Studying the Impact of Store Brand Entry: A Within Category Analysis

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Abstract

Researchers have recently been interested in studying the drivers of store brand success as well as factors motivating the introduction of a store brand by a retailer. In this paper, we study the effects of introducing a store brand into a particular product category. Specifically, we are interested in the effect of the entry (assumed to be exogenous) on the demand as well as the supply side. On the demand side, we investigate the effects of the store brand’s introduction on the preference distributions of the national brands and on the price sensitivity distribution. On the supply side, we study the effects of the new entrant on the interactions between the national brand manufacturers and the retailer introducing the store brand. In particular, we are interested in whether or not the store brand introduction results in a shift of relative channel power from the national brand manufacturers to the retailer. For the demand specification we use a random coefficients logit model and explicitly account for endogeneity in retail prices. Our empirical results obtained from two product categories reveal that the store brand introduction does have an effect both on the demand as well as the supply side. However, the magnitude of the effect is category specific. Interestingly, in one category we find that relative channel power appears to have shifted in the direction of the retailer after introduction of a store brand.
1 Introduction

It is vital that a retailer understands demand conditions which make it attractive to introduce a store brand to a product category, and the subsequent impact of this introduction on customer demand for both the store brand and national brands. This study carefully examines and compares demand conditions before and after entry of a store brand. The analysis also takes into account the retailer’s interactions with the manufacturers of the national brands both prior to as well as subsequent to the introduction of the store brand.

Past research has examined conditions which make it attractive for a store brand to be introduced to particular product categories (Hoch and Banerji, 1993; Raju, Sethuraman and Dhar, 1995). Raju et al. identify three circumstances under which a store brand raises a retailer’s category profits. First, if the cross price sensitivity among the national brands is low. Second, if the cross price sensitivity between the national brand and the store brands, is high. Third, if the category has a large number of national brands. Category share has also been studied as a performance measure for store brands. Hoch and Banerji (1993) find that the category share of store brands is likely to be lower when there exist a larger number of national brand manufacturers, or when advertising expenditures per manufacturer is high. However, their findings also suggest that store brands’ category share is more likely to be higher in large categories which offer high margins. An important feature of these previous studies is that the analyses are conducted across product categories (and in some instance, across retailers). Hence, they are ideally suited to providing stylized facts and empirical regularities by exploiting variations in store brand performance across categories and retailers.

The primary contribution of this study is to provide a deeper understanding of how, within a category, various demand characteristics change as a result of the store brand entering that category. Consequently, it can be seen as complementing earlier, cross-category empirical research by studying within category factors that are manifested as across category variations found in previous research. Why is it important to study the impact of store brand introduction within a product category? On the demand side, it is clear why one needs to look within a category to identify the effects of a store brand introduction. For example, if a manager of a national brand
is interested in understanding whether consumer preferences, after controlling for the effects of marketing activities, have shifted from the national brand she or he manages to a store brand, then it is necessary to measure these preferences both prior to as well as post entry in order to address this issue. Similarly, an increased price sensitivity due to store brand introduction will necessitate marketing actions by the manufacturers as well as the retailer. To determine what actions need to be taken (e.g., increase advertising expenditures), the channel members will need to know the extent to which price sensitivities have been altered. For this the demand for the different brands within a product category needs to be studied.

A “within category” analysis is also necessary, in some instances, to understand macro-level strategic issues. Consider, for example, an issue that has increasingly been raised not only in the popular press (Progressive Grocer 1992) but also by academic researchers—the shift in channel power from manufacturers to retailers. Table 1 reports the Progressive Grocer (1982) findings based on surveys of managers at manufacturer, wholesaler as well as retailer organizations. The findings appear to indicate that power has indeed shifted from manufacturers to retailers.

The exact nature or definition of power could still be an issue of contention. For example, there are economic definitions of power—the fraction of total channel profits accruing to each of the channel members. And there are behavioral definitions—the ability to negotiate a better deal. Nevertheless, the survey results seem to indicate a shift in power. Using aggregate data on profitability in the manufacturing and retailing industry on the other hand however, Messinger and Narasimhan (1995), find little or no evidence for a shift in power. This result is useful when one is interested in the industry as a whole. But if one is interested in a particular product—market, a within category analysis will be required. We bring up the issue of channel power for a specific purpose. One of the many reasons for the shift in power is considered to be the introduction of store brands by the retailer. In this study, we examine the strategic issue of whether power has indeed shifted from manufacturers to retailers in the product categories we analyze. We use a specific measure of power—the proportion of total channel profits (by this we mean the retail price—manufacturer costs for each manufacturer-retailer interaction) accruing to the manufacturer and retailer. Such a measure of power has been used in the previous marketing literature (see for example, Kadiyali, Chintagunta and Vlakassim 2000).
Implications of a store brand introduction in a product category on preferences as well as price sensitivities, as noted before, require an understanding of the demand functions before and after such introduction. To study strategic issues like power shifts from manufacturers to the retailer, one will also have to study the supply side. In other words, what is the nature of interactions among the channel members and how are these interactions affected as a consequence of store brand introduction. Studying the supply side also helps us address the question of power shift in the channel. Recall from the definition of economic power above that in order to study power we need the retail price, the wholesale price (charged the retailer by the manufacturer) and the manufacturer’s costs. In the data available to us, both retail as well as wholesale prices are available, though not manufacturers’ costs. It is reasonable to assume that the wholesale price for a brand is the sum of the manufacturer’s cost for that brand and a markup. The magnitude of the markup will obviously, depend upon the demand functions, nature of interaction among the manufacturers and between the manufacturers and the retailer. Once the demand function parameters and the nature of interaction has been identified, one can compute the markup. Knowledge of the markup and wholesale price will give us the manufacturer costs. Hence, the issue of channel power can be addressed.

On the demand side, we begin with a random coefficients logit model. There are several reasons for this choice. First, the model is not subject to the “proportional draw” property of the logit model at the aggregate level (see Nevo 2000). Consequently, it is not subject to the criticisms discussed in Currim (1982) about using the model to study new product entry. Second, the model is quite parsimonious as compared to specifications such as linear, log-log or other demand models commonly used. Finally, in the context of store brand introduction, it provides us with some insights into not just the effects on the mean preference and price sensitivity levels but also the extent of variance in these measures before and after the introduction. Such information on changes in the heterogeneity distribution could be of value to managers.

Given the above specification of the demand function, we derive the retailer’s pricing equations assuming that the retailer maximizes total category profits. The expressions for retail prices also reflect the nature of interactions between the manufacturers and the retailer in how they impact the retail prices. We measure these interactions both before and after introduction. Since our data
are available for a single retailer, we cannot explicitly consider retail competition in the analysis. For the two categories in our analysis—oats and frozen pasta—it appears reasonable to assume that retail competition is not a major driver of prices. There are two reasons for this - first, our conversations with the retailer seemed to indicate that no loss leader pricing was going on for these categories. Second, research by Walters and his colleagues (see, for example, Walters 1989; Walters and MacKenzie, 1988) seems to indicate that there is little impact of retail prices on store traffic. While other researchers have found evidence for store traffic and retail competition effects in other product categories such as soda and analgesics (see Drèze 1995), there is little evidence to indicate such effects for the categories we investigate. We discuss this assumption in further detail in the concluding section. Finally, manufacturer prices are obtained assuming that these players set prices by maximizing brand profits.

We estimate the parameters of the demand and supply equations simultaneously taking into account the data both prior to as well as after introduction. We use recently developed methods in the economics literature (Berry, Levinsohn and Pakes 1995) to do this. The estimation allows several key parameters to change with the store brand introduction. Our results indicate that the store brand introduction generates notable changes within a category, both from the perspective of the consumers, the retailer, and the position of the retailer versus the manufacturer. For the oats category, the distribution of brand preferences and of price sensitivities are found to be different before versus after the store brand appears on the shelves. The store brand in both categories raises category profitability for the retailer. However, we find that the retailer’s share of total channel profits increases only for the oats category. Furthermore, for the same category, we find that the manufacturer appears takes a softer stance in its interactions with the retailer subsequent to the store brand entry.

The paper is structured as follows. In the next section, we review what is understood about the impact and performance of store brands with respect to consumers and various channel members. The subsequent three sections outline the model, data and the empirical strategy with which we measure the various behaviors of these groups of decision makers. Section 6 presents the results. The final section discusses these results and concludes.
2 The Introduction and Performance of Store Brands

The focus of this study is on understanding changes in brand preferences and category price sensitivities within a category, and changes in channel behavior, resulting from the introduction of the store brand. Two perspectives of the introduction of a store brand are thereby discussed. First is the perspective of the customers. The introduction of the store brand increases the set of brands from which they can choose, and can alter rates of substitution within this set. The second perspective is that of the channel members. In what follows, we assume that the retailer carries the weight of the decision on whether or not to introduce the store brand. The manufacturers adjust their channel policy given that the store brand entry has occurred. In the next two sections, we discuss behavior of the channel members, and consumers respectively.

