's decision whether to purchase or not. Clearly, if a consumer is more likely to purchase a brand when it is on display, then the consumer's perception of the brand must somehow be different (holding all else constant). To this end, we might think that consumers view a brand differently depending upon whether that brand has premium shelf space or not. Possible explanations are that a brand on display may be perceived as being more popular or of a higher quality.[12]

To capture consumer taste for each brand (independent of product characteristics), I use brand-specific dummy variables. As Table 1 shows, ketchup, the product used in this research, is essentially a homogeneous good. It seems likely, then, that brand dummies will capture consumer tastes for each brand in a manner that cannot be captured through product characteristics.[13]

An advantage of using brand dummies is that it eliminates the need to use instrumental variables to account for the endogeneity of prices. Many of the discrete-choice structural models follow BLP's convention and introduce an unobserved (to the econometrician) prod-

[12] An alternative approach could be to allow shelf space to inform consumers about the existence of a particular product. The shelf space allocation, therefore, would determine a consumer's choice set. Goeree (2001) takes this approach in modeling the effects of advertising on the demand for personal computers. Because ketchup is the product used in this paper, I feel that knowledge of available options is less of an issue than it may be in other categories.

[13] One problem with the use of fixed effects is that any variation in tastes across markets will be overlooked. It will not be possible, for example, to determine whether there is a difference between how Heinz is perceived in Pittsburgh and how it is perceived in Atlanta.

uct characteristics term (ξ_j) into the indirect utility function. Because the retail price is likely to be correlated with these unobserved product characteristics, econometricians have been forced to employ instrumental variables estimation techniques in order to obtain unbiased estimates. Since ketchup is a homogeneous good, I argue that unobserved product characteristics are captured through the brand dummies. This eliminates the necessity of using instruments.

To allow a consumer's tastes for each brand to vary depending on whether that brand is on display or not, two β's per brand are estimated: one capturing the mean taste for brand j when it is on display (β_j^j) and another capturing the mean taste for brand j when another brand is featured (β_j^0).

In order to account for this possibility, I allow each brand's observable characteristics (brand dummies) to vary according to whether the brand is on display or not. The probability, then, that a consumer i in market m purchases brand j when brand j is featured is given by:

$$s_{ijm|D=j} = \frac{\exp\{\beta_{ij}^j - \alpha_i p_{jm}^j\}}{1 + \exp\{\beta_{ij}^j - \alpha_i p_{jm}^j\} + \sum_{k \neq j} \exp\{\beta_{ik}^0 - \alpha_i p_{km}^j\}} \tag{3}$$

where β_{ij}^j represents consumer i's taste for brand j when brand j is on display, β_{ik}^0 represents consumer i's taste for brand k when brand k is not on display, and p_j^j (p_k^j) represents the retail price of brand j (k), conditional upon brand j being the displayed brand.[14] In a similar manner, the probability that a consumer i in market m purchases brand j when another brand k is the featured brand may be expressed:

$$s_{ijm|D=k} = \frac{\exp\{\beta_{ij}^0 - \alpha_i p_{jm}^k\}}{1 + \exp\{\beta_{ik}^k - \alpha_i p_{km}^k\} + \sum_{g \neq k} \exp\{\beta_{ig}^0 - \alpha_i p_{gm}^k\}} \tag{4}$$

By estimating these differing taste components, we gain insight into the perceived differences between a brand with premium shelf space and that same brand in an unfeatured position (if there are, indeed, any differences). A priori, we might assume that $\beta_j^j > \beta_j^0$ (i.e.

[14]For simplification, the conditional share in the two brand case would be: $s_{i1m|D=1} = \frac{\exp\{\beta_{i1}^1 - \alpha_i p_{1m}^1\}}{1+\exp\{\beta_{i1}^1 - \alpha_i p_{1m}^1\} + \exp\{\beta_{i2}^0 - \alpha_i p_{2m}^1\}}$.

higher perceived quality when in the premium position). Empirical results will indicate not only whether this assumption is valid, but will also help determine the magnitude of any perception "boost."

By integrating over the distribution of demographics, I obtain conditional market shares (s_{jm}) for each brand in each market.

3.3 Behavior of the Firms

3.3.1 The Retailer's Problem

A retailer takes the offers from all J manufacturers and decides how to allocate the premium shelf space by comparing the expected profit earned under all possible display configurations. Retailer r's expected profit, conditional on choosing to feature manufacturer j's brand, is:

$$\Pi_{r|D=j} = \pi_j + A_j + e_j \tag{5}$$

In this manner, the retailer's expected profit can be thought of as having a variable component, a merchandising allowance component, and a fixed component. The variable component (π_j) is the amount of profit that depends on the retailer's optimal pricing and output choices. A_j is the merchandising allowance offer from brand j. The retailer, by design, collects an allowance only from the chosen brand. The $(-e_j)$ term can be thought of as a display-specific fixed cost.[15] The display and retailer-specific fixed cost might encompass such things as the fact that certain contracts may require the building of displays, certain brands may require more time to stock or unpack, employees may need to be trained for certain promotional activities, etc. at a particular retail outlet. The retailer knows the true value of the fixed cost it faces, but manufacturers only have knowledge about the distribution of these fixed costs.

We can further characterize the expected profit retailer r receives when displaying brand j as:

[15] This specification is similar to that used in Berry's (1992) paper on entry in the airline industry.

$$\Pi_{r|D=j} = \left(p_j^j - w_j^j\right) Q_{j|D=j} + \sum_{k \neq j} \left(p_k^j - w_k^0\right) Q_{k|D=j} + A_j + e_j \tag{6}$$

where p_j^j (p_k^j) is the retail price of brand j (k) when brand j has been chosen for display, w_j^j (w_k^0) is the wholesale price of brand j (k) when brand j has been chosen for display, A_j is the lump sum allowance paid by manufacturer j, and $Q_{j|D=j}$ ($Q_{k|D=j}$) is the demand for brand j (k) when brand j is chosen for display. The conditional demand for brand j is equal to $Ms_{j|D=j}$, where M is the size of the market and $s_{j|D=j}$ is the share of consumers purchasing brand j when brand j is on display.

The retailer determines optimal conditional prices p_j^j and p_k^j ($\forall k \neq j$) by solving the following system of first order conditions:

$$\begin{aligned}
\frac{\partial \Pi_{r|D=j}}{\partial p_j^j} &= Q_{j|D=j} + \left(p_j^j - w_j\right) \frac{\partial Q_{j|D=j}}{\partial p_j^j} + \sum_{k \neq j} (p_k^j - w_k) \frac{\partial Q_{k|D=j}}{\partial p_j^j} = 0 \\
\frac{\partial \Pi_{r|D=j}}{\partial p_k^j} &= Q_{k|D=j} + \left(p_k^j - w_k\right) \frac{\partial Q_{k|D=j}}{\partial p_k^j} + \sum_{i \neq k} (p_i^j - w_i) \frac{\partial Q_{i|D=j}}{\partial p_i^j} = 0
\end{aligned}$$

For J brands, the retailer will generate a system of $J * J$ conditional prices.[16] The specification of retail profit presented in equation (5) allows the retailer's display-selection problem to be analyzed in a familiar discrete-choice setting. This enables the probability that brand j is chosen (for display or feature) by retailer r to be calculated. Let ϕ_{jr} represent the (conditional) probability that manufacturer j is chosen by retailer r:

$$\begin{aligned}
\phi_{jr} &= \Pr(D = j) \\
&= \Pr\left(\pi_j + A_j + e_j > \pi_k + A_k + e_k \ \forall \ k \neq j\right)
\end{aligned} \tag{7}$$

The retailer chooses to feature the brand that yields the highest expected profit. In the two good case ($j = 1, 2$), the probability that brand 1 is chosen would be given by:

[16] Each brand will have a conditional price for each possible display choice and one there will be a display choice for each brand.

$$
\begin{aligned}
\phi_{1r} &= \Pr\left(\pi_1 + A_1 + e_1 > \pi_2 + A_2 + e_2\right) \\
&= \Pr\left(e_2 - e_1 < \pi_1 - \pi_2 + A_1 - A_2\right)
\end{aligned}
$$

In the more general case with J brands, the display probability can be represented:

$$
\begin{aligned}
\phi_j &= \int_{-\infty}^{\pi_j - \pi_1} \int_{-\infty}^{\pi_j - \pi_2} \dots \int_{-\infty}^{\pi_j - \pi_J} f(e_i - e_j) d(e_i - e_j) \\
&= \prod_{i \neq j}^{J} \int_{-\infty}^{\pi_j - \pi_i} f(e_i - e_j) d(e_i - e_j) \qquad (8)
\end{aligned}
$$

Making an assumption about the distribution of the e's allows for analytical computation of this probability. A more thorough discussion of this assumption and its implications appears in Section 6. I now turn to the manufacturer's problem.

