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Investigating the Effects of Store-Brand Introduction on Retailer Demand and Pricing Behavior

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Researchers have recently been interested in studying the drivers of store-brand success as well as factors that motivate retailers to introduce store brands. In this paper, we study the effects of the introduction of a store-brand into a particular product category. Specifically, we are interested in the effect of store-brand introduction on the demand as well as on the supply side. On the demand side, we investigate the changes in preferences for the national brands and price elasticities in the category. 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, including how these interactions influence the retailer’s pricing behavior. In doing so, we are also able to test whether the observed data are consistent with some of the commonly used assumptions regarding retailer pricing behavior. For the demand specification we use a random coefficients logit model that allows for consumer heterogeneity. The model parameters are estimated using aggregate data while explicitly accounting for endogeneity in retail prices.

Our empirical results obtained from the oats product category based on store-level data from a multistore retail chain indicate that the store-brand introduction generates notable changes within the category. The store-brand introduction coincides with an increase in the retailer’s margins for the national brand. We find that the preferences for the national brand are relatively unaffected by the introduction of the store-brand. While consumers are, in general, more price sensitive (in terms of elasticities) than they were prior to store-brand introduction, a statistical test of the differences in mean price elasticities across stores and between the two regimes fails to reject the hypothesis of no change in these elasticities. Elasticities in specific stores however, do increase after the store brand is introduced. We also find that there is considerable heterogeneity in the preferences for the store-brand. On the supply side, we test several forms of manufacturer–retailer interactions to identify retailer pricing behavior most consistent with the data. Our results indicate that the data reject several, commonly imposed, forms of interactions. In examining the nature of manufacturer interactions with the retailer, we find that the manufacturer of the national brand appears to take a softer stance in its interactions with the retailer subsequent to store-brand entry. This finding is consistent with academic research and with articles in the popular press which suggest that the store brand enhances the retailer’s bargaining ability vis-à-vis the manufacturers of the national brands. We also provide results from a second product category (frozen pasta) that are largely consistent with those found in the oats category.

(Retailer Pricing; Store Brands; Manufacturer-Retailer Interactions)
Introduction
Retailers in fast-moving consumer goods typically enjoy very slim profit margins in their product categories. It is therefore vital that the retailer understands the impact of the introduction of a store brand (or a private label) on customer demand for both the store brand and national brands. This study carefully examines and compares demand conditions before and after the 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 that make it attractive for a store brand to be introduced to particular product categories (Hoch and Banerji 1993, Raju et al. 1995). Raju et al. identify three circumstances under which a store brand raises a retailer’s category profits. First, category profits are higher if the cross price sensitivity among the national brands is low. Second, these profits tend to be higher 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 profits tend to rise. 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 for each manufacturer are high. However, their findings also suggest that store brands’ category share is likely to be higher in large categories that 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 entry; consequently, it can be seen as complementing earlier, cross-category empirical research on store-brands (Dhar and Hoch 1997).

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. A retailer contemplating store-brand introduction faces a fundamental demand-side trade-off. On the one hand, introducing the store-brand may enable the retailer to attract more consumers into the product category who previously did not buy, or it could encourage current consumers to buy more because of the availability of the lower-priced store brand. On the other hand, introducing the store brand could raise the level of price sensitivity in the market. This may require the retailer to lower prices on the national brands thereby cutting into retail margins. The net effect could be either positive or negative, and understanding these effects would be critical to the retailer.

Similarly, if a manager of a national brand is interested in understanding whether consumer preferences, after controlling for the effects of marketing activities, have shifted away from the national brand she or he manages, to a store brand, then it is necessary to measure these preferences both prior to and after entry. The manager can then decide if it is necessary to increase advertising expenditures to improve brand perceptions in a given market area. Increased price sensitivity due to store-brand introduction will necessitate marketing actions by the manufacturers. To determine what actions need to be taken (e.g., increase advertising expenditures), manufacturers 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 to identify potential changes in preferences and price sensitivities.