2.1 Consumer Demand for Private Labels

The impact of a store brand introduction critically depends on the perceptions and behavior of consumers. Past research has examined the characteristics of both consumers and product characteristics that determine the likelihood of purchasing private labels (Bellizzi et al, 1994; Hoch and Banerji, 1993).

For the consumer the primary benefit that the national brand has over a store brand is supposed to be some assurance of higher quality. This higher quality often incurs a premium price relative to the price of the perceived lower quality store brand. Prior to the entry of a store brand, the consumer enters a purchase situation faced with a choice from a set of well known, nationally branded, products. This situation is also well understood by the marketers of national brands, who position the brand in product spaces containing diverse taste preferences as well as the locations of other national brands’ (Hotelling, 1929 or Salop, 1979).

How does the heterogeneity in taste preferences change once the store brand enters? An important dimension of this heterogeneity in tastes involves the perceptions of quality. (These perceptions may or may not be based on trial of the the store brand in this category.) From the consumer’s perspective there is a great deal of uncertainty about the relative quality of the store brand. This uncertainty arises from the perceived source of the store brand. Most consumers are aware that the store brand is not produced by the retailer that distributes the store brand. However, consumers
are uncertain who actually produces this store brand. Even if the consumer knew who produced the store brand, there still remains uncertainty over whether that brand was produced with the same degree of quality control or with similar ingredient quality as that of the comparable national brands.

Finally, it is useful to consider past research on how marketing mix instruments of national brands affect the demand parameters of the private labels, or vice versa. Studies on the impact of price-promotions on private labels versus national brands demand suggest that there can be considerable substitution among the private label and national brands (e.g. Sethuraman, 1995). Other empirical research has also drawn comparisons of marketing instruments often used at point of purchase to encourage brand switching or repeat purchasing behaviors (e.g. Blattberg and Wisniewski, 1989; Lal, 1990). This research also finds evidence for asymmetry in switching behavior between national brands and store brands.

2.2 The Impact of Store Brands on Channel Behavior

When the retailer enters a store brand into the category, they evolve from a condition of cooperation as the national brand’s customer, to being a competitor of the national brand. It is therefore vital to consider the change in relations with the manufacturer when store brands are present (introduced), and extremely important to understand the retailer’s rationale for introducing a private label.

Researchers have identified several key reasons that retailers have to introduce a store brand into an existing category. First the retailer may wish to improve its negotiation power vis a vis the manufacturers (Krishnan and Soni, 1997; Narasimhan and Wilcox 1998; Scott-Morton and Zettelmeyer, 2000). Second, the retailer may wish to price discriminate among consumers that have different willingness to pay for different quality levels (Scott-Morton and Zettelmeyer, 2000). This can be shown to raise total channel profits. A case where this is especially attractive exists where the manufacturer of one of the national brands uses its excess capacity to produce the store brand.

The third reason the retailer may introduce a store brand is to exploit “gaps” in the product space of competing national brands. Although the manufacturers have successfully created barriers to entry (e.g. via accumulated advertising, or superior distribution—Bain 1959) these barriers to
entry may not apply to the retailer. The retailer often uses an umbrella brand for the store brand, and the only cost of distribution is the opportunity cost of the shelf space for the national brands. Hoch and Banerji (1993) report that private labels tend to capture higher market share in categories where there exist low levels of advertising expenditure (per brand), and where there exist a smaller number of national brand manufacturers (see also Narasimhan and Wilcox, 1998).

In the previous section, we discussed some of the demand side implications of a store brand entry. However, we are also very interested in how the retailer uses the private label to gain channel power. (We note that the decision to launch the store brand is assumed to be exogenous—we do not attempt to model negotiation of whether or not to enter the store brand, e.g. via wholesale price, or the quality level of this store brand.) When faced with multiple manufacturers, the retailer’s decision to introduce a store brand can generate a multitude of different reactions from the manufacturers. This, of course, depends heavily on how “close” the store brand is to the national brand. Indeed, an important facet of the decision to enter the store brand by the retailer is that the retailer can choose the product space location of this store brand. This strategic decision will clearly impact the negotiating position of the “closest” of the national brands first (Scott-Morton and Zettelmeyer, 2000). A limitation on the ability to locate this brand anywhere in the product space, may be the brand association built around the entire store. This holistic brand association has been termed an “umbrella” brand (Wernerfelt, 1988). This constraint arises from the ability for a single product, as a member of the store brand, to damage this umbrella brand. To illustrate, the Dominick’s chain often communicates the overall quality of its supermarket as a relative high quality brand. For example, Dominick’s is the fresh Foods Company. If Dominick’s entered a low quality (example: oats that are not fresh) store brand into a category, consumers who try this brand may reduce their perceptions of the quality of other products marketed under the Dominick’s brand name.

Research on “pioneering advantage”, suggests that brands that are first in a product space tend to enjoy a perceived superiority to subsequent entrants, or are able to tap some pool of risk averse consumers (Schmalensee, 1982). It is therefore typically thought that store brand preferences will not be higher than that of the national brand they are positioning against.

This positioning defines how products are differentiated in the minds of customers. In models
of competition, a typical result when brands can simultaneously choose the locations for their products in common product space, is that firms choose locations with maximal differentiation (d'Aspremont et al, 1979). This differentiation manifests itself in the brand. For manufacturers of nationally branded goods, the branding challenge involves generating a set of positive associations for the brand in the minds of the target market. Positive associations with a brand are sometimes referred to as a brand personality (Aaker, 1997). Many marketers spend vast sums of money in creating and protecting these associations with their brands. Such communication efforts lead to this branding association that is supposed to distinguish the national brand from the store brand. However, in recent years, researchers have suggested that manufacturers are struggling to establish and maintain this brand preference relative to the retailer (e.g. Buzzell, Quelch and Salmon, 1990; Blattberg and Neslin, 1990; Messinger and Chu, 1994). Evidence for this power shift often cited include increased emphasis on trade promotions, slotting allowances, and the use of scanner technologies by retailers. The growing use of private labels is also often cited to be evidence consistent with the growing power of retailers (Raju, Sethuraman and Dhar, 1992).

A critical issue that is the focus of this paper, is how channel power can change as a result of some action of the retailer. In this case, we are interested in the change in relative channel power when the retailer introduces the store brand. However, as has been indicated in past research, an analysis of this issue requires that we study three groups of decision makers: consumers, retailers and manufacturers. In the following sections we build a model which takes into account the different (and often adverse) incentives of these three groups, and test how relative channel power changes before and after a store brand entry to the category.

3 The Model

The model formulation is based on an analysis of interactions and decisions by three groups of decision makers: retailers, manufacturers and consumers. We start by building a model of demand before store brand entry. The model is then expanded to incorporate the behavior of all constituents given a store brand exists in the category. Our reported results are based on “before” versus “after” comparisons while using information from both regimes simultaneously. An important caveat to our analysis is that the available data (see section 5) are limited to a single retail chain, so we do
not explicitly model retailer-retailer interactions.

We begin our model formulation by stating structural equations for consumer demand, and for retailer and manufacturer pricing decisions. These identify, for each group of decision makers, the objective functions with regard to the marketing of the focal brand(s) within this channel. For simplicity, dynamic and lagged (or carryover) effects are not studied in this model. We thereby also rule out the possibility that consumers are “strategic”, in the sense that they use information from the observed marketing mix (e.g. price and quality) to infer the actions arising within this market structure. We then discuss the primary changes in interactions among channel members before and after the entry of the store brand. We follow the methodology developed by Berry (1994) and Berry, Pakes and Levinsohn (1995), for empirically analyzing market equilibria in differentiated product markets. This technique allows the researcher to generate parameter estimates for both demand and supply equations in multiproduct oligopoly markets.

3.1 Demand Equations for Brand Choice of Retailer’s Products

A representative consumer $i$ who chooses and consumes product $j$ ($j \in J$) at time $t$ has indirect utility:

$$U_{ijt} = \alpha_{ij} + \beta_i p_{jt} + \gamma d_{jt} + \mu_{jt} + e_{ijt}$$  

(1)

where $d_{jt}$ is a deal variable, $p_{jt}$ is retail price, $\beta_i$ is price sensitivity, $\alpha_{ij}$ is a brand specific preference parameter, and $\gamma$ is the sensitivity to the retailer’s deal activity (e.g. display or feature). The value $\mu_{jt}$ is a mean zero demand shock. Other than being mean zero, we make no additional assumptions on the distribution of $\mu_{jt}$. This demand shock is specific to brand and time period and stems from factors such as shelf space and shelf location that vary from week to week. $\mu_{jt}$ can therefore, be correlated with the prices, $p_{jt}$. The term $e_{ijt}$ denotes the consumer, brand and time-specific error term that is observed by the consumer but not by the researcher. A notational convention used throughout this paper to represent the number of brands in the choice set is $J$ for the number of national brands and $J + 1$ for the number of national brands plus the store brand.