3.3.2 The Manufacturer's Problem

The profit-maximizing manufacturer faces two problems: choosing conditional wholesale prices (w's) and a lump sum merchandising allowance (A) to offer retailers. The selection of these strategic variables follows from maximization of the manufacturer's expected profit function ($E\Pi_j^m$):

$$
\begin{aligned}
E\Pi_j^m &= \Pr(D = j) * \Pi_{j|D=j}^m + \sum_{k \neq j} \Pr(D = k) * \Pi_{j|D=k}^m \\
&= \phi_j \left(\left(w_j^j - c\right) Q_{j|D=j} - A_j\right) + \sum_{k \neq j} \phi_k \left(w_j^0 - c\right) Q_{j|D=k} \qquad (9)
\end{aligned}
$$

where c is the (constant) marginal cost of production. The optimal conditional wholesale prices, w_j^j and w_j^0, are the solutions, respectively to the following first order conditions:

$$
\begin{aligned}
\frac{\partial E\Pi_j^m}{\partial w_j^j} &= \phi_j\left(Q_{j|D=j} + \left(w_j^j - c\right)\frac{\partial Q_{j|D=j}}{\partial w_j^j}\right) + \left(\left(w_j^j - c\right)Q_{j|D=j} - A_j\right)\frac{\partial \phi_j}{\partial w_j^j} \\
&\quad + \sum_{k\neq j}\left(w_j^0 - c\right)Q_{j|D=k}\frac{\partial \phi_k}{\partial w_j^j} \\
&= 0
\end{aligned}
\tag{10}
$$

$$
\begin{aligned}
\frac{\partial E\Pi_j^m}{\partial w_j^0} &= \left(\left(w_j^j - c\right)Q_{j|D=j} - A_j\right)\frac{\partial \phi_j}{\partial w_j^0} \\
&\quad + \sum_{k\neq j}\left[\phi_k\left(Q_{j|D=k} + \left(w_j^0 - c\right)\frac{\partial Q_{j|D=k}}{\partial w_j^0}\right) + \left(w_j^0 - c\right)Q_{j|D=k}\frac{\partial \phi_k}{\partial w_j^0}\right] \\
&= 0
\end{aligned}
\tag{11}
$$

While the expressions might look complicated, the intuition is rather straightforward: if manufacturer j changes the conditional wholesale price w_j^j, for example, the conditional profit ($\Pi^m_{j|D=j}$) would be impacted, but so would each of the display probabilities (ϕ_j for all $j = 1, ..., J$). It is necessary, however, to briefly discuss the derivative of sales with respect to wholesale price ($\frac{\partial Q_j}{\partial w_j}$).[17] Note that this derivative can be simplified as:

$$\frac{\partial Q_j}{\partial w_j} = \frac{\partial Q_j}{\partial p_j}\frac{\partial p_j}{\partial w_j}$$

Evaluating the first term ($\frac{\partial Q_j}{\partial p_j}$) is relatively straightforward in the logit model. The second term ($\frac{\partial p_j}{\partial w_j}$), however, requires some additional explanation. As Besanko, Dube, and Gupta (2003) point out, in the structural models of vertical competition, there has not been a consensus regarding the value of $\frac{\partial p_j}{\partial w_j}$, which they call the retailer's "pass-through" rate. For example, Besanko, Gupta, and Jain (1998) assume that the own brand pass-through ($\frac{\partial p_j}{\partial w_j}$) is 1 and the cross brand pass-through ($\frac{\partial p_j}{\partial w_k}$) is 0.[18] Sudhir (2001), on the other hand, assumes that pass-through rates are between 0 and 1 (or between 0 and -1 if referring to

[17] For simplicity, I will temporarily ignore the superscript associated with the conditional display choices.

[18] A common way this assumption is justified is by saying that the retailer sets a mark-up (m) over the wholesale price he receives. Therefore, $p = m + w$, so $\frac{\partial p}{\partial w} = 1$.

cross brand pass-throughs) and are inversely proportional to market share. Sudhir's result can be easily shown using properties of the logit model.

As Besanko, Dube, and Gupta (2003) do, I evaluate the pass-through rates by totally differentiating the retailer's profit maximizing first-order conditions. This is specification is less restrictive than some alternatives and appears to be supported by empirical evidence (Besanko, Dube, and Gupta 2002).

Recall that, in addition to the wholesale prices, the manufacturer selects a merchandising allowance to offer the retailer. To determine the optimal merchandise allowance, each manufacturer, again, maximizes its expected profit ($E\Pi_j^m$). The optimal allowance offer, then, is the solution to the first order condition:

$$\frac{\partial E\Pi_j^m}{\partial A_j} = (w_j^j Q_{j|D=j} - A_j)\frac{\partial \phi_j}{\partial A_j} - \phi_j + \sum_{k \neq j} w_j^0 Q_{j|D=k}\frac{\partial \phi_k}{\partial A_j} = 0 \tag{12}$$

Notice that the chosen merchandising allowance offer not only affects manufacturer profit, conditional upon having its brand chosen for display, but also affects the probability that a given brand is chosen for display.

The system of J^2retailer first order conditions and $3*J$ manufacturer first order conditions characterize the equilibrium.

4 The Market for Ketchup

I have, thus far, kept the model as general as possible, so it might be applied to different products or industries. To conduct the empirical examination, however, it is necessary to choose a particular product or category. This paper estimates the structural model using data from the ketchup industry.

Ketchup is a fairly homogeneous product. Though there are over twenty brands of ketchup currently produced in the U.S., most brands use only slightly different formulas or ingredients. The market is dominated by three national brands: Heinz, Del Monte, and Hunts. Heinz is the clear industry leader with approximately a 55 percent market share. The combined market share of Heinz, Hunts, and Del Monte is roughly 82 percent.[19] In 1992, the final year in my data set, ketchup sales in the U.S. were $723 million.

There are several aspects of the ketchup market that make it attractive for this empirical study. First of all, with Heinz being a clear market leader in many markets, one would expect there to be rivalry between the remaining firms, competing for the residual consumers. It is commonly believed that powerful market leaders are often exempt from allowances and, instead, it is the second and third place brands that, ultimately, end up paying or offering the highest amounts. By estimating allowance offers, the model allows me to empirically evaluate this belief. The display probabilities will also show whether it is the market leader receiving the premium space most often or one of the rivals.

According to industry reports, annual sales in the ketchup industry are generally flat, neither growing nor decreasing noticeably from year to year. In fact, Figures 2 and 3 show that ketchup sales are slightly declining over my sample period. As Sullivan argued, slow sales growth, in part, may contribute to the use of merchandising/slotting allowances in this category.

5 Data

To estimate the model presented in this research study, data on a number of different elements are necessary. In general, the data can be divided into several broad categories: brand unit sales in each market, brand market shares, prices of each brand for each market, the percentage of a brand's units sold through merchandising efforts in each market, brand characteristics, and demographic information.[20]

[19] This figure does not include the "Private Label" brand. Section 5 contains more information about the combined market share of these three brands.

[20] I adopt the notation of Nevo (2001) and define a "market" as a city-quarter combination.