A category-level analysis is also necessary, in some instances, to understand other strategic issues. The introduction of the store brand could influence the nature of the relationship between the retailer and the national brand manufacturers. Wal-Mart’s introduction of a store-brand laundry detergent whose

1 According to conventional wisdom, the retailer makes a larger margin on the store brand, so pure brand switching to the lower-priced store brand would enhance retailer markups.
packaging closely resembled that of Tide, the leading national brand, has been reported as having a deleterious effect on its interactions with Procter & Gamble, the manufacturer of Tide. As noted previously, the introduction of the store brand could raise the level of price sensitivity in a category, thereby putting downward pressure on the retail prices of the national brands. This would lower the margins made by the retailer on the national brands if the wholesale prices charged by their manufacturers remained the same. However, store-brand introduction could raise the retailer’s bargaining power vis-à-vis the manufacturers (Scott-Morton and Zettelmeyer 2000). As a result of this change in the nature of interactions between the channel members, the manufacturers could lower the wholesale prices to the retailer. This lower wholesale price could potentially offset the reduction in retail price because of increased price sensitivity. A better understanding of the supply side, i.e., the retailer’s pricing decisions, and how these decisions are influenced by interactions between manufacturers and retailers, is critical for evaluating the effects of store-brand introduction.

As noted earlier, an understanding of the implications of a store-brand introduction in a product category on preferences as well as price sensitivities requires an understanding of the demand functions before and after such introduction. To investigate strategic issues like the nature of manufacturer–retailer interaction, one will also have to study changes in the supply side across the two regimes. Hence, a complete examination of the various issues of interest requires us to analyze both demand and supply characteristics.

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. We estimate the parameters of the demand functions for the different brands within a product category both before and after the introduction of a store brand into the category. The parameters are allowed to change post-entry of the store brand to accommodate preference shifts or changes in the composition of the category’s customers (i.e., heterogeneity) because of the introduction. Once the demand function parameters are estimated, the retailer’s implied markups on the various brands can be computed under alternative assumptions of pricing behavior.

We derive the retailer’s markups (retail price–wholesale price) for each of the brands in the category assuming that the retailer maximizes total category profits during both regimes (pre- and post-entry). Using the estimated parameters for the demand functions, we compute the implied markups for the retailer for the national brands as well as for the store brand. Our data provide us with information on the retailer’s actual markups for the various brands in the category. The deviation between the implied markup (given by the demand specification above) and the observed markup in the data gives us insights into the nature of manufacturer-retailer interactions. For example, if the observed markup is larger (smaller) than the implied markup for a specific national brand, this indicates that after controlling for demand effects, the manufacturer’s interactions with the retailer are such that the latter is able to charge a higher (lower) markup for that brand. Further, if the amount by which the observed markup exceeds (is less than) the implied markup is amplified by the introduction of a store brand by the retailer, this indicates that the manufacturer takes an even “softer (tougher) stance” towards the retailer after the store-brand introduction.

2 This potentially begs the question: Why do we need a supply-side analysis when the markups are observed? Note that our objective is to determine the nature of channel interactions that influence retailer pricing and how these interactions are influenced by the introduction of the store brand after controlling for demand-side effects.
Such a finding could imply a change in the nature of manufacturer–retailer interactions after the retailer launches the store brand.

The focus of the supply-side analysis described above is on studying channel interactions in how they influence the retailer’s pricing behavior. Additionally, we are interested in how these interactions change when a store brand is introduced. Our approach to inferring the nature of manufacturer–retailer interactions is similar in spirit to that proposed by Berto Villas-Boas (2001), although while we restrict our attention to the retailer’s pricing decisions, Berto Villas-Boas also analyzes the manufacturers’ pricing decisions (see also Kadiyali et al. 2000 and Sudhir 2001). In that paper, the objective is to identify the nature of channel interactions using only retail price data with no information either on wholesale prices or fixed payments. By contrast, in this study, we have access to not just retail prices but also the wholesale prices charged by the manufacturers to the retailer. Consequently, we are able to directly check various specifications concerning retailer behavior. For example, the fact that our data indicate nonzero retailer margins for all brands considered precludes certain pricing contracts in which the retailer makes zero margins on the national brands.