The demand system also includes the option of an “outside good”. The use of an outside good allows for the consumer to decide not to choose any of the brands in the category. The indirect
utility for the outside good is:

\[ U_{i0t} = \alpha_{i0} + \lambda S_d + \mu_{0t} + \epsilon_{i0t} \]

Where \( S_d \) is a seasonal (or event) dummy used to control for seasonality in the utility for the product category. By setting \( \alpha_{i0} \) to zero, the mean utilities of included brands can be identified and estimated relative to the outside good’s mean utility.

For the remainder of the demand specification, decompose the \( U_{ijt} \) from (2) and (1) into the following components:

\[ U_{ijt} = V_{ijt} + e_{ijt} \]
\[ U_{i0t} = V_{i0t} + e_{i0t} \] (2)

In our characterization of demand, we allow for consumer heterogeneity. Consumer heterogeneity takes two forms: one is with respect to intrinsic brand preferences (taste) and the other is with respect to price sensitivity. The heterogeneity is captured in the demand specification (1) by the use of random coefficients, for brand intrinsic preferences \( (\alpha_i = \{\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{iJ} \text{ or } \alpha_{iJ+1}\}) \) and for the price sensitivities \( (\beta_i) \):

\[ \alpha_i = \alpha + \epsilon_i \quad \text{where} \quad \epsilon_i \sim N(0, \Sigma) \] (3)
\[ \beta_i = \beta + \epsilon_{i\beta} \quad \text{where} \quad \epsilon_{i\beta} \sim N(0, \sigma^2_{\beta}) \] (4)

The parameters \( \beta \) and \( \alpha \) represent means of the distributions of consumers. In the empirical analysis, we will obtain estimates for the means and variances of these heterogeneity distributions. By estimating the parameters of the covariance matrix \( \Sigma \), we will be able to say something about which of the national brands the store brand is drawing much of its preference share from. Further, the result is a very flexible market share model at the aggregate that avoids the IIA property. For simplicity, it is assumed that the \( \epsilon_{ij} \) and \( \epsilon_{i\beta} \) are uncorrelated. We assume that the \( e_{ijt} \) and \( e_{i0t} \) are iid and drawn from an extreme value distribution. Given our assumption on these terms, the probability of consumer \( i \) purchasing brand \( j \) at time \( t \) has a closed form and is given by the ubiquitous multinomial logit model(McFadden, 1974). At the individual consumer level, this is stated as the probability that consumer \( i \) will choose brand \( j \) from \( J \) or \( J+1 \) at time (week) \( t \):

\[ P_{ijt} = \frac{\exp(V_{ijt})}{1 + \sum_{k=1}^{J \text{ or } J+1} \exp(V_{ikt})} \] (5)
Predicted market shares are obtained by aggregating the individual level choice probabilities aggregated over the choice probabilities of all consumers \(i\) in a given week \(t\). The unknown parameters are estimated by matching up predicted market share \((s_{jt})\) with observed market share \((S_{jt})\). We describe the estimation procedure in Section 5. However, for the simple case where this is no heterogeneity in intrinsic preferences or in the price sensitivity parameter this matching is straightforward. This is accomplished by linearizing the shares which results in a system of (in the pre-entry period) \(J\) linear equations, and then estimating the parameters (see for example, Besanko, Gupta and Jain 1998):

\[
\ln(S_{jt}) = \ln(S_{0t}) + \alpha_j + \beta p_{jt} + \gamma d_{jt} + \lambda S_d + \mu_{jt}
\]

A complication with estimating the parameters in this system is the possible correlation of prices \(p_{jt}\) and \(\mu_{jt}\) mentioned previously. This correlation means we need to use instruments for retail prices. We discuss these instruments in the subsequent sections.

Seasonality is assumed to only affect the choice of the sub-category. That is, seasonality impacts only the value of the “outside good”. By this assumption, the effect of season (Summer) on oatmeal consumption is assumed to not affect the preference ordering of Quaker oats versus the Dominick’s brand. One potential problem with this assumption occurs where the preference ordering is affected by seasonality. This assumption can be challenged if, for example, the Quaker brand is positioned as suitable for (hot) consumption in winter, and the Dominick’s brand is considered better for (cold) consumption during the summer.

### 3.2 Pricing Equations of Channel Members

The supply side problem is complicated by the interactions among retailers and manufacturers. Each national brand manufacturer is assumed to maximize profits for its brand (or set of brands) in the category. Similarly, the retailer is assumed to choose retail price (margins), given the manufacturers’ wholesale prices. This section first reviews the general framework used to model the price equilibria studied in this paper. Then specific assumptions are made about the types of reactions and interactions that are likely to exist among the manufacturers, and between the manufacturers and retailer.
The retailer’s objective is to maximize category profits by setting \( r_{jt} \), or:

\[
\max_{r_{jt}} \pi_r = \sum_{j=1}^{J \text{ or } J+1} r_{jt} M_t s_{jt}
\]  

(6)

where \( r_j = p_j - w_j \) is the retailer’s margin on product \( j \), with retail price \( p_j \). The term \( M_t \) denotes the potential category size at time \( t \) and \( s_{jt} \) is the share of brand \( j \) in week \( t \), given before. The retailer must take into account its interactions with each of the national brand manufacturers that could affect the retailer’s markup on the brands sold in the category. These interactions exist in the first-order conditions generated from the retailer’s maximization problem, and are:

\[
s_{jt} + \sum_{k=1}^{J} r_{kt} \frac{\partial s_{kt}}{\partial r_{jt}} + \frac{\partial s_{jt}}{\partial r_{jt}} = 0
\]  

(7)

where

\[
\begin{align*}
\frac{\partial s_{jt}}{\partial r_{jt}} &= (1 + \theta(w_{jp_j}, r_j)) s_{jt}^j \\
\frac{\partial s_{kt}}{\partial r_{jt}} &= (1 + \theta(w_{jp_j}, r_j)) s_{kt}^j \\
\frac{\partial s_{jt}}{\partial r_{jt}} &= s_{jt}^j
\end{align*}
\]  

(8)

The terms \( s_{jt}^j \) and \( s_{kt}^j \) denote, respectively, the derivatives of the shares of brands \( j \) and \( k \) in week \( t \) with respect to price of brand \( j \). The share expressions themselves are quite complicated given our assumptions on the heterogeneity distribution made previously. Hence, we use simulation to evaluate these expressions (more on this in the next section). Assuming \( R \) draws from the heterogeneity distribution, the derivatives above are given as follows:

\[
s_{kt}^j = -\frac{1}{R} \sum_{r=1}^{R} \beta_r P_{rjt} P_{kt}
\]

and

\[
s_{jt}^j = -\frac{1}{R} \sum_{r=1}^{R} \beta_r P_{rjt} (1 - P_{rjt})
\]

and \( P_{rjt} \) is the probability corresponding to the \( r^{th} \) draw, see (5).

The parameter \( \theta(w_{jp_j}, r_j) \) captures the interactions between the manufacturer of brand \( j \) and the retailer in terms of how this interaction affects the retailer’s margin on brand \( j \). We call this term the interaction or conduct parameter. Consider the simple case with only one brand where
\[-1 < \theta(wp_j, r_j) < 0; \]

\[
r_{jt} = \frac{-s_{jt}}{(1 + \theta(wp_j, r_j))s_{jt}^2} > \frac{-s_{jt}}{s_{jt}^2}
\]

The nature of the interaction between the manufacturer of brand \( j \) and the retailer results in a larger markup than the retailer would have obtained under the “vertical Nash” (see Lee and Staelin 1997) scenario wherein all the conduct parameters are equal to zero. As the value of the conduct parameter approaches zero from below, behavior becomes increasingly similar to the vertical Nash structure. As the conduct parameter approaches -1 from above, the retailer can charge an increasingly higher markup for the brand. Our interest is measuring this conduct parameter before and after the store brand entry to understand whether the retailer is able obtain a higher markup for the national brand.

We now study the manufacturer interactions. In this, we assume that all the national brand manufacturers behave strategically with respect to the retailer. However, we assume that the manufacturer of the store brand does not do so. This enables us to keep the analysis tractable without being too unrealistic.