5.1 Sales Data

The variables unit sales, prices, and the percentage of units sold with merchandising (PUAM) were obtained from the Food Marketing Policy Center's IRI Infoscan Data Base.[21] Founded in 1979, IRI is a sales and marketing research firm that uses supermarket checkout "scanners" to collect sales data in a national random sample of supermarkets. These supermarkets are located throughout the U.S. The IRI data used in this research ranges from the first quarter of 1988 to the fourth quarter of 1992 (20 total quarters) and includes 40 metropolitan areas. The full dataset, therefore, covers 800 markets. A list of the included metropolitan areas appears in Table 2. It is important to note that the IRI data are reported at the aggregate level for each market. This means two things: that all Heinz ketchup bottles sold, regardless of size, are recorded as one brand and that there is no distinction (in the data) between different retailers.[22] Unit sales, then, refer to the number of items, for a particular brand, scanned at the grocery store checkout. Because of variation in bottle size and, therefore, price, the price reported by IRI represents an average price per unit, which is calculated as a brand's total dollar sales divided by the total unit sales. The final IRI variable, the percentage of units sold with merchandising, is necessary because information on allowance spending is closely guarded by firms. According to IRI's description, this measure represents the percentage of a brand's sales directly attributable to merchandising/display efforts at the retail level. For the purposes of this research, I assume that sales attributed to "any merchandising" can be thought of as sales resulting from being the retailer's featured brand. Therefore, the number of units sold due to any merchandising effort is assumed to equal the number of units sold while the product is the retailer's featured brand. Information about the use of this variable appears in Section 7. Summary statistics for the three IRI variables appear in Table 3.

The model is estimated using the four top selling brands of ketchup: Heinz, Hunts, Del

[21]My thanks to Dr. Ronald Cotterill, director of the Food Marketing Center at the University of Connecticut, for making the data available.

[22]Cohen (2001) has shown that manufacturers may use product size as a way to price discriminate between consumers, based on storage or transportation costs. The aggregate level data in this research, however, does not allow me to account for this possibility.

Monte, and retailers' Private Label. The first three are national brands, while the fourth typically refers to a lower-priced brand that displays the name of the supermarket on its label. Private Label brands can be thought of as vertically integrated brands in which the supermarket is not only the retailer, but also the manufacturer.[23] As such, I assume that the Private Label brand pays no wholesale price or merchandising allowance. The retailer, therefore, receives no merchandising allowance payment if the Private Label brand is selected for display. The remaining brands of ketchup are omitted. As Table 3 shows, Heinz, Hunts, Del Monte, and Private label, combined, have a national market share of roughly 98 percent. Looking at combined regional market shares (for Northeast, South, Midwest, and West), the four top brands have market shares between 94 percent and 99 percent.

Observable product characteristics for ketchup are readily available and have not changed in any significant way since the sample period. Observable product characteristics that we might initially be interested in are quality measures such as calories and sodium per serving. Due the high level of homogeneity in ketchup, however, there is virtually no variation in product characteristics across brands.[24] This makes identification of the consumers' taste for sodium or calories, for example, impossible. As stated in Section 3, brand dummies will be the only product characteristics used in this study.

5.2 Demographic Data

Data on demographic distributions were obtained through the Census Bureau's Current Population Survey (CPS). The CPS has been used by the Census Bureau since the late 1940's to collect data on the U.S. labor force. The CPS sample selection process is designed to ensure accurate representation across metropolitan areas and participation in the survey is completely voluntary. Survey respondents are asked to provide personal information on a number of measures, including age, educational attainment, family size, employment status, housing situation, and occupation (as well as many others).

[23] Technically, the private label brand may be produced by an independent manufacturer, but strategically, it behaves like a subsidiary of the retailer.

[24] Several product characteristics are presented in Table 1 to illustrate the homogeneity.

In this study, I use CPS demographic information on two variables: a household's total income and the number of children in the household under the age of 18.[25] The household income level should be an important factor in determining consumer price sensitivity. Because ketchup is commonly used with "fun food" (hot dogs, hamburgers, french fries), we might imagine that a household's demand for ketchup depends, in part, on the number of children present in the household. A thorough discussion of how demographic data is used in calculating brand choice probabilities appears in an appendix.

As Table 3 shows, there is a degree of variation in sales across geographic regions. This might be due to differences in demographics across the regions, although it seems likely that other (unobserved) factors may be influencing this result. To help control for this variation, I use a dummy variable to indicate those CPS respondents residing in "Northeastern" markets.[26]

6 Estimation

In this section, I outline the algorithm used to estimate the model presented in Section 3. For notational convenience, let me define the vector of parameters to be estimated as: $\theta = \{\alpha, \beta, \Delta, \Pi\}$. I begin by choosing initial starting values for the parameters in θ. For these parameter values, I compute the implied market shares as a function of price for each brand and each display choice: $s_{j|D=k} = s_{j|D=k}(p_j^k, p_{-j}^k)$. Because random coefficients are used to allow for heterogeneity in the choice probabilities, computing the shares requires simulating a multidimensional integral. The simulation technique employed to evaluate this integral is similar to Nevo (2001) in that I will, for each city, sample a number of individuals from the CPS. Details on this sampling technique appear in an appendix.

The next step is to numerically solve the system of retailer and manufacturer first order conditions to determine the profit-maximizing merchandising allowances and the conditional

[25] Ideally, I would like to include more than two demographic characteristics. Unfortunately, because of the high computation time involved in estimating my model, it is necessary to restrict the number of demographic characteristics included.

[26] Therefore, the vector D_i is 3×1 for each i.

wholesale and retail prices associated with each possible display choice. The prices can then be used to calculate the implied (conditional) sales for each brand under each possible display choice. Using the price-quantity pairs, I calculate the variable portion of retailer profit (π_j).

Using the retailer's sales (variable) profit and the merchandising allowances, I compute the unconditional display probabilities (ϕ), where computation of this $(J-1)$ dimensional integral is simplified by assuming that the e's are distributed type II extreme value, which allows for expressing the probabilities in multinomial logit form:

$$\phi_{jr} = \frac{\exp\{\pi_{r|D=j} + A_j\}}{\sum_k \exp\{\pi_{r|D=k} + A_k\}}$$

The model is estimated using a method of moments technique. So, the next step is to use the information above to derive expected values for the expected average per unit price, the expected brand market share, and the expected percentage of units sold with merchandising (PUAM), where:

$$E\left(\widehat{p}_j\right) = \int_e (p_j|D)\left(\frac{Q_j|D}{TotalQ_j}\right)\Pr(D=d|e)dF(e) \tag{13}$$

$$E\left(\widehat{S}_j\right) = \frac{\int_e (Q_j|D)\Pr(D=d|e)dF(e)}{\sum_k \int_e (Q_k|D)\Pr(D=d|e)dF(e)} \tag{14}$$

$$E\left(\widehat{PUAM}_j\right) = \frac{E\left(Q_j|D=j\right)}{\int_e (Q_j|D)\Pr(D=d|e)dF(e)} \tag{15}$$

Next, calculate the residual vector ω, where:

$$\omega = \begin{bmatrix} \widehat{p} - p_{IRI} \\ \widehat{S} - S_{IRI} \\ \widehat{PUAM} - PUAM_{IRI} \end{bmatrix}$$

Finally, I search for the parameter values that minimize the objective function $\omega' W \omega$, where ω is an $(800*3*4)\times 1$ vector of residuals and W is an $(800*3*4)\times(800*3*4)$ weighting matrix. For the first iteration of the objective function, W will be an identity matrix. For each iteration thereafter, the weighting matrix is updated using the covariance matrix.

7 Results

7.1 Parameter Estimates

Coefficients for price and the brand dummies appear in Table 4. For each brand j, the two coefficients reported represent the brand-effect when on display (β_j^j) and the brand-effect when a rival is on display (β_j^0). I refer to the difference between the estimated coefficients as the brand's "quality boost." These quality boosts are positive for Heinz, Hunts, and Del Monte, indicating that consumers, on average, tend to have a better perception of these brands when they appear on display. The Private Label brand actually has a higher brand-effect when not on display. This reaffirms the Private Label's strength in positioning itself as a low-cost alternative brand. Del Monte receives the most substantial boost from premium shelf space, whereas the perception of Heinz varies little depending on Heinz's shelf space allocation. As the market leader for a considerable number of years, it may be that public awareness of Heinz is so great that Heinz receives very little benefit from improved shelf space.

Figure 4 illustrates this fact by comparing two demand curves for Heinz ketchup. The solid line represents the demand for Heinz when it has premium shelf space, while the dashed line represents the demand for Heinz when another brand has received the premium shelf space. The latter demand curve, as we would anticipate, lies below the demand curve Heinz faces when receiving premium shelf space. The difference between the two, however, is negligible. The maximum horizontal difference between the curves (i.e. the difference in shares for a given price level) is approximately 0.02. This implies that, at most, the premium shelf space will increase Heinz's market share by 2 percent.