There are two caveats to our proposed analysis. The first is that we do not observe any fixed or lump-sum payments made by manufacturers to retailers, also referred to as brand-development funds. Presence of such funds will not affect our conclusions on the demand side of the analysis. Even on the supply side, they will not affect our inferences regarding manufacturer–retailer interactions in how they influence retail prices. However, without knowledge of these payments, we will not be able to fully characterize the nature of channel interactions. In particular, if we find that after store-brand introduction, the deviation in the observed markup above the implied markup becomes smaller, it would be difficult to conclude that the manufacturer takes a tougher stance overall towards the retailer. This is because there could be a fixed payment from the manufacturer to the retailer that compensates for the latter’s lower markup. Hence our conclusions regarding the interactions are based solely on observed (marginal) pricing behavior and not on additional payments made. A second caveat to our analysis is the issue of retail competition. Since our data are available for a single retailer, we cannot explicitly consider retail competition in the analysis. However, for the oats product category used in our empirical analysis, it appears reasonable to assume that retail competition is not a major driver of prices (see also Walters and MacKenzie 1988 and Walters 1989 for evidence that prices in one store have a bigger effect on sales in that store than on sales in competing stores). Further, we proxy for the effects of retail competition when estimating the parameters of the demand function.

We estimate the parameters of the demand equations, taking into account the data both prior to as well as after introduction. We use recently developed methods in the economics literature (Berry et al. 1995, Nevo 2001) to do this. The estimation allows several key parameters to change with the store-brand introduction. We then use this information along with the observed retailer markups to identify how manufacturer–retailer interactions influence retail prices. Our results indicate that the store-brand introduction generates notable changes within the category. For the oats product category, the store-brand introduction raises the retailer’s (share-weighted) margin in the category. We find that the preferences for the national brand are relatively unaffected by the introduction of the store brand. Consumers are, in general, more price sensitive (in terms of elasticities) than they were prior to store-brand introduction. However a formal statistical test of the differences in mean price elasticities across the two regimes fails to reject the hypothesis of no change in these elasticities. On the supply side, we test several forms of retailer pricing to identify the behavior most consistent with the data. Our results indicate that several commonly imposed forms of manufacturer-retailer interactions that drive retailer pricing behavior are rejected by the data. In examining the nature of manufacturer interactions with the retailer, we find that the manufacturer of the national brand appears to take a softer stance in its interactions with the retailer subsequent to store brand entry.

The remainder of the paper is structured as follows. The next three sections outline the model,
data, and the empirical strategy with which we estimate the demand parameters and measure the interactions among the manufacturers and the retailer. The subsequent section discusses empirical results. The penultimate section presents some robustness checks including the analysis of a second product category—frozen pasta. The final section presents our conclusions.

Model

A critical issue, and the focus of this paper, is how manufacturer–retailer interactions can change as a result of some action of the retailer. In this case, the action we are interested in is the retailer’s introduction of the store brand. We investigate the influence of these interactions on the markups charged by the retailer. We note that this is not an investigation into whether or not power has shifted in the retail channel, since such an analysis will require examining the effects of channel member interactions on the retailer and manufacturers’ profits. This also requires information regarding fixed-payment transfers between the channel members, information that is unavailable to us. We start by building a model of demand before store-brand entry. The model is then expanded to incorporate the retailer’s pricing decisions 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.

We begin our model formulation by stating equations for consumer demand, and for retailer pricing decisions. These identify 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 manufacturers and the retailer before and after the entry of the store brand in how these interactions influence retail markups. We follow the methodology developed by Berry (1994) and Berry et al. (1995), for empirically analyzing market demand in differentiated product markets. This technique allows the researcher to generate parameter estimates for the demand equations in multiproduct oligopoly markets.

Demand Equations for Brand Choice of Retailer’s Products

Our specification of demand is at the store level, although the specification is based on individual level utilities, aggregated across heterogeneous consumers within a given store. A representative consumer i who chooses and consumes product \( j \) \((j = 1, 2, \ldots, J)\) (before store-brand introduction) or \( j + 1 \) (after introduction) at time \( t \) has indirect utility

\[
U_{ijt} = \alpha_{ij} + \beta_j p_{jt} + \gamma d_j + \mu_{jt} + \epsilon_{ijt}.
\]

(1)