Given costs, \( c_j \), the manufacturer of brand \( j \) chooses a wholesale price to charge to the retailer, \( wp_j \), to maximize profits. The wholesale price and cost will be the same for all retailers within a given area—the manufacturer thereby sets wholesale price to maximize:

\[
\pi_{jt} = (wp_{jt} - c_j) M_t s_{jt}
\]

Solving this for \( wp_{jt} \) gives the first order condition:  

\[
(wp_{jt} - c_j) \frac{\partial s_{jt}}{\partial wp_{jt}} + s_{jt} = 0
\]

(9)

As with the retailer’s first order conditions, we can write:

\[
\frac{\partial s_{jt}}{\partial wp_{jt}} = (1 + \theta(r_j, wp_j)) s_{jt}^2
\]

\(^1\)Note that for multiple brands, manufacturer \( f \) chooses wholesale prices for \( J_f \) brands to maximize

\[
\pi_f = \sum_{j \in \mathcal{J}_f} (wp_{jt} - c_j) M_s
\]

Where \( \mathcal{J}_f \) represents the set of brands produced by manufacturer \( f \), \( wp_j \) is wholesale price charged to retailers by the manufacturer for brand \( j \), and \( c_j \) is the corresponding marginal cost. This gives \( J_f \) first order conditions:

\[
s_j + \sum_{j \in \mathcal{J}_f} (wp_{jt} - c_j) \frac{\partial s_j}{\partial wp_{jt}} = 0
\]
Here $\theta(r_j, wp_j)$ captures the nature of interactions between the manufacturer of brand $j$ and the retailer in terms of how this interaction affects the manufacturer’s margin on brand $j$.

We observe wholesale prices charged to the retailers by the manufacturers of national brands. However, in our data we do not observe marginal costs $c_j$. One job of the estimation is to estimate these marginal costs, based on what we observe from manufacturers’ pricing behavior, as specified in (9). Once the costs are estimated, we can compute total channel profits before and after store brand introduction.

3.3 The Measure of Relative Channel Power

Our measure of power is based on the share of channel profits enjoyed by various channel members. For the retailer, total channel profit generated by brand $j$ is $r_{jt} M_{t'sjt}$, where $r_{jt} = p_{jt} - wp_{jt}$ is the retailer’s margin. The channel profit for the manufacturer of brand $j$ is $(wp_{jt} - c_j) M_{t'sjt}$.

Consequently, we can write the share of channel profits for the manufacturer:

$$SC_{\pi_m} = \frac{(wp_{jt} - c_j) M_{t'sjt}}{(p_{jt} - wp_{jt}) M_{t'sjt} + (wp_{jt} - c_j) M_{t'sjt}} = \frac{(wp_{jt} - c_j)}{(p_{jt} - c_j)}$$

The share of channel profits for the retailer is:

$$SC_{\pi_r} = \frac{(p_{jt} - wp_{jt}) M_{t'sjt}}{(p_{jt} - wp_{jt}) M_{t'sjt} + (wp_{jt} - c_j) M_{t'sjt}} = \frac{(r_{jt})}{(p_{jt} - c_j)}$$

As noted previously, it is necessary to generate estimates of manufacturer’s costs. Our estimation approach enables us to do this.

4 Estimation Procedure

Our analysis represents an equilibrium model, where we allow output and demand to interact to generate the equilibrium prices. We have assumed that the equilibrium can be characterized using the equations (5), (9) and (6). The challenge for the estimation is to simultaneously estimate:

1. The parameters of the logit demand function (5), i.e. the brand intercepts and the effects of marketing mix variables

2. The parameters characterizing the distribution of unobserved heterogeneity. In particular, we can estimate the mean and variance of the distribution of preferences and price sensitivities across households.
3. The manufacturer marginal costs for each of the brands in the category under consideration.

4. The conduct parameters that reflect the nature of interactions between the manufacturers and the retailer.

In addition there are three key issues to also be confronted in the estimation. First, data is only observed at the aggregate level. That is, what we observe are category shares, and the corresponding price and promotional variables at level of the chain or store. Second, price endogeneity implies that there exists a potential correlation between \( p_{jt} \) and \( \mu_{jt} \). The third issue concerns how retailers and manufacturers interact in determining retail prices (after resolving the endogeneity issue).

The solution lies in the use of methods in discrete choice models developed by Berry (1994), BLP (1995) and Nevo (2000). Generalized method of moments estimation is used with the demand equations, as well as with each of the first order conditions stemming from the manufacturer retailer interactions.

For full details of the estimation procedure, the interested reader is referred to BLP (1995) or Nevo (1998/2000). In the following, we outline the estimation procedure. As mentioned in the introduction, we do not observe individual brand choices in our data. Instead the observed brand choices take the form of market share, which can be viewed as an aggregation of individual probabilities \( P_{ijt} \) across all consumers \( i \) within a given week \( t \). Nevo (1998) explains the details behind the simulation that is required to aggregate the logit choice probabilities to market shares.

Next we make some initial guesses for the model parameters, \( \theta = \{ \alpha_j, \beta, \gamma, \lambda, \sigma_j, \sigma_\beta \} \) One way to obtain these initial estimates, is to run a simple OLS regression on a logit-transformed market share demand equation. This will give us values for the mean intrinsic preferences, mean price sensitivity and the effects of other variables included in the demand model. For the variance terms characterizing the heterogeneity distribution, we pick small non-zero starting values.

Given the data, the initial guesses of the model parameters, and the logit specification for brand choice probabilities in (5), we simulate the individual probabilities by drawing from the distribution of the random effects. The individual probabilities are then aggregated to obtain predicted category shares. In the estimation we used 200 draws to simulate the choice probabilities.
It is now possible to obtain the model parameters that minimize the distance between the observed brand shares and the shares computed earlier. A problem with this is that \( \mu_{jt} \) is an unobserved “error” term. In comparing observed brand shares with predicted shares, we cannot easily disentangle the brand specific error terms from the unobserved error term \( \mu_{jt} \). For this to be estimated, we first note that for consumer \( i \) we can decompose \( V_{ijt} \) as follows:

\[
V_{ijt} = \{ \alpha_j + \beta p_{ijt} + \gamma d_{ijt} + \lambda S_d + \epsilon_{ij} + \beta \epsilon_{ij} \} + \mu_{jt} \\
= \phi_{ijt} + \mu_{jt}
\]

(12)

(13)

We now treat \( \mu_{jt} \) as an unknown brand and week specific quantity. Given the data and the model parameters, draw \( D (=200 \text{ in our case}) \) draws from the heterogeneity distribution and compute \( \phi_{ijt} \).

To estimate \( \mu_{jt} \), the algorithm must numerically solve for \( \phi_{ijt} \) by minimizing the distance between observed brand shares and the shares computed by aggregating the individual probabilities obtained using \( \phi_{ijt} \). BLP show that for the triple \( \{s_{jt}, P_{jt}, \theta\} \), there exists a pointwise contraction mapping which allows a minimization of \( (s_{jt} - P_{jt}) \), from the choice of the \( \mu_{jt} \). Moreover, the contraction mapping property implies that we can solve for \( \mu_{jt} \) recursively.

The result of this minimization is a vector \( \mu = \{\mu_1, \mu_2, \ldots, \mu_{J+1,t}\} \). This vector represents the “error term” that we use to drive the GMM objective function, for the demand side. With the set of instruments \( Z_t \) we know that \( \text{E}(\mu_t Z_t) = 0 \), and the model parameters can be estimated using generalized method of moments.

However, we have not yet considered the pricing equations arising from our study of channel members’ behavior. For simplicity in exposition, we describe the pricing equations for a two-brand case - a national brand \( j \) and a store brand \( J \). As noted previously, we will have 2 retailer pricing equations and one manufacturer pricing equation (given the assumption of non-strategic behavior by the store brand manufacturer). Then, from the first order conditions in (9) and (7):

\[
p_{jt} - wp_{jt} = \frac{(s_{jt} s_{jt}^f/(1 + \theta(wp_j, r_j))) - s_{jt}^i s_{jt}}{s_{jt} s_{jt}^f - s_{jt}^i s_{jt}} = \xi_{jt} \\
= \xi_{jt} \\
p_{jt} - wp_{jt} = \frac{(s_{jt} s_{jt}^f/(1 + \theta(wp_j, r_j))) - s_{jt}^i s_{jt}}{s_{jt} s_{jt}^f - s_{jt}^i s_{jt}} = \xi_{jt} \\
wp_{jt} - c_j + \frac{s_{jt}}{(1 + \theta(r_j, wp_j)) s_{jt}^f} = \eta_{jt}
\]
First, note from the above equations that the unique parameters to be estimated from the retailer pricing equations are the interaction parameters. And those from the manufacturer equations are the costs and the interaction parameters. Where do the residuals in the above equations come from? Recall that in the retailer pricing equations, the wholesale prices are observed. However, these observed wholesale prices may not reflect the actual prices precisely due to the way in which the retailer accounts for the weekly costs of the items sold. Hence the error in the retailer pricing equations. Similarly, in the manufacturer pricing equations, the residuals denote the errors in estimating the manufacturer marginal costs. The residuals are assumed to be mean zero, so can therefore be stacked on to the vector of demand residuals $\mu_t$, previously obtained. Let the vector $\Gamma_t = \{\mu_{1t}, \mu_{at}, \ldots, \mu_{jt}, \xi_{1t}, \xi_{2t}, \ldots, \xi_{jt}, \eta_{1t}, \eta_{2t}, \ldots, \eta_{jt}\}$. We call this vector a “structural” residual, since they are generated by considering the economic behavior that underlie the models which generate such residuals.