The coefficient on price (α) is statistically significant and the predicted sign. Figure 5 shows the distribution of individual price coefficients for each of the individuals "sampled" from the CPS.[27] The distribution appears to be a normal distribution. Notice that some of the coefficients are positive, indicating that the individual's utility actually increases with price. While we may be able to think of products for which this seems reasonable, it does

[27] In total, characteristics for 10,000 individuals were included.

not seem to be appropriate in the case of ketchup. Fortunately, only 2.02 percent of the individuals have positive price coefficients.[28]

In Table 6, estimated wholesale prices are presented. The reported wholesale prices are averaged over all markets and all display configurations. As the brand with the largest market share and the highest average retail price, it is not surprising to see that Heinz charges the highest wholesale price, followed by Hunts, and, finally, Del Monte. Average retail mark-ups (percentage) are also presented in Table 6. The mark-ups for Hunts (32.13 percent) and Del Monte (29.75 percent) are of similar magnitude, while the mark-up for Heinz is considerably lower (23.76 percent). A more thorough discussion of ketchup mark-ups appears below in the section on goodness of fit.

Table 7 shows average conditional wholesale prices for the sample. These prices represent the average estimated wholesale prices for each brand (w_j^j, w_j^0). Both Heinz and Del Monte charge their highest wholesale prices when their respective brand is in the premium space. This is due to the fact that premium shelf space, in this model, acts as a demand shifter (increase). The exception is Hunts, which has a higher wholesale price when not chosen for the premium shelf space. This result seems counterintuitive. However, a possible explanation might be that Hunts and Heinz are strategic complements, so Hunts benefits from having Heinz on display because this allows them to raise their price.

Display probabilities (ϕ) are shown in Table 8. Overall, Heinz has the highest average probability of being chosen for display in each of the markets. The largest average display probability is approximately 32 percent (Heinz) and the smallest is around 8 percent (Private Label). Comparing the maximum and minimum display probabilities, Heinz appears to receive the premium shelf space most often. This provides some support to the theory that the market leader is most likely to receive premium space.

Merchandising allowance estimates, expressed as a percentage of the retailer's conditional profit, are presented in Table 9.[29] The average allowance payments range from 8 percent

[28] For comparison, in Nevo (1997) as much as 13 percent of the individual price coefficients are positive, while in Nevo (2001) only 0.7 percent are positive.

[29] I express the allowances as a percentage of profit to ensure that the value of the allowances are not over- or understated due to misspecification of the size of the market.

(Hunts) to 9.5 percent (Del Monte). Heinz and Del Monte are the manufacturers that offer the largest allowances, which should not be surprising, given that Del Monte receives the largest "quality boost" from the premium shelf space and Heinz has, of all brands, the largest brand coefficient (β_j^j) when in the premium position.

7.2 Perception Maps

The use of perceptual maps or brand maps has become commonplace in the marketing literature.[30] The basic idea behind the technique is that every brand has a number of latent attributes for which consumers have tastes and preferences. For feasibility, it is usually assumed that each brand has two latent attributes. The perception map, then, is a two-dimensional representation of each brand's latent attributes.[31] A brand's position on the perception map is independent from its price. The location of a brand depends solely on its characteristics. When each brand is plotted on the same set of axes, a brand's proximity to the other brands represents how closely consumers view these two brands. The closer two brands are plotted, the more similar these brands are perceived. The further apart, the more dissimilar these brands are perceived.

While the perception map allows one to compare how consumers view different brands, it is important to note that a brand's location in two-dimensional space cannot be used to categorize that brand as being "better" or "worse" than another brand. For example, consider the case of refrigerated orange juice. It is likely that consumers view Minute Maid orange juice with pulp as a closer substitute to Tropicana orange juice with pulp than a third brand that is pulp-free. This is what the perception map shows. It does not indicate that orange juice with pulp is more attractive or "better" than pulp-free orange juice.[32]

Figure 6 shows the perception map for Heinz, Hunts, Del Monte, and Private Label when none of the brands has premium shelf space. This plot represents how consumers view

[30] My thanks to Jean-Pierre Dube for helping me understand the technique.

[31] From a technical standpoint, one recovers these latent attributes by performing a Cholesky decomposition of the covariance matrix of the brand dummies. For a more thorough description of this technique, please see Elrod (1988), Elrod and Keane (1995), or Chintagunta, Dube, and Singh (2003).

[32] That would depend on individual preferences.

the four brands, disregarding any benefit for better shelf space. Del Monte and Private Label are grouped together closely in the upper right-hand corner, while Hunts and Heinz are positioned in the lower left-hand corner. Though not paired quite so closely together, the distance between Heinz and Hunts indicates that these two brands are seen as being relatively similar. The close placement of Del Monte and the Private Label brand indicates that consumers view these two products as being very similar, as well. An implication of this is that the "premium" brands are perceived differently than the low-cost brands.

Figure 7 illustrates how premium shelf space may alter the consumer perceptions shown in Figure 6. Figure 7 plots the case where Del Monte is in the premium/display position. As one can see, this "moves" Del Monte closer to Heinz in the consumers' eyes. The two brands are, now, seen as being significantly more similar. This graph provides some intuition into the benefits of premium shelf space.

7.3 Goodness of Fit

It is useful to examine some tests which allow the performance of the structural model to be evaluated.

7.3.1 Chi-square Tests

First, I conduct a traditional chi-square test to see how well the model's predictions compare with what is observed in the data. I examine (separately) how well the model predicts each brand's prices and also the percentage of units sold with merchandising (PUAM) for each brand. In both cases, the null hypothesis tested is that the model's prediction equals reality. The results of these two tests, unfortunately, are mixed. With a test statistic of approximately 0.35, I am unable to reject the hypothesis that the model's predicted prices are equal to the observed prices. On the other hand, the hypothesis that the model's predicted percentages of units sold with merchandising are equal to the observed values is rejected. Upon closer examination of the values, it appears that the model generally understates how many units each brand sells with merchandising (i.e. $\widehat{PUAM} < PUAM_{observed}$). If the benefit of premium shelf space is being undervalued, that may provide some explanation as to why the estimated merchandising allowance payments are not particularly high.

7.3.2 Predicting Mark-Ups

The second test I present is more of a qualitative test. Thanks to work by Besanko, Dube, and Gupta (2002), we have some information regarding the size of mark-ups on ketchup. Using confidential supermarket data, the authors calculate the average percentage retail mark-up on ketchup to be around 34.5 percent. This number is close to the percentage retail mark-up implied their model (39.5 percent). Recall the average predicted mark-ups presented in Table 6. For Hunts and Del Monte, the predicted mark-ups are 32.1 percent and 29.7 percent, respectively. These numbers are close to the mark-ups observed in the data, as well the mark-ups implied by Besanko, Dube, and Gupta's model. The predicted mark-up for Heinz is lower than the average observed mark-up, however.

Recall that, according to Desiraju's (2001) model, retail mark-ups should be negatively correlated with allowance payments. The empirical results above provide mixed support for this prediction. Heinz and Del Monte have the lower mark-ups (compared with Hunts) and they make the largest average merchandising allowances. However, Heinz, which has a lower mark-up than Del Monte, makes lower allowance payments (on average) than Del Monte.

7.4 Counterfactual and Welfare Analysis

Whether merchandising allowances lead to higher prices (and, therefore, lower consumer surplus) is one of the more interesting questions to explore. To provide some insight into this question, I use the parameter estimates to conduct a counterfactual experiment. Specifically, firms will no longer be permitted to offer merchandising allowances in order to obtain the shelf space. Allowances are set to zero and the retailer chooses a brand for the premium shelf space based solely on the conditional sales profit. Manufacturers must strategically set their wholesale prices in order to maximize their expected profit. I assume that, as before, each manufacturer chooses two conditional wholesale prices: one wholesale price when they receive the premium shelf space and another price for when another brand has been chosen for the premium shelf space.