In the above equation, \( d_j \) is a deal variable, \( p_{jt} \) is the retail price, \( \beta_j \) is price sensitivity, \( \alpha_j \) 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 this term. This demand shock is specific to each store, each brand, and each time period, and stems from factors such as store coupons, shelf space, and shelf location that vary among stores and across weeks. Therefore, \( \mu_{jt} \) can be correlated with the prices, \( p_{jt} \). The term \( \epsilon_{ijt} \) 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 included in the choice set. Including the outside good in this manner means that the preference ordering within the choice set is assumed to be unaffected by the preference orderings in any choice sets that make up the outside good (“weakly separable”). The indirect utility for the outside good is as follows:

\[
U_{0it} = \alpha_{0i} + \lambda \text{SEAD} + \epsilon_{0it},
\]
where SEAD is a seasonal (or event) dummy used to control for seasonality in the utility for the product category. By this assumption, the effect of season (Summer) on consumption (of the category) is assumed to not affect the preference ordering of the brands in the choice set. 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 (1) into the following components:

$$U_{ijt} = \tilde{V}_{ijt} + e_{ijt},$$

$$U_{i0t} = \tilde{V}_{i0t} + e_{i0t},$$

$$\tilde{V}_{ijt} = a_{ij} + \beta_j p_{jt} + \gamma d_{jt} + \mu_{jt},$$

$$\tilde{V}_{i0t} = \lambda \text{SEAD} \quad \text{and} \quad \alpha_{i0} = 0.$$  (2)

We allow for consumer heterogeneity in our characterization of demand in Equation (1). Besides the idiosyncratic error terms $e_{ijt}$ and $e_{i0t},$ consumer heterogeneity takes two forms: one is with respect to intrinsic brand preferences (taste) and the other is with respect to price sensitivity. Consumer heterogeneity is captured in the demand specification (1) by the use of random coefficients for brand intrinsic preferences ($\alpha_i = \{\alpha_1, \alpha_2, \ldots, \alpha_{iJ} \text{ or } \alpha_{i,J+1}\}$) and for the price sensitivities ($\beta_j$)

$$\alpha_i = \alpha + e_i \quad \text{(3)}$$

$$\beta_j = \beta + e_{ij\beta} \quad \text{(4)}$$

where $(e_i, e_{ij\beta}) \sim N(0, \Sigma).$

The parameters $\beta$ and $\alpha$ represent means of the distributions of heterogeneity across 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 how the store brand draws share from the national brands. Further, Assumptions (3) and (4) result in a flexible market-share model that can be estimated using aggregate (store-level) data and that avoids the IIA property. We assume that the shocks $e_{ijt}$ and $e_{i0t}$ are i.i.d. and are drawn from extreme value distributions. 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 multinomial logit model (McFadden 1974). At the individual consumer level, this is the probability that consumer $i$ will choose brand $j$ from $J$ or $J+1$ brands at time (week) $t$:

$$p_{ijt} = \frac{\exp(V_{ijt})}{1 + \sum_{k=1}^{J+1} \exp(V_{ikt})},$$

where $V_{ijt} = \tilde{V}_{ijt} - \tilde{V}_{i0t},$ or

$$p_{ijt} = \frac{\exp(\alpha_j + \beta_j p_{jt} + \gamma d_{jt} - \lambda \text{SEAD} + \mu_{jt})}{1 + \sum_{k=1}^{J+1} \exp(\alpha_k + \beta_j p_{kt} + \gamma d_{kt} - \lambda \text{SEAD} + \mu_{kt})}.$$  (5)

Predicted market shares are obtained by aggregating the individual-level choice probabilities over 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 a subsequent section. For the simple case where there is no heterogeneity in intrinsic preferences or in the price sensitivity parameter, however, this matching is straightforward. We accomplish this by using a logarithmic transformation of the shares. This results in a system of (in the pre-entry period) $J$ linear equations whose parameters can then be estimated using simultaneous equation methods with the $\mu_{jt}$ as the error terms (see for example, Besanko et al. 1998):

$$\ln(S_{jt}) = \ln(S_{j0}) + \alpha_j + \beta_j p_{jt} + \gamma d_{jt} - \lambda \text{SEAD} + \mu_{jt}.$$  

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.