Given a set of instruments $Z_t$, we know that $E[\Gamma_t Z_t] = 0$. So the parameters in the model can be estimated using GMM. Then, given the vector structural residuals just described, $\Gamma_t$, and the instruments $Z_t$, and a “true” parameter vector, $\theta^*$ the population moments are:

$$E[Z_m \cdot \Gamma(\theta)] = 0, \quad \forall \ m = 1, \ldots, M$$

(14)

At the true parameter values $\theta^*$ this population moment is equal to zero.

The corresponding GMM estimate based on these population moments is:

$$\hat{\theta} = \arg\min_{\theta} \quad \Gamma_t(\theta)'Z_tA_t^{-1}Z_t\Gamma_t(\theta)$$

(15)

Estimation then involves finding the values for $\theta$ which solves (15). The weight matrix $A$ is essentially a variance-covariance matrix of the moments, and is thereby used as a metric to measure how close to zero we are in (15). This weight matrix gives less weight to moment conditions which have higher variance. We generate the moment conditions both prior to and after introduction of the store brand. Given that some of the parameters remain the same in both time regimes, we estimate the entire set of parameters simultaneously rather than estimate the before and after parameters separately.
4.1 Identification Issues

We allow the mean preference and price effect parameters of the demand functions to change with the introduction of the store brand. We also set the variance of the price effect to change into the introduction. However, with a large number of brands, the covariance matrix of preferences involves a large number of parameters. We impose the following restrictions. For the oats data, as we have only one national brand and one store brand, we assume \( \Sigma \) to be diagonal. For the pasta data we have four national brands and one store brand. In principle, this implies estimating 10 parameters before and 15 parameters after introduction. We decrease the computational burden via the following parameterization:

\[
\epsilon_{ij} = \sigma_{NB} \rho_{ij} + \sigma_j \rho_i
\]

where \( \sigma_{NB} \) is a parameter common to all national brands, \( \sigma_j \) is a parameter specific to brand \( j \), \( \rho_{ij} \) is a draw from \( N(0, 1) \) for brand \( j \) and \( \rho_i \) is a draw from \( N(0, 1) \) common to all brands. Hence we have five parameters to be estimated before introduction and six after. We further impose the condition that the \( \sigma_j \)'s are invariant to the introduction, resulting in a total of seven parameters.

In the retailer pricing equations, we allow the interaction parameter \( \theta(wp_j, r_j) \) to change with the introduction of the store brand. Given one parameter for each equation, these parameters are all identified for the manufacturer pricing equations (note that \( wp_{jt} \) is observed), we cannot uniquely identify both the marginal cost and the interaction \( \theta(r_j, wp_j) \) parameters either before or after introduction. We can impose one of two sets of identifying restrictions. The first strategy is to keep the manufacturer cost-to-serve (the retailer) parameters the same both before and after introduction (albeit brand specific). In this way, we can estimate one set of interaction parameters (either before or after introduction) and say something about the relative nature of interactions pre- and post-introduction. The alternative approach, the one we adopt here, is to allow the manufacturer cost parameters to change with the introduction but constrain \( \theta(r_j, wp_j) = 0 \) both before and after introduction. This will enable us to draw inference about the possible shift in channel power—one of our objectives in the paper.

Before proceeding to the empirical results we address an important issue dealing with the change in parameters post entry. If we do find the demand and supply parameters to be affected,
could it be because of factors other than the store brand entry. These could be either systematic or random factors. When choosing the specific product categories to include in the analysis, we attempted not to include those categories in which there did appear to be systematic effects. One such category is toothbrushes. While this was a largely dormant category till about the early 1990s, the manufacturers of the national brands started accelerating their brand development efforts by the mid 1990s. As a result a number of innovations were introduced in the marketplace with an associated increase in the average retail prices of toothbrushes. Hence, there was an external event driving the category during the time period of the data. This drove our choice not to include the toothbrush product category in our analysis.

5 Description of the Data

The data is based on scanner data from a large mid-western supermarket chain. This supermarket chain with 96 stores around the metropolitan area of Chicago IL, is one of the two largest supermarket chains in this area. A number of variables are available to the analysis, at various levels of aggregation. The variables include unit sales at the UPC level, retail and manufacturer prices, a summary variable on retail level “deals”, seasonality dummies and store traffic.

A total of 399 weeks are available, from 09/14/89 to 05/01/97. Our estimation sub-sample is chosen around the entry of the store brand. There are several criteria used to select the estimation subsample. First, at least one year of data must be available prior to entry of the store brand. Second, we allow a number of weeks to elapse after entry of the store brand to allow the market to stabilize to an equilibrium. This allows full distribution to take effect (the majority of consumers have the opportunity to choose this brand) and time to stabilize to a new equilibrium.

Sales data at the UPC level are aggregated across both sizes (e.g. 40oz, 12oz) and brand variants (e.g. Quaker quickcook rolled oats is combined with Quaker regular rolled oats). Sales data at the store level is available for all categories. The analysis tests the entry of a new store brand to a sub-category wherein store brands had not existed previously. From a total of 142 sub-categories as defined by IRI, we found six categories for which there existed sufficient data on storebrand entry and enough data before and after the entry of the store brand. Another 62 categories contain the DFF brand. Thus about 10 per cent of the categories saw a store brand
entry within the observation period.

Out of the six categories where we found a store brand entry, the categories selected for analysis are oats and pasta. No major brands were introduced to the supermarket shelves over the estimation period. There existed four incumbent national brands in the pasta category and one incumbent brand in the oatmeal category.

Weekly level store traffic figures are available and are used to help compute the “outside good”. This is a market potential figure, estimated based on the average quantity purchased by households and aggregated to the total number of people visiting the stores, then aggregated across stores if necessary. The outside good is used to normalize the brand preferences to a common good. If brands are normalized to one of the national brands, there is some difficulty in comparing brand preferences of national brands pre and post entry of the store brand.

These categories vary with the profitability and sustained performance of the new store brands. Table 2 reports selected descriptive statistics for both categories studied, with a comparison of data before and after entry of the store brand. Each row reports individual brands’ prices, sales and retailer margins, as an average (mean) per week and aggregated across all stores.

Wholesale and retail prices are deflated using the consumer price index (source: BLS, Bureau of Labor Statistics). Although the CPI index is reported monthly, weekly estimates of this figure are generated by assuming the CPI index is constant over each week of the corresponding month. The base (=100) is week one of our observation series (week beginning 09/14/89).

5.1 Instruments

Exogenous instruments are required for identification of the population moment conditions in (15). We need to identify and use instruments $Z_t$ such that $E[\Gamma Z_t] = 0$. Instruments for price can be generated based on the attributes of the products (e.g. Nevo, 2000; Berry et al. 1995), other stores’ or retail zones’ pricing activities, raw materials costs and so on. After considering and testing several groups of such instruments, we selected lagged wholesale prices for our instruments of retail prices. The argument for using lagged wholesale prices is that time-varying unobserved attributes are likely to correlated with in-store activities such as shelf space and shelf location. These activities are likely to correlated with retail prices, but less likely to be correlated with
wholesale prices. Wholesale prices are usually set over a larger area (e.g. the Chicago metropolitan area). Hence, while it can be argued that manufacturers take the conditions in the local chains into account while setting prices, this is much less likely to be the case. In other words, activities such as shelf space and location are less likely to be correlated with lagged wholesale prices. This drives our choice of instruments for price. For the retailer pricing equations, we use the additional information on lagged promotional variables and seasonality to instrument for the shares. A similar strategy is used for the manufacturer pricing equations. We did attempt to study sensitivity of our results to the choice of instruments. However, given the limited amount of information at our disposal, this is not an easy task.

6 Results
6.1 Descriptive

Table 2 reports descriptive statistics for both oats and pasta categories. We focus on reporting aggregate sales, market share, wholesale prices, retail prices and deal statistics. We describe the changes in the descriptive statistics for each category in turn.

Oats category - The Dominick’s label of store brand was introduced during the month of October (1993), the beginning of the fall season in the Chicago metropolitan area. A total of five UPCs (Universal Product Code) were introduced in the same week: regular oats quick cook (18oz and 40oz), regular oatmeal (12oz), brown sugar and maple flavored oatmeal (15oz) and variety oatmeal (13.8oz). The flavor: “apple and cinnamon” was introduced in May of 1995, but otherwise there was no further brand activity for Dominick’s subsequent to entry date. The national brand dropped three UPCs around the time of the store brand entry: cinnamon and spice flavored oatmeal, raisin and spice, raisin and brown sugar. No significant UPCs were added by Quaker until Fall of the year following the store brand entry.