The wholesale prices are determined by maximizing the manufacturer's expected profit. With no allowances, manufacturer j's two first order conditions can be written:

$$\frac{\partial E\Pi_j^m}{\partial w_j^j} = \phi_j \left(Q_{j|D=j} + w_j^j \frac{\partial Q_{j|D=j}}{\partial w_j^j} \right) + \left(w_j^j Q_{j|D=j} \right) \frac{\partial \phi_j}{\partial w_j^j} + \sum_{k \neq j} w_j^0 Q_{j|D=k} \frac{\partial \phi_k}{\partial w_j^j} = 0$$

$$\frac{\partial E\Pi_j^m}{\partial w_j^0} = \left(w_j^j Q_{j|D=j} \right) \frac{\partial \phi_j}{\partial w_j^0} + \sum_{k \neq j} \left[\phi_k \left(Q_{j|D=k} + w_j^0 \frac{\partial Q_{j|D=k}}{\partial w_j^0} \right) + \left(w_j^0 Q_{j|D=k} \right) \frac{\partial \phi_k}{\partial w_j^0} \right] = 0$$

Note that, because the retailer takes the manufacturers' wholesale prices as given when setting retail prices, the retailer's first order conditions are unchanged. Any change in the retail price, then, is driven through changes in the wholesale prices.

The results of the counterfactual appear in Tables 10 through 13. As Table 10 shows, mean expected retail prices are lower for all four brands when merchandising allowances are forbidden. On a market-by-market basis, the average price of Heinz falls in almost 95 percent of the markets when allowances are prohibited. On the other hand, the average price of the Private Label falls in only about 57 percent of the markets. This reaffirms Shaffer's (1991) findings regarding the use of slotting allowances and its impact on retail prices.

Counterfactual wholesale prices appear in Table 11. On average, the wholesale prices for Heinz, Hunts, and Del Monte are all lower. The lower wholesale prices explain why retail prices are also lower in the counterfactual. This result is similar to arguments put forth in the vertical restraints literature. In the literature, it is not uncommon for manufacturers to reduce their wholesale price in an effort to increase the retailer's margin (thereby giving the retailer a greater incentive to promote the manufacturer's brand). In my model, when merchandising allowances are not permitted, the wholesale price becomes the primary instrument for manufacturers to compete for the premium shelf space. It should not seem surprising, then, that manufacturers lower their wholesale prices in an effort to make their brand more attractive to the retailer. A question raised in the vertical restraints literature, and not addressed here, is whether the retailer actually "passes the savings on" to the customer by lowering the retail price when wholesale prices are lowered. My model allows that the retailer to re-optimize in the counterfactual and set their desired price.

The new display probabilities appear in Table 12. Relative to the state where merchandising allowances are permitted, the average display probabilities for each of the brands, except Del Monte, rise in the counterfactual experiment. Recall from Table 9 that Del Monte offered the largest merchandising allowances. It appears that the elimination of merchandising allowances hampers Del Monte's ability to compete for the premium shelf space. This loss is translated into gains for the other three brands, including the Private Label brand which becomes more likely to be chosen for the premium display space now that the retailer does not have to forgo receiving an allowance payment when the Private Label brand is selected.

To help quantify the effect of eliminating merchandising allowances, I calculate the change in consumer welfare associated with its elimination. To evaluate the change in consumer welfare, I rely on consumer surplus. I measure the amount of money consumers would need to be given (under the conditions of the counterfactual) in order to maintain their initial level of utility. Consumer i's change in welfare, therefore, can be expressed:

$$CS_i = \sum_{k=1}^{4} \phi_k^{noallow} \left[\log \left(\sum_{j=0}^{J} \exp \left(V_{ij|D=k}^{noallow} \right) \right) \right] - \sum_{k=1}^{4} \phi_k^{allow} \left[\log \left(\sum_{j=0}^{J} \exp \left(V_{ij|D=k}^{allow} \right) \right) \right]$$

where $\phi_k^{noallow}$ (ϕ_k^{allow}) is the display probability of brand k when merchandising allowances are prohibited (allowed), and $V_{ij|D=k}^{noallow}$ ($V_{ij|D=k}^{allow}$) is consumer i's expected utility from consuming brand j when brand k has the premium shelf space and merchandising allowances are prohibited (allowed). Using these definitions, the above equation may be interpreted as the average expected maximized utility under the counterfactual minus the average expected maximized utility with merchandising allowances. This value represents, in dollars, how much better or worse off an individual consumer is because of merchandising allowances.[33]

I find that consumer surplus is diminished because of merchandising allowances. On average, each consumer loses approximately \$0.11 in welfare annually, due to merchandising

[33]By excluding income from an individual's indirect utility function, I am inherently assuming that the marginal utility of income is equal to 1.

allowances. This aggregates to an annual decrease in welfare of approximately $10 million for the metropolitan areas included in this sample. Two comments are worth noting here. First, the figures above refer only to the ketchup industry. However, it is difficult to generalize on the overall impact of merchandising allowances because there is likely to be a great deal of variation across industries. The second comment is that I have not allowed for the possibility that the retailer might choose to not carry all four brands. If merchandising allowances are prohibited and the retailer decides that, without the allowance payment, it is not worthwhile to carry all four brands, then we might actually see higher retail prices for the remaining brands. In addition, the loss of choice may negatively impact consumer welfare, regardless of any price change.[34] When I compare manufacturer and retailer profit with and without merchandising allowances, I found that manufacturer profit goes up when merchandising allowances are eliminated. Retail profit, on the other hand, goes down. The fact that we often observe the use of merchandising allowances, then, might indicate the presence of retail power.

8 Conclusions and Extensions

Merchandising allowances are an important part of the vertical channel. Firms are increasingly relying on their use and yet our understanding of their impact is limited. This research makes a step towards providing insight.

In this paper I estimated a structural model of merchandising allowances. The utility function was a discrete-choice, random coefficients model modified to allow space and promotion to affect the consumer's choices. To account for the way in which retail allowances affect the decisions of manufacturers and retailers, the behavior of both groups is explicitly modeled. Parameter estimates were then used to conduct a counterfactual to determine how consumers, manufacturers, and retailers might be expected to respond to changes in the current system. The results of the counterfactual imply that merchandising allowances decrease

[34]For example, Petrin (2002) develops a calculation for consumer welfare that takes into account the addition (or possible deletion) of products from the consumer choice set.

social welfare. While the practice allows retailers to increase their profit, this benefit is more than offset by the dramatic decrease in consumer welfare.

One should be careful in relying too heavily on the aggregate welfare loss calculation presented above. There is a concern, particularly when discussing slotting allowances, that the retailer may change not only the shelf allocation but, possibly, also the number of products available. The welfare results in the preceding section do not account for this possibility or its consequences.

Some of the points to be considered in future research include: observing actual shelf space configurations to account for the possible introduction/deletion of products from the consumers' choice set, alternative retailer-manufacturer bargaining approaches, and allowing for multiple retailers to capture downstream competition as well as retailer size differences.

This research presents one of the first rigorous empirical examinations on merchandising allowances. In this paper, I have attempted to add an empirical element to the theoretical work begun by Sullivan, Shaffer, Desiraju, and others. It also extends and contributes to the literature on structural models of vertical competition that follows from BLP's seminal paper. Rather than the definitive word on allowances, I view this paper as the beginning of a new vein of research aimed at empirically examining the affects of merchandising allowances.

A Theoretical Appendix

A.1 Simulating Individuals

Random coefficients models add a degree of realism to conventional logit models by allowing consumer taste parameters (α, β) to vary across individuals. This added realism comes at a computational cost, however. More specifically, the random coefficients model requires the econometrician to integrate over the distribution of demographics in order to obtain brand market shares. While there are various ways to simulate over the demographic distribution, I choose to approximate this integral by sampling a set of individuals from the Census Bureau's March Current Population Survey (CPS). This smooth simulator is preferable to the simple frequency simulator for two reasons. Firstly, the frequency simulator requires a large number of draws to ensure non-zero probabilities, whereas the smooth simulator can produce non-zero probabilities from a single draw. Also, the frequency simulator, based on an indicator function, is not smooth so the use of a gradient method in minimizing the objective function is not possible.