Pricing Equations for the Retailer

The supply-side problem involves the retailer’s pricing decisions and the manner in which these decisions are influenced by the retailer’s interactions with the
manufacturers of the national brands (and that of the store brand). The retailer is assumed to choose retail price (margins), given the manufacturers’ wholesale prices. The retailer’s objective is to maximize category profits by setting retail margins \( r_{jt} \), or:

\[
\max r_{jt} = \sum_{j=1}^{J} M_j r_{jt} s_{jt}.
\]

(6)

In the above equation, \( r_{jt} = p_{jt} - w_{jt} \) is the retailer’s margin on product \( j \) at time \( t \), with retail price \( p_{jt} \). The wholesale price is denoted by \( w_{jt} \). The term \( M_j \) denotes the potential category size at time \( t \) and \( s_{jt} \) is the share of brand \( j \) in week \( t \). 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. The first-order conditions for brand \( j \) are:

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

(7)

where

\[
\frac{\partial s_{kt}}{\partial r_{jt}} = (1 + \theta(w_{jt}, r_j)) s_{jt}^j.
\]

(8)

The terms \( s_{jt}^j \) denote the derivatives of the shares of brand \( k \) in week \( t \) with respect to price of brand \( j \) in that week. 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:

\[
s_{jt}^j = \frac{1}{R} \sum_{r_{jt}=1}^{R} \beta_r P_{rjt} P_{rkt}.
\]

(9)

The parameter \( \theta(w_{jt}, r_j) \) 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 and where \(-1 < \theta(w_{jt}, r_j) < 0\):

\[
r_{jt} = \frac{-s_{jt}}{1 + \theta(w_{jt}, r_j)} > s_{jt}. \tag{9}
\]

The nature of the interaction between the manufacturer of brand \( j \) and the retailer results in a higher 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. Finally, when the conduct parameter exceeds zero \((\theta(w_{jt}, r_j) > 0)\), the retailer makes a lower markup than under the vertical Nash scenario. Our interest lies in 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 after introduction.

Equation (9) can also be written as follows:

\[
p_{jt} = w_{jt} - \rho_{j} s_{jt} / s_{jt}^j, \tag{10}
\]

where

\[
\rho_{j} = \frac{1}{1 + \theta(w_{jt}, r_j)}. \tag{11}
\]

Equation (10) essentially tells us that the retailer’s price for brand \( j \) \((p_{jt})\) is the sum of the wholesale price \((w_{jt})\) and the markup term \((-s_{jt}/s_{jt}^j)\). The parameter \(\rho_{j} \) “toggles” the markup by taking values above and
below 1. Hence, our interaction parameters are similar in spirit to the markup parameters in Villas-Boas and Zhao (2001) and Berto Villas-Boas (2001). The key point of departure with the latter study, however, is that BVB uses these parameters to check the model specification rather than as a measure of the departure of the markup from a (vertical Nash) baseline. In the following discussion, we will refer to $\theta(wp, r_j)$ as $\theta_j$ for notational parsimony.

Testing Alternative Forms of Retailer Behavior
In this section, we describe how we are able to test various forms of retailer behavior using our modeling framework. We use the various scenarios for channel interactions discussed in BVB for the purpose. Note however, that we are only interested in the retailer’s pricing decisions.

Scenario 1: Sequential Nash-Pricing Model. Under this specification, the parameters $\theta_j$ in Equation (10) above would be zero for all brands $J$ (before entry) or $J + 1$ (after entry). In other words, the observed markup in the data would be equal to the markup predicted by the retailer’s category profit-maximizing problem. Hence, a test of this scenario would involve testing whether the $\theta_j$ parameters are statistically significantly different from zero.

Scenario 2: Nonlinear Pricing Models. There are two cases here. The first is when wholesale prices are equal to manufacturers’ marginal costs and retailers make pricing decisions. Given that we observe retail markups in the data, a test of this case would be identical to the test in Scenario 1. Hence, if we reject the hypothesis that the $\theta_j$ parameters are all equal to zero, we reject both Scenario 1 as well as the first case of Scenario 2. Failing to reject the hypothesis will imply that we need to look at the manufacturers’ margins to distinguish between the two sets of interactions. However, this is not germane to the current paper.

The second case under Scenario 2 is where the retailer makes zero margins and the manufacturers have pricing decisions. We can test this scenario by checking whether retail margins are significantly different from zero for the national brands. Since the margins are directly observed, this test is straightforward to perform.