A graphic inspection of the time series of sales and prices (Figure 1) suggests that the entry of the store brand results in a raised volatility in the retail sales and wholesale price (per ounce) of the national brand. The manufacturer now appears to be in the position where there is greater need to offer deals for the retailer in this category. Focusing on the sales subsequent (in Figure 1a), it
appears as if the unit sales baseline is slightly lower, but the periodic spikes are more pronounced. Overall average sales appear about the same. This appears to be confirmed by panel (b) in Figure 1. The wholesale price shows dramatic spikes corresponding to the weeks where the sales spikes occur.

First note that the store brand coincides with a substantial shift in category level demand, of about 16.2%. The store brand also commands a substantial share relative to the national brands. The store brand captures just under 16% of the category share (excluding the outside good). Average (deflated) wholesale prices declined by 7.3%, while average deflated retail price declines by 4%. This is consistent with Narasimhan and Wilcox (1997), who state that this effect arises from the improved negotiating position of the retailer relative to manufacturers. Hence, the first key effect of the store brand introduction appears to be a reduction in the selling price the manufacturer is able to command from the retailer. As a consequence, the resulting margin that the retailer enjoys for the Quaker brand increases by about 14%.

The last row of Table 2 reports the change in weekly profits for the retailer, before versus after store brand entry. The total weekly profits increased by 35.3%, with the store brand accounting for over 25% of the weekly profits. Interestingly, the retailer has also enjoyed an increase in profits from the Quaker brand. This is from the increase in retail margin, combined with only a small offset in sales for the Quaker brand.

Finally, the entry of the store brand appears to be accompanied by quite aggressive promotional effort by the retailer. As Dhar and Hoch (1997) point out, this is a hallmark of a successful store brand introduction by a retailer. The national brand, on the other hand, promoted at about half the intensity as before the store brand entry.

Figure one goes here—sales and price time series

**Pasta category** - The pasta category consisted of four major national brands. The Dominick’s brand was added late November 1994, with five products, including Lasagna (80oz), Tortellini and Ravioli, (regular and cheese, 16oz).

There were no new brands introduced by the incumbent manufacturers. Among the existing brands, Floresta added Gnocchi and Tortellini about 10 weeks after the store brand entry. Rosetto added a range of Ravioli UPCs about one year later. There was one other brand that prior to store
brand entry accounted for about 1.4% of category share, and after store brand entry accounted for about 0.4%. This brand was owned by Belgo Foods Products, which also markets the Mrs Belgos pasta brand.

Studying the descriptive statistics in Table 2 we observe that the store brand managed to capture quite a significant amount of share within the category, relative to the incumbent national brands. Also a notable feature is that both categories witnessed a substantial increase in the category size after store brand entry. Average (retailer) weekly profits for the entire Pasta category increased by 14%. Table 2 gives the impact of the store brand entry on individual national brands’ margins, a discussion to which we will return to later.

Of note is the mixed reactions and consequences of the retailer’s store brand on prices, promotions and category share. The interesting feature about changes in retail prices is how the store brands were positioned after entry. Both Italia and Mrs Belgos, each with about the same share, saw retail prices diminishing slightly by about five per cent. Wholesale price for Mrs Belgos declined by about the same amount. It appears as if the entire decline in wholesale price was passed on to the consumer. Moreover, Mrs Belgos had little promotional activity which indicates that price is the key negotiation mechanism between the manufacturer and the retailer. Italia’s wholesale price declined by about 15%, and promotional activity increased quite significantly.

From the descriptive statistics, two of the national brands appear to have improved their position with retail chain. Floresta, which actually gained share, saw an increase in retail price by about 13%, with a decline in wholesale price of around 26%. Likewise, the dominant share brand, Rosetto, also gained significant category share, but saw its retail price unchanged. There is, however, a notable change in promotional activity by both these brands.

We hold off any speculation and discussion of these descriptive results until after we have more closely examined the estimates of both demand and of relative channel power parameters. The results of which we report in the next subsection. However, it is important to note that the wholesale price for the store brand is quite high relative to the wholesale prices of the national brands. This indicates that the retailer does not have a significant cost advantage in this category (unlike in the oats category). It is of interest to determine whether this affects the outcomes for the retailer in the pasta category.
6.2 Results From Estimation

We now report results from the estimation. We generated the outside good based on weekly store traffic data. For this we assume that each person entering the store has the potential to purchase in the category. Given a customer purchases in the category, the “potential purchase” volume is simply the average amount purchased by this person in a given week. This average amount was calculated using a weighted average of the packsizes available within the focal category.

The parameter estimates generated by the GMM estimation procedure, for both categories studied, are reported in Table 3. The summer seasonal dummy was estimated for the entire category, and we assume that this value does not change as a result of the entry of the store brand. For each of the categories, we first report the parameter estimates for the impact of the store brand entry on the distributions of brand preferences and price sensitivities. We then report on the changes in channel profits, and the estimated relative shares enjoyed by each channel member.

Oats category - Starting with the oats category, the store brand entry had a significant impact on the brand preference of the Quaker brand. Specifically, the mean brand preference for Quaker has increased with the amount of heterogeneity associated with this preference level, as measured by \( \hat{\sigma}_{NB} \), declining from the pre-entry period. A possible explanation for this finding is that prior to the entry of the store brand, consumer preferences in the category were driven by a single brand at different price levels (recall that prior to entry, Quaker was promoted more frequently by the retailer). After store brand introduction, consumers have a choice and their preferences get clustered around their preferred brand with many more customers preferring Quaker to the store brand. This also explains the estimated heterogeneity parameter being quite small for the store brand relative to that of the post-entry national brand. Another explanation is that the preference distribution is affected by the way the store brand is positioned relative to the national brand. We discuss this in greater detail in the pasta category. As Table 2 indicates, the store brand introduction is accompanied by an increase in the units sold in the oats category.

Changes in the distribution of price sensitivity are also observable in Table 3, and are graphically displayed in Figure 2(a,b). First we note that the mean price sensitivity parameter increases by around 50% after the store brand enters the category. The heterogeneity is measured by the
estimated value $\sigma_{\text{Price}}$. This also increases by about 50%, consistent with greater heterogeneity post-entry. What this implies is what national brand manufacturers have been fearful of - that store brands have increased price sensitivity. Our results indicate this to be true, at least for the oats category.

Figure two goes here - price distributions

Having discussed the estimates of the demand function parameters, we turn now to those from the pricing equations. The bottom four rows of Table 3 report the estimates of the conduct parameters discussed in the model section. Recall that the lower values for these conduct parameters result in a stronger position for the retailer. For the oats category, the value for $\theta(w_{pj}, r_j)$ was 2.162 prior to store brand entry. After the store brand entered, this declined to 0.891. Although much of the power in the channel still exists with the manufacturer as we shall see below, this result is very much in favor of the retailer. What are the implications of these conduct parameters for channel power?

Table 5 summarizes the differences in relative channel power before and after store brand entry, for each of the brands in both categories. The estimated manufacturer costs are listed in the first column of numbers. The increase in the Quaker oats manufacturer cost can be explained by the need to increase trade promotions and other costs involved in continuing to encourage the merchandising efforts of the retailer, now that the retailer has a private label.

The column entitled “TCP” refers to the average weekly Total Category Profit, per unit (oz) sold within the category. This can be computed since we estimate manufacturers’ costs. We are now able to report the (estimated) share of channel profits accruing to the retailer and manufacturer, and compare this before and after entry of the store brand. For the oats category, we find that, although the total category profits declined by about 17% due to the higher costs faced by the manufacturer, the share of category profits to the retailer increases by about 54%. Moreover, as reported in the descriptive statistics earlier, the category sales increase after the store brand enters. Hence, relative channel power has indeed shifted from Quaker to the retailer in this category.

**Pasta category** - Consistent with the results reported for descriptive statistics, the store brand had mixed effects on the pasta category national brand preferences. First note that the relative
ordering of brand preferences remains unchanged after store brand introduction. The extent of relative movement in preferences across national brands may be explained by the positioning of the store brand relative to national brands. We return to this issue later in the section. However, as Heilman et al. (2000) point out, preferences for brands do evolve over time. While we do not explicitly study this evolution (given the aggregate nature of our data), we are able to detect a shift due to the introduction of a new brand. Looking at the heterogeneity in brand preferences, we find from the table that, similar to the oats category, the heterogeneity for the national brands is higher than for the store brand. However, unlike the results from the oats data, we find that the extent of heterogeneity increases with store brand introduction. This could be due to the fact that frozen pasta being a "prepared" meal is more likely to elicit diverse reactions than compared to a product like oats. One could argue that the presence of multiple brands in that case, itself results in a wide dispersion in preferences across brands.