The simulator I employ here requires the econometrician to sample individuals from each metropolitan area and calculate the individual's choice probabilities for each brand. So, for each metropolitan area and year in the period, I sample 50 individuals.[35] Simultaneously, I also draw a $(K+1) \times 1$ vector of individual taste parameters from the distribution of ν. Given the draws (ν, D) and the extreme value assumption on ε, the predicted (unconditional) market share of brand j in market m can be expressed as:

$$\begin{aligned} s_{jm} &= \frac{1}{50}\sum_{i=1}^{50} s_{ijm} \\ &= \frac{1}{50}\sum_{i=1}^{50} \left[\begin{array}{c} \phi_j \frac{\exp\{\beta_{ij}^{j} - \alpha_i p_{jm}\}}{1+\exp\{\beta_{ij}^{j} - \alpha_i p_{jm}\} + \sum_{k \neq j} \exp\{\beta_{ik}^{0} - \alpha_i p_{km}\}} \\ + \sum_{k \neq j} \phi_k \frac{\exp\{\beta_{ij}^{0} - \alpha_i p_{jm}\}}{1+\exp\{\beta_{ik}^{k} - \alpha_i p_{jm}\} + \sum_{g \neq k} \exp\{\beta_{ig}^{0} - \alpha_i p_{km}\}} \end{array} \right] \end{aligned}$$

In order to compute the prices and implied sales, conditional on a specific display

[35] The CPS is an annual survey so I use the same sampled individuals for each quarter in the given year.

choice, in the estimation algorithm, it is necessary to compute conditional market shares ($s_{j|D=j}, s_{j|D=k}$). These can be expressed:

$$\begin{aligned}
s_{j|D=j} &= \frac{1}{50}\sum_{i=1}^{50} s_{ij|D=j} \\
&= \frac{1}{50}\sum_{i=1}^{50}\left[\frac{\exp\{\beta_{ij}^{j}-\alpha_i p_j\}}{1+\exp\{\beta_{ij}^{j}-\alpha_i p_j\}+\sum_{k\neq j}\exp\{\beta_{ik}^{0}-\alpha_i p_k\}}\right]
\end{aligned}$$

$$\begin{aligned}
s_{j|D=k} &= \frac{1}{50}\sum_{i=1}^{50} s_{ij|D=k} \\
&= \frac{1}{50}\sum_{i=1}^{50}\left[\frac{\exp\{\beta_{ij}^{0}-\alpha_i p_j\}}{1+\exp\{\beta_{ik}^{k}-\alpha_i p_j\}+\sum_{g\neq k}\exp\{\beta_{ig}^{0}-\alpha_i p_k\}}\right]
\end{aligned}$$

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TABLE 1
Product Characteristics

Per Serving Information	Heinz	Hunts	Del Monte
Calories	15	15	15
Sodium(mg)	190	190	190
Carb.(g)	4	4	4
Sugars(g)	4	4	4
Vitamin A(%)	6	0	0

TABLE 2
Metropolitan Markets

Atlanta, GA	Hartford, CT	Milwaukee, WI	Raleigh, NC
Balt., MD - Wash., DC	Houston, TX	Nashville, TN	Sacramento, CA
Birmingham, AL	Indianapolis, IN	New Orleans, LA	Salt Lake City, UT
Chicago, IL	Jacksonville, FL	New York, NY	San Antonio, TX
Cincinnati, OH	Kansas City, MO	Oklahoma City, OK	San Diego, CA
Columbus, OH	Little Rock, AR	Omaha, NE	San Francisco, CA
Dallas, TX	Los Angeles, CA	Orlando, FL	Seattle, WA
Denver, CO	Louisville, KY	Philadelphia, PA	St. Louis, MO
Detriot, MI	Memphis, TN	Phoenix, AZ	Tampa, FL
Grand Rapids, MI	Miami, FL	Portland, OR	Wichita, KS

TABLE 3
Measure Summary Statistics

Market Share by Region (all years)					
	South	Northeast	Midwest	West	National
Heinz	42.81	66.31	57.49	45.23	54.36
Hunts	31.38	8.64	16.33	16.99	17.81
Del Monte	13.01	2.82	6.75	17.36	9.01
Private Label	11.87	21.69	13.55	19.53	16.84
Combined	99.07	99.46	94.12	99.11	98.02

		1988	1989	1990	1991	1992
		Mean (Std.Dev.)	Mean (Std.Dev.)	Mean (Std.Dev.)	Mean (Std.Dev.)	Mean (Std.Dev.)
Heinz	Price	1.53	1.47	1.46	1.52	1.54
		(0.149)	(0.116)	(0.112)	(0.166)	(0.153)
	PUAM	41.81%	38.50%	38.33%	33.68%	34.41%
		(0.163)	(0.156)	(0.151)	(0.138)	(0.133)
Hunts	Price	1.39	1.29	1.28	1.33	1.36
		(0.173)	(0.128)	(0.145)	(0.201)	(0.180)
	PUAM	47.69%	45.92%	46.47%	44.92%	47.36%
		(0.155)	(0.192)	(0.183)	(0.166)	(0.157)
Del Monte	Price	1.18	1.17	1.13	1.18	1.21
		(0.160)	(0.145)	(0.151)	(0.170)	(0.159)
	PUAM	61.89%	53.13%	54.79%	51.89%	54.34%
		(0.155)	(0.192)	(0.183)	(0.166)	(0.157)
Private Label	Price	1.03	0.97	0.97	1.03	1.06
		(0.146)	(0.074)	(0.064)	(0.121)	(0.117)
	PUAM	37.32%	34.09%	32.86%	32.71%	31.79%
		(0.153)	(0.180)	(0.160)	(0.152)	(0.154)

TABLE 4
Parameter Estimates

α	-10.8515* (4.0273)		Number of Markets	800

	Heinz	Hunts	Del Monte	Private Label
β_j^j	4.6218*	2.9936	1.1970[a]	0.0497
	(0.4407)	(2.0411)	(0.7343)	(0.2469)
β_j^0	4.4581[a]	2.4888*	-0.1491	3.1291*
	(2.7346)	(1.1312)	(0.3540)	(1.3479)
"Quality Boost"	0.1637	0.5048	1.3461	-3.0794

* - Significant at 5% level
a - Significant at 10% level

TABLE 5
Demographic Characteristics

	Income	Children	Northeast
Price	0.3412*	-0.7027[a]	0.0523
	(0.1605)	(0.4176)	(0.0512)
Heinz	0.3773*	0.1844	0.3340[a]
	(0.1397)	(0.1941)	(0.1855)
Hunts	0.2091	-0.5214	-0.6785*
	(0.2063)	(0.4344)	(0.3342)
Del Monte	-0.0643	0.0621	-0.2071
	(0.0824)	(0.2485)	(0.1726)
Private Label	-0.2719*	0.6124	0.3676
	(0.1266)	(0.4082)	(0.2467)

* - Significant at 5% level
a - Significant at 10% level

TABLE 6
Wholesale Prices

	Heinz	Hunts	Del Monte
Mean	1.1529	0.9658	0.8429
St. Dev.	0.3604	0.3642	0.5941
Av. % Mark-up	23.76	32.13	29.75

TABLE 7
Conditional Wholesale Prices

	Heinz	Hunts	Del Monte
D =Own	1.3644	1.0365	1.0711
D = Other	1.1772	1.1103	0.7147

TABLE 8
Display Probabilities

	Heinz	Hunts	Del Monte	Private Label
Mean	0.3219	0.2894	0.3123	0.0763
Max	0.9060	0.6680	0.5600	0.1140
Min	0.1400	0.0265	0.0483	0.0102

TABLE 9

Merchandising Allowance Payments (% of Retail Profits)

	Heinz	Hunts	Del Monte
Mean	9.049%	8.020%	9.494%
Max	10.299%	9.901%	20.534%
Min	3.247%	0.001%	0.001%

TABLE 10

Counterfactual Experiment

With Merchandising Allowances				
	Heinz	Hunts	Del Monte	Pr. Label
Average Expected Price per Unit	1.5025	1.3999	1.2029	0.9825
Without Merchandising Allowances				
	Heinz	Hunts	Del Monte	Pr. Label
Average Expected Price per Unit	1.3573	1.2545	1.0786	0.9049
Price Change	Lower	Lower	Lower	Lower
% of Time Price is Higher with Allowances	94.38	76.38	83.13	56.75