Scenario 3: The Hybrid Model. This model assumes that the retailer behaves as a vertically integrated firm with respect to its private label brand. Once again, this scenario results in retailer markups similar to Scenario 1. And from the retailer’s perspective, testing for this scenario is identical to testing for Scenario 1.

Scenario 4: The Manufacturer Collusion Model. Here manufacturers collude to set wholesale prices. Once again, this does not influence retailer markups differently than in Scenario 1, so the test remains the same.

Scenario 5: The Retail Collusion Model. This assumes that retailers in a market collude to set retail prices. As noted previously, we cannot test this scenario as we have data from a single chain. However, if we do observe markups in the data that exceed those predicted by Scenario 1, we cannot rule out Scenario 5 as a potential explanation.

Scenario 6: Efficient Pricing Model. According to this scenario, there is both horizontal as well as vertical joint pricing. From the retailer’s perspective, this is similar to Scenario 5 above. That discussion applies here also.

The above discussion indicates that according to BVB there are three unique scenarios for retailer markups—(i) equal to those under the vertical Nash scenario, (ii) equal to zero, and (iii) equal to markups under retailer collusion. We can test the first two explicitly within our framework. We cannot reject the third because of the availability of data from a single retailer. However, it is important to note that the retailer’s margins can, in reality lie anywhere in the continuum from zero to the level corresponding to retailer collusion. A key advantage of the framework we propose is that it allows for the actual markups to lie in that continuum.

Estimation Procedure
Our estimation is carried out in two steps. In the first step, we estimate the parameters of the demand function, both prior to, as well as subsequent to, store-brand introduction, after accounting for the effects of price endogeneity (i.e., the correlation between $p_{jt}$...
and $\mu_{ji}$) and heterogeneity in preferences and price sensitivities. In the second step, we estimate the interaction parameters in the retailer’s pricing equations. This approach is consistent with that proposed by Nevo (2001) and BVB. However, it does differ from previous studies that estimate the parameters of the demand as well as the pricing equations in a simultaneous framework (e.g., Sudhir 2001). Using the two-step approach significantly simplifies the estimation task. While the estimates thus obtained are consistent, they are not efficient. However, as most of the key parameters are statistically significantly different from zero in our two-step approach, doing the simultaneous analysis only serves to lower standard errors conditional on the correct specification. After estimation via the two-step approach, we also estimated the system of equations simultaneously. We discuss these results in the section on robustness checks.

The estimation objective is to obtain estimates for the following parameters:

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

2. The parameters characterizing the distribution of unobserved heterogeneity. In particular, the variances of the distribution of preferences and price sensitivities across households.

3. The parameters in the retailer’s pricing equations that reflect the nature of interactions between the manufacturers and the retailer.

In addition there are three key issues to be confronted in the estimation. First, data are only observed at the aggregate level. We observe brand shares in the category, and the corresponding price and promotional variables at the level of the chain or store. Second, price endogeneity implies that there exists a potential correlation between $p_{ji}$ and $\mu_{ji}$. The third issue concerns how the retailer 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), Berry et al. (1995), and Nevo (2000). Generalized method of moments (GMM) estimation is used with the demand equations, as well as with the first-order conditions stemming from the retailer’s profit maximizing behavior. For full details of the estimation procedure, the interested reader is referred to Berry et al. (1995) or Nevo (2000, 2001). 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 $P_{j|i}$ across all consumers $i$ within a given week $t$. Nevo (2000) explains the details behind the simulation that is required to aggregate the logit choice probabilities to market shares. Next, we consider the retailer’s pricing equations. For simplicity in exposition, we describe the pricing equations for a two-brand case—a national brand $j$ and a store-brand $J+1$. As noted previously, we will have two retailer pricing equations. Then, from the first-order conditions in (7) and (8), we obtain the following expressions:

\[
p_{j|i} - wp_{j|i} - \rho_{j+1,j+1} \frac{s_{j+1,i} - s_{j+1,t}}{s_{j+1,i} - s_{j+1,t}} = \xi_{j|i} \tag{12}
\]

\[
p_{j+1,i} - wp_{j+1,i} - \rho_{j+1,j+1} \frac{s_{j+1,i} - s_{j+1,t}}{s_{j+1,i} - s_{j+1,t}} = \xi_{j+1,i} \tag{13}
\]

where

\[
\rho_{j+1,j+1} = 1/(1 + \theta_{j+1,j+1}) \quad \text{and} \quad \rho_{j+1,j} = 1/(1 + \theta_{j+1,j})
\]