Table 3 (see also Figure 2c,d) also seems to indicate a decline in mean price sensitivity and also in the amount of heterogeneity in price sensitivity post store brand entry. To verify this, estimated price elasticities are presented for the pasta category in Table 4. The table indicates only a slight decline in price elasticity for all national brands. The apparent discrepancy between the price sensitivity parameter and the elasticities stems from the estimated price-promotion interaction variables. We find that the national brands have roughly equal own price elasticities prior to entry of the store brand. Post entry, however, some differences emerge. These could be due to differences in store brand introduction. Turning to the cross elasticities in Table 4, we find the following. There appears to be mixed asymmetries in the cross-price sensitivities. Focusing on the store brand, high cross-price asymmetry is reported in \{ Dominick’s-Rosetto \} and low asymmetry for \{ Mrs Belgos-Dominick’s \}. It is interesting to see what happened to the cross-price elasticities themselves after the store brand entered this category. In particular, the ability for the brands national brands to attract buyers of all other national brands declined somewhat. The effect seems most pronounced for Mrs Belgos and Italia. Interestingly, the estimated relative brand preferences of Italia and Mrs Belgos declined substantially also (relative to the declines in the other brands).

Returning to Table 3, we find some changes in the conduct parameter estimates for the pasta category. However, these changes are quite small. For Mrs. Belgos, Italia and Rosetto, we find
almost no change in the conduct parameter estimates. However, for Floresta, the retailer seems worse off after the store brand introduction. To verify this, we present the estimates of the manufacturer costs and the sharing of total channel profits in Table 5. The manufacturer costs estimates indicate that Italia and Rosetto seem to have managed some “belt-tightening” after the store brand introduction. The costs of Mrs. Belgos have remained almost the same, with Floresta indicating an increase in costs.

We find that the total retail profit (per unit) of both Mrs Belgos and Floresta stays about the same, since there is a slight increase in the profit per unit and a slight decline in the retailer’s share of this profit. For Italia, both total unit profit and the share the retailer gets from this increase, which leads to a slightly improved position for the retailer with this manufacturer. While the retailer’s profits from Floresta remain about the same, the retailer nevertheless appears to be worse off relative to the manufacturer of Floresta. Why might this be the case? In Table 6 we present the preference correlation matrix (obtained from $\Sigma$) after the store brand introduction. This table indicates that there is high negative correlation between Dominick’s (the store brand) and Floresta. In contrast, there is a positive correlation between the store brand and Italia. This implies that, of the national brands, Floresta is the least threatened by the store brand introductions, whereas Italia is the most threatened. This is reflected in the retailer share of category profits (Table 5) and also the sales data in Table 2. These findings also seem to support those of Scott-Morton and Zettelmeyer (2000) that the retailer’s positioning of the store brand relative to a national brand could have consequences for its relationship with the national brands.

An interesting question therefore, is what explains the differences in results from the oats and pasta categories in terms of relative channel power. In other words, why did we find a shift in oats but not so in frozen pasta? Our explanation for this is the retailer’s relative cost advantage in the oats category (its costs, i.e., the wholesale prices for the store brand are about half of those for the national brand). Consequently, the retailer is able to pose more of a threat by potentially increasing the retail price gap between the national and store brands. Further, given the virtual monopoly of Quaker in this product category, it is quite likely that the firm was making large profits in the category. This made it more vulnerable to entry by the store brand (of course, it is an interesting issue as to why there is so little branded competition to Quaker. While this could
be due to the close association of the Quaker brand name to the oats category, it is nevertheless an issue that needs further investigation). In the pasta category, the retailer has little or no cost advantage. Hence, it is unable to use the store brand to extract a significantly better deal from the national brands.

7 Conclusions

In this paper, we have attempted to provide a within category analysis of the effects of store brand entry. These effects are examined from two perspectives - the demand side and the supply side. On the demand side, our main focus has been on investigating the impact of store brand entry on the preferences of the national brands in the category. The effects on the mean preference levels and also on the heterogeneity of preferences are examined. Additionally, we have also studied the impact of the introduction on the price sensitivities of consumers.

On the supply side, the study has attempted to accomplish several things. First, we have attempted to measure the nature of manufacturer-retailer interactions prior to and post store brand introduction. And we have estimated the manufacturer costs of serving the retailer under the two regimes. Answering these questions has enabled us to shed some light on the issue of relative channel power and how it is affected by store brand entry.

There are of course, several caveats to our analysis. First, while we have tried to focus our attention only on those product categories in which the store brand entry was the dominant event, there could have been other systematic factors affecting our ”before and after” estimates. Second, having data from a single retailer could affect our conclusions on various levels. We have assumed that the retailer is a multi-product monopolist. This is not the case as there is a very big competing chain to the one analyzed in the market under consideration. We did attempt to partially account for the effects of retail competition by including lagged values of the store traffic variable in the retailer’s pricing equation. The logic for this is as follows. Suppose, due to retail competition, store traffic at the chain falls in a particular week. Then the retailer might be inclined to lower its prices in response to this reduction in order to attract consumers back into its stores. If this is the case, then the lagged store traffic variable must have a negative effect on the retail prices for some of the brands in the product categories under consideration. We did not find any significant effects
for the two product categories analyzed. While this does not necessarily imply their are no retail competition effects, it is perhaps a useful starting point.

Another consequence of our data constraint is reflected in our assumptions driving the manufacturer pricing equations. Specifically, we assumed that a manufacturer’s cost to serve a retailer varies across retailers. However, manufacturers set base price levels taking into account the total demand in a local market. (although net prices could vary across retailers due to quantity discounts, brand development funds, etc.). Further, one would expect a single retailer’s introduction of a store brand to differentially impact the manufacturer interactions across retailers. Hence, it would be important to investigate the sensitivity of our assumption regarding manufacturers’ “one to one” interactions with the retailer. This would require a more complete characterization of manufacturer pricing and is left for future research.

In summary, we find there to be both demand as well as supply effects of store brand entry. However, these effects vary across product categories. In one category, oats, we find an increase in price sensitivity as well as a shift in relative power from the manufacturer to the retailer. Whereas in the pasta category, we find small demand effects and virtually no impact on relative channel power.
References


Table 1: “The Balance of Power Keeps Shifting...”

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<td>26%</td>
<td>74%</td>
<td>55%</td>
<td>45%</td>
<td></td>
</tr>
<tr>
<td>Manufacturers</td>
<td>15%</td>
<td>85%</td>
<td>87%</td>
<td>13%</td>
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</table>

Notes:
Table 2: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Sales</th>
<th>Share</th>
<th>Retail Price ($ per 10 oz)</th>
<th>Wholesale Price</th>
<th>Margin (%)</th>
<th>Promotion</th>
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<tbody>
<tr>
<td><strong>OATS CATEGORY</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td><strong>Brand</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Dominicks</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>After</td>
<td>71,164</td>
<td>0.0023</td>
<td>0.0836</td>
<td>0.0401</td>
<td>0.511</td>
<td>0.2089</td>
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<tr>
<td>Quaker</td>
<td></td>
<td></td>
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<tr>
<td>Before</td>
<td>384,777</td>
<td>0.0115</td>
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<td>After</td>
<td>375,986</td>
<td>0.0124</td>
<td>0.1152</td>
<td>0.0884</td>
<td>0.233</td>
<td>0.0860</td>
</tr>
<tr>
<td><strong>PASTA CATEGORY</strong></td>
<td></td>
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</tr>
<tr>
<td>Dominicks</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>After</td>
<td>21,743</td>
<td>0.011</td>
<td>1.027</td>
<td>0.812</td>
<td>0.199</td>
<td>0.238</td>
</tr>
<tr>
<td>Mrs Belgos</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before</td>
<td>16,490</td>
<td>0.008</td>
<td>1.457</td>
<td>0.935</td>
<td>0.358</td>
<td>0.086</td>
</tr>
<tr>
<td>After</td>
<td>12,804</td>
<td>0.007</td>
<td>1.398</td>
<td>0.888</td>
<td>0.364</td>
<td>0.133</td>
</tr>
<tr>
<td>Floresta</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before</td>
<td>27,989</td>
<td>0.013</td>
<td>1.113</td>
<td>0.532</td>
<td>0.504</td>
<td>0.177</td>
</tr>
<tr>
<td>After</td>
<td>34,979</td>
<td>0.017</td>
<td>1.261</td>
<td>0.669</td>
<td>0.451</td>
<td>0.242</td>
</tr>
<tr>
<td>Italia</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before</td>
<td>17,516</td>
<td>0.009</td>
<td>1.145</td>
<td>0.758</td>
<td>0.336</td>
<td>0.085</td>
</tr>
<tr>
<td>After</td>
<td>12,161</td>
<td>0.006</td>
<td>1.091</td>
<td>0.644</td>
<td>0.410</td>
<td>0.161</td>
</tr>
<tr>
<td>Rosetto</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before</td>
<td>39,301</td>
<td>0.020</td>
<td>1.092</td>
<td>0.701</td>
<td>0.355</td>
<td>0.119</td>
</tr>
<tr>
<td>After</td>
<td>50,305</td>
<td>0.026</td>
<td>1.093</td>
<td>0.692</td>
<td>0.366</td>
<td>0.150</td>
</tr>
</tbody>
</table>