TABLE 11

Expected Wholesale Prices

With Merchandising Allowances			
	Heinz	Hunts	Del Monte
Average Expected WholesalePrice per Unit	1.1529	0.9658	0.8429
Without Merchandising Allowances			
	Heinz	Hunts	Del Monte
Average Expected WholesalePrice per Unit	1.0153	0.8711	0.6871
Price Change	Lower	Lower	Lower

TABLE 12
Counterfactual Display Probabilities

	Heinz	Hunts	Del Monte	Pr. Label
Mean	0.3391	0.3073	0.1917	0.1620
Max	0.4480	0.4160	0.3530	0.1860
Min	0.2980	0.2220	0.1160	0.1060

FIGURE 1: Basic Game Structure

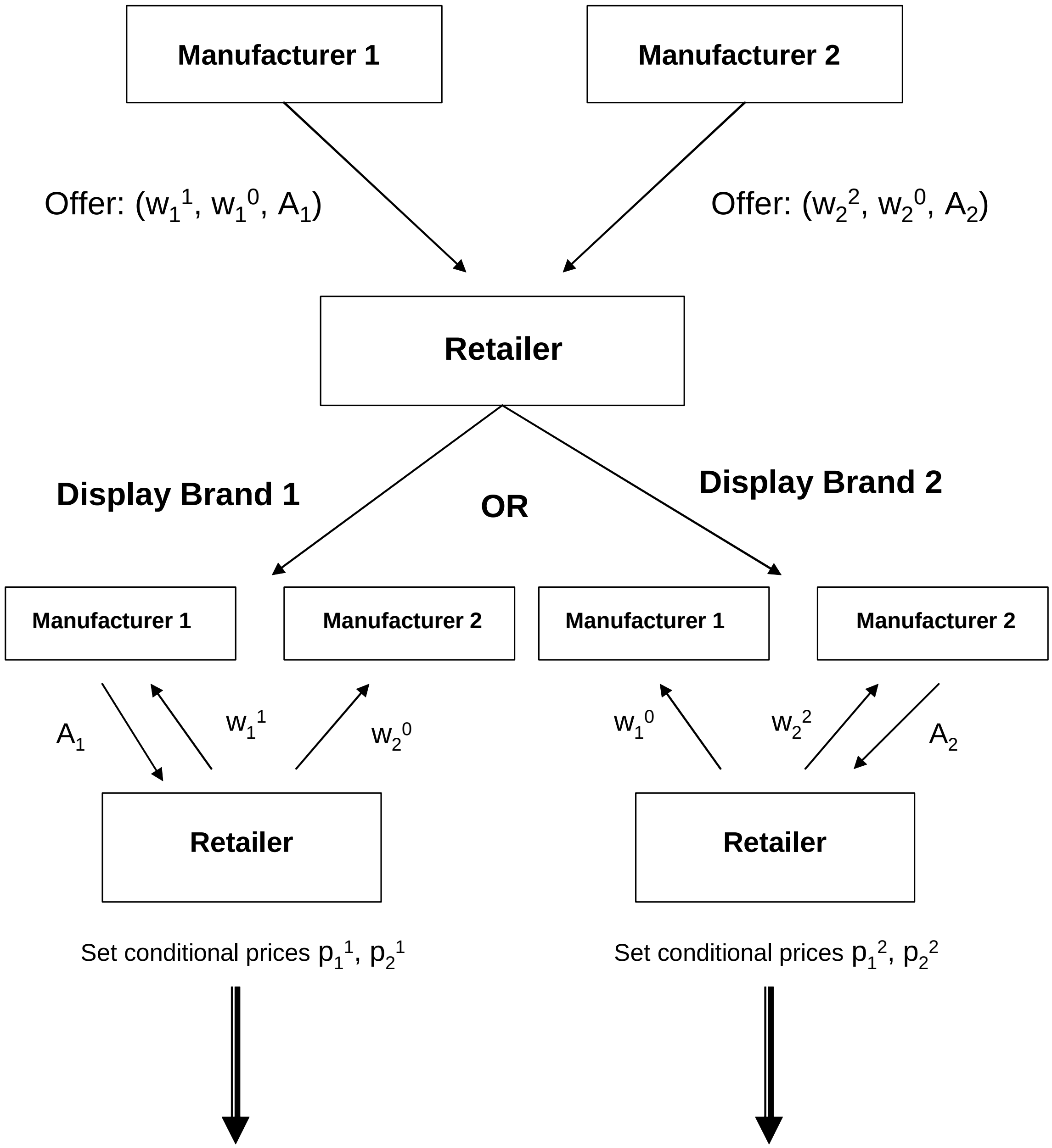


FIGURE 2: Ketchup Unit Sales

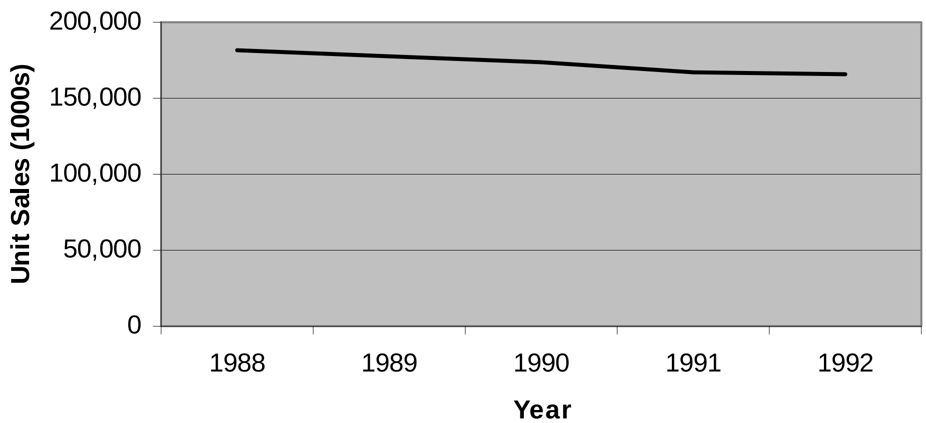


FIGURE 3: Ketchup Sales ($)

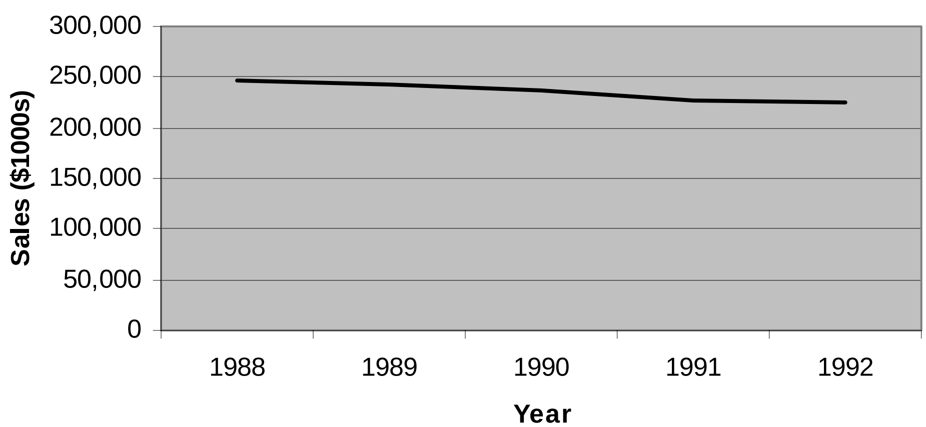


FIGURE 4: Demand Curves for Heinz
(Other Brand Prices Fixed at Sample Average Levels)

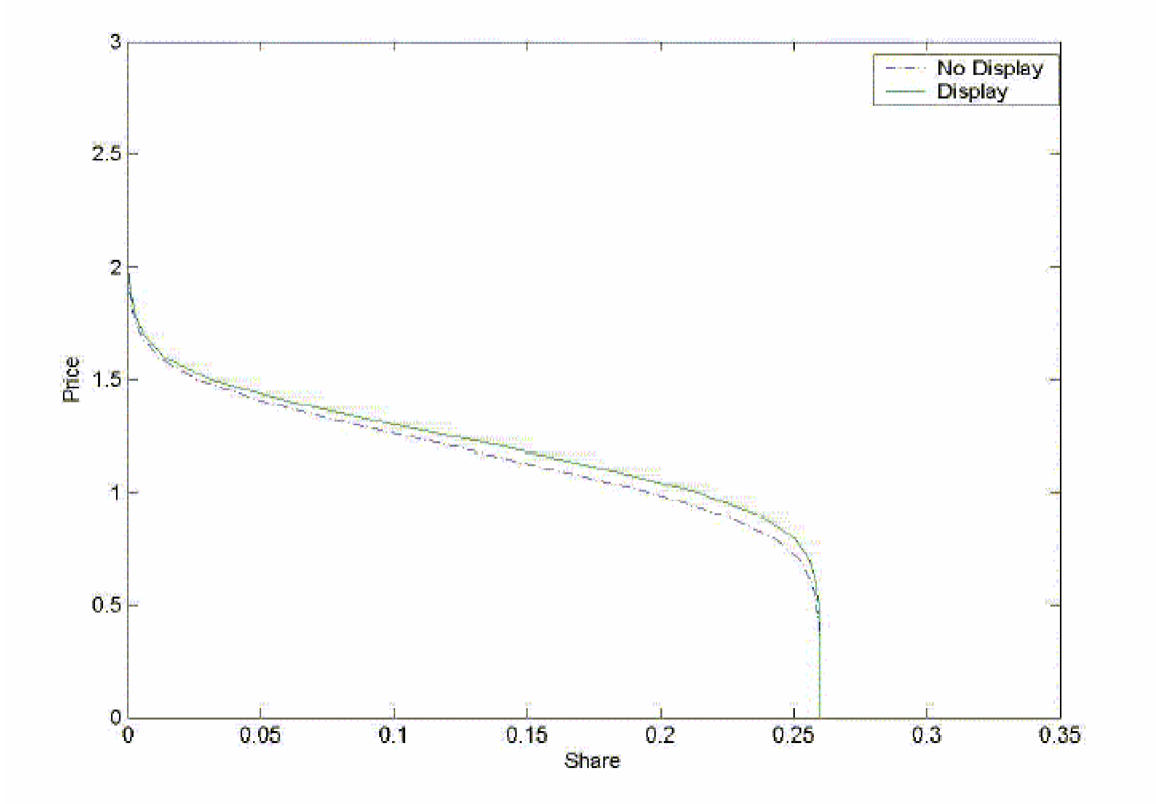


FIGURE 5: Frequency Distribution of Price Coefficient

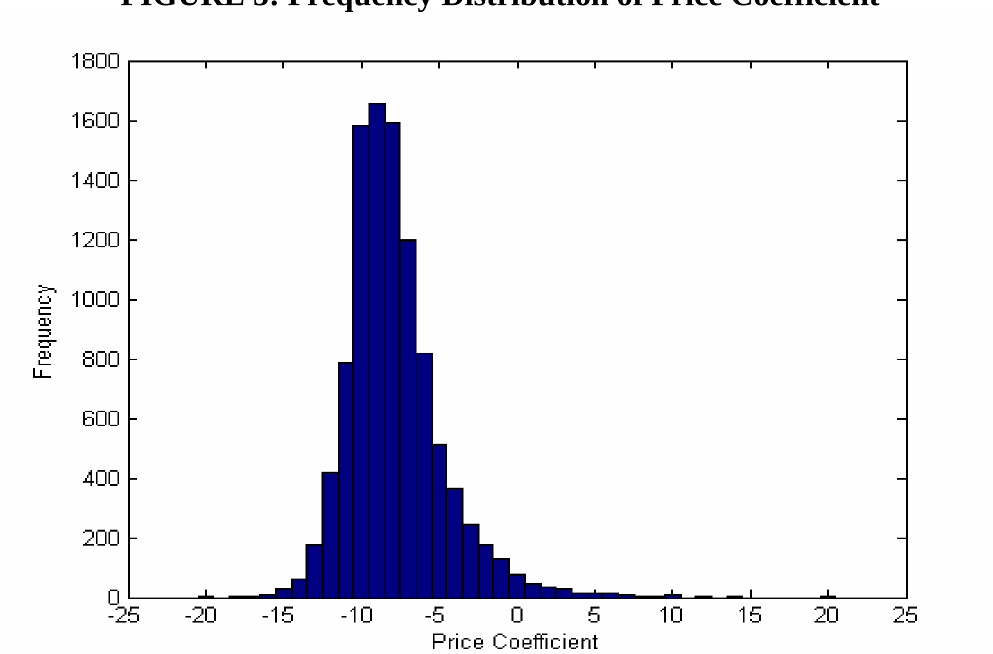


FIGURE 6: Perception Map #1

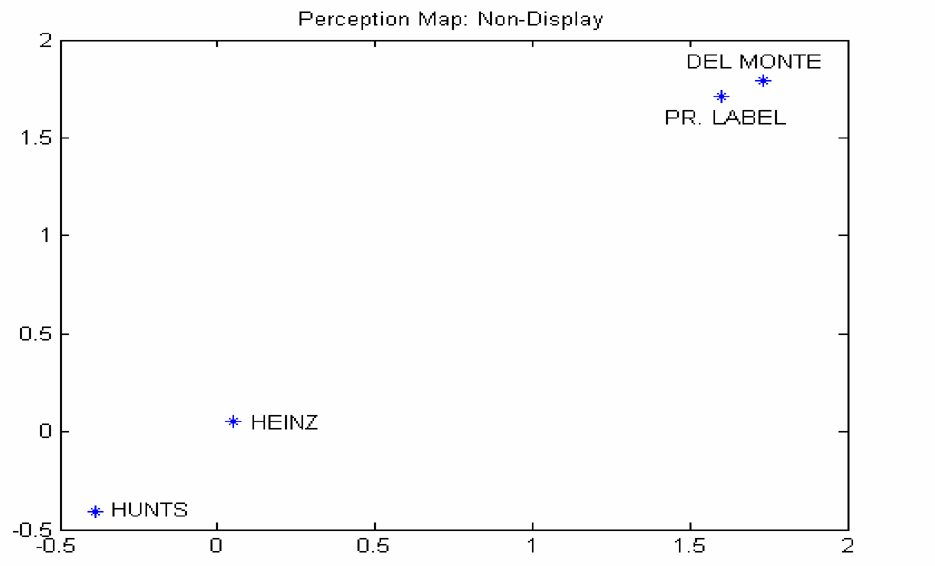
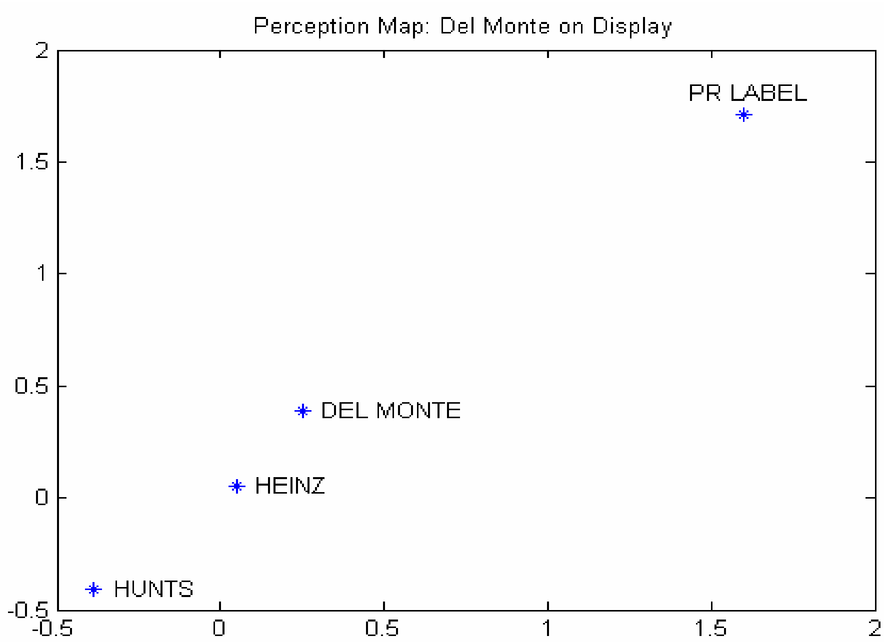


FIGURE 7: Perception Map #2



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