Notes:
1. Deals (promotions) are expressed as the percentage of deals run for the UPCs accounted for by the focal brand.
2. All prices are deflated by the Consumer’s Price Index (CPI) to the base month: December, 1989
3. Retail and wholesale prices are expressed as $ per oz (Oats) and $ per 10oz (Pasta)
4. Share is expressed as a fraction of the total market potential, which includes the outside good.
<table>
<thead>
<tr>
<th></th>
<th>Oats</th>
<th></th>
<th>Pasta</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before</td>
<td>After</td>
<td>Before</td>
<td>After</td>
</tr>
<tr>
<td>Dominicks</td>
<td></td>
<td>-3.712 (0.027)</td>
<td></td>
<td>-2.401 (0.164)</td>
</tr>
<tr>
<td>Quaker</td>
<td>-2.634 (0.110)</td>
<td>-1.493 (0.113)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mrs Belgos</td>
<td></td>
<td></td>
<td>1.227 (0.117)</td>
<td>-2.164 (0.140)</td>
</tr>
<tr>
<td>Floresta</td>
<td></td>
<td></td>
<td></td>
<td>-2.281 (0.116)</td>
</tr>
<tr>
<td>Italia</td>
<td></td>
<td></td>
<td></td>
<td>0.684 (0.106)</td>
</tr>
<tr>
<td>Rossetto</td>
<td></td>
<td></td>
<td></td>
<td>1.457 (0.094)</td>
</tr>
<tr>
<td>( \hat{\sigma}_{\text{Quaker}} )</td>
<td>0.797 (0.061)</td>
<td>0.699 (0.080)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \hat{\sigma}_{\text{Mrs Belgos}} )</td>
<td></td>
<td></td>
<td>1.388 (0.138)</td>
<td>2.031 (0.168)</td>
</tr>
<tr>
<td>( \hat{\sigma}_{\text{Floresta}} )</td>
<td></td>
<td></td>
<td>3.119 (0.119)</td>
<td>3.439 (0.142)</td>
</tr>
<tr>
<td>( \hat{\sigma}_{\text{Italia}} )</td>
<td></td>
<td></td>
<td>0.486 (0.044)</td>
<td>1.537 (0.035)</td>
</tr>
<tr>
<td>( \hat{\sigma}_{\text{Rossetto}} )</td>
<td></td>
<td></td>
<td>0.437 (0.009)</td>
<td>1.523 (0.024)</td>
</tr>
<tr>
<td>( \hat{\sigma}_{\text{Dominicks}} )</td>
<td></td>
<td>0.145 (0.086)</td>
<td></td>
<td>1.308 (0.136)</td>
</tr>
<tr>
<td>Price</td>
<td>-1.905 (0.084)</td>
<td>-3.212 (0.118)</td>
<td>-6.905 (0.139)</td>
<td>-3.900 (0.085)</td>
</tr>
<tr>
<td>( \hat{\sigma}_{\text{Price}} )</td>
<td>0.588 (0.039)</td>
<td>0.875 (0.041)</td>
<td>2.228 (0.044)</td>
<td>1.142 (0.035)</td>
</tr>
<tr>
<td>Promotion</td>
<td>0.489 (0.013)</td>
<td>0.178 (0.011)</td>
<td>-0.054 (0.009)</td>
<td>1.047 (0.024)</td>
</tr>
<tr>
<td>Price\timespromotion</td>
<td></td>
<td></td>
<td>0.095 (0.007)</td>
<td>-0.595 (0.016)</td>
</tr>
<tr>
<td>Summer season</td>
<td></td>
<td>-0.745 (0.007)</td>
<td></td>
<td>-0.185 (0.004)</td>
</tr>
<tr>
<td>( \theta(\omega p_j, r_j) )</td>
<td>(Quaker) - 2.162 (0.153)</td>
<td>0.891 (0.154)</td>
<td>(Mrs Belgos) - 0.048 (0.018)</td>
<td>-0.098 (0.009)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Floresta) - - -</td>
<td>0.072 (0.018)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Italia) - - -</td>
<td>0.075 (0.016)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Rossetto) - - -</td>
<td>0.103 (0.016)</td>
</tr>
</tbody>
</table>

Notes:
1. \( \hat{\sigma}_i \) = estimated standard deviation for heterogeneity parameter \( i \)
2. Estimated standard errors in parentheses. For the pasta category we do not report estimated standard errors for \( \hat{\sigma}_i \) as we estimate only a specific decomposition of the covariance matrix.
### Table 4: Price Elasticities

<table>
<thead>
<tr>
<th></th>
<th>Mrs Belgos Before</th>
<th>Mrs Belgos After</th>
<th>Floresta Before</th>
<th>Floresta After</th>
<th>Italia Before</th>
<th>Italia After</th>
<th>Rosetto Before</th>
<th>Rosetto After</th>
<th>Dominicks Before</th>
<th>Dominicks After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mrs Belgos</td>
<td>-3.474</td>
<td>0.296</td>
<td>0.093</td>
<td>0.323</td>
<td>–</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>-3.350</td>
<td>0.176</td>
<td>0.019</td>
<td>0.140</td>
<td>0.013</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Floresta</td>
<td>0.369</td>
<td>-3.253</td>
<td>0.026</td>
<td>0.221</td>
<td>–</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>0.159</td>
<td>-2.919</td>
<td>0.010</td>
<td>0.129</td>
<td>0.003</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Italia</td>
<td>0.107</td>
<td>0.029</td>
<td>-3.232</td>
<td>0.265</td>
<td>–</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>0.027</td>
<td>0.019</td>
<td>-2.936</td>
<td>0.102</td>
<td>0.068</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Rosetto</td>
<td>0.188</td>
<td>0.107</td>
<td>0.133</td>
<td>-3.272</td>
<td>–</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>0.049</td>
<td>0.054</td>
<td>0.024</td>
<td>-2.764</td>
<td>0.030</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dominicks</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.012</td>
<td>0.005</td>
<td>0.045</td>
<td>0.084</td>
<td>-2.830</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:**
1. Price and cross price elasticities for the pasta category only. Market shares used to calculate elasticities are relative to the outside good.
Table 5: Changes in Channel Power

<table>
<thead>
<tr>
<th></th>
<th>Manufacturer Costs</th>
<th>Retailer Markup</th>
<th>TCP</th>
<th>Retailer Share</th>
</tr>
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<tbody>
<tr>
<td><strong>Oats</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quaker</td>
<td>Before</td>
<td>0.028</td>
<td>0.068</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>0.046</td>
<td>0.043</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Pasta</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mrs Belgos</td>
<td>Before</td>
<td>0.493</td>
<td>0.442</td>
<td>0.522</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>0.444</td>
<td>0.444</td>
<td>0.510</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Floresta</td>
<td>Before</td>
<td>0.160</td>
<td>0.372</td>
<td>0.581</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>After</td>
<td>0.192</td>
<td>0.477</td>
<td>0.592</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Italia</td>
<td>Before</td>
<td>0.393</td>
<td>0.365</td>
<td>0.387</td>
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<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>After</td>
<td>0.273</td>
<td>0.371</td>
<td>0.447</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rosetto</td>
<td>Before</td>
<td>0.362</td>
<td>0.339</td>
<td>0.391</td>
</tr>
<tr>
<td></td>
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<td>(0.005)</td>
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<tr>
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<td>After</td>
<td>0.292</td>
<td>0.400</td>
<td>0.401</td>
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<td>(0.005)</td>
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</tbody>
</table>

**Notes:**
1. TCP - Total Category Profit.
2. Estimated standard errors for national brands’ manufacturer costs in parentheses.
Table 6: **Correlation Matrix of Brand Preferences (from Σ)**

<table>
<thead>
<tr>
<th></th>
<th>Dominicks</th>
<th>Mrs Belgos</th>
<th>Floresta</th>
<th>Italia</th>
<th>Rosseto</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominicks</td>
<td>1.00</td>
<td>-0.69</td>
<td>-0.90</td>
<td>0.30</td>
<td>-0.26</td>
</tr>
<tr>
<td>Mrs Belgos</td>
<td>1.00</td>
<td>0.62</td>
<td>-0.21</td>
<td>0.18</td>
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</tr>
<tr>
<td>Floresta</td>
<td>1.00</td>
<td>-0.27</td>
<td>0.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Italia</td>
<td></td>
<td></td>
<td></td>
<td>1.00</td>
<td>-0.08</td>
</tr>
<tr>
<td>Rosseto</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.00</td>
</tr>
</tbody>
</table>
Figure 1: This figure is a time series of the observed sales and wholesale price per ounce of the Quaker brand, allowing the reader to visually compare the effect of the store brand entry.
Figure 2: Visual illustration of the price sensitivity distributions for both categories, depicted as histograms—comparing distributions before and after store brand entry.