First, note from the above equations that the unique parameters to be estimated from the retailer pricing equations are the interaction parameters (transformed into the $\rho$ parameters). Next, a pertinent question that needs to be addressed is, what is the source of the residuals in the above equations? Recall that in the retailer pricing equations, the wholesale prices are observed. However, these observed wholesale prices might not reflect the actual prices precisely because of the way in which the retailer accounts for the weekly costs of the items sold (if the retailer stores...
Empirical Issues

We begin with a discussion of the demand function and then describe the identification of the parameters of the retailer pricing equations. Before store-brand entry, the demand function for brand \( j \) is given by

\[
s_{j} = \frac{\exp(\alpha_{ij} + \beta_{ij}p_{jt} + \gamma_{ij}d_{jt} - \lambda_{ij}SEAD + \mu_{jt})}{1 + \sum_{k=1}^{J} \exp(\alpha_{ik} + \beta_{ik}p_{kt} + \gamma_{ik}d_{kt} - \lambda_{ik}SEAD + \mu_{kt})} \times f^{s}(\alpha, \beta) \, d\alpha \, d\beta.
\]

After store-brand entry, the demand function is given as follows:

\[
s_{j} = \frac{\exp(\alpha_{j} + \beta_{j}p_{jt} + \gamma_{j}d_{jt} - \lambda_{j}SEAD + \mu_{jt})}{1 + \sum_{k=1}^{J} \exp(\alpha_{k} + \beta_{k}p_{kt} + \gamma_{k}d_{kt} - \lambda_{k}SEAD + \mu_{kt})} \times f^{s}(\alpha, \beta) \, d\alpha \, d\beta.
\]

The regions of integration in the above expressions are those that result in the choice of brand \( j \). The superscript “\( B \)” refers to before introduction and superscript “\( A \)” refers to the after introduction. In the empirical analysis, we approximate the above integrals by simulating from the distributions of the heterogeneity parameters. Specifically, we assume the following (from Equations (3) and (4)):

\[
\alpha_{i} = \alpha + \varepsilon_{i},
\]

\[
\beta_{i} = \beta + \varepsilon_{i\beta},
\]

where

\[
(\varepsilon_{i}, \varepsilon_{i\beta}) \sim N(0, \Sigma).
\]

With \( J + 1 \) brands, \( \Sigma \) is of dimension \((J + 2) \times (J + 2)\). In the estimation, we allow the model parameters to change before and after introduction of the store-brand. We do this to understand whether or not preferences and price sensitivities are influenced by the introduction. Prior to the estimation, we make the following modifications to the demand specification based on the data available to us.

The data available to us are at the store level for several stores within a supermarket chain. Rather than aggregate the data across stores, we choose to retain the information from all stores. To allow for systematic store-level differences in brand preferences and price responsiveness across stores, one could use store dummies and also interact these dummies with prices. Instead of doing this, we allow for store differences in the systematic effects by exploiting the information available in the store characteristics of the market areas in which the stores are located. Specifically, the preferences (and price sensitivities) for the brands for consumer \( i \) in store-area \( s \) are given as follows:

\[
\alpha_{is} = \alpha_{j} + X_{s}\delta_{j} + \varepsilon_{jis},
\]

\[
\beta_{is} = \beta + X_{s}\delta_{j} + \varepsilon_{i\beta s}.
\]

In the above expression, \( X_{s} \) denotes the (average) demographic profile of store-area \( s \). The portion of heterogeneity accounted for by the store characteristics can then be thought of as the observed heterogeneity component, whereas that from the random component as the unobserved heterogeneity component.

Recall that the retailer’s pricing equations prior to store-brand introduction can be written as:

\[
\rho_{j}^{B} \, s_{jt} + \sum_{k=1}^{J} \rho_{kj}^{B} s_{kt} = 0, \quad j = 1, 2, \ldots, J
\]

\[5\]

Note that in the estimation we use store-level data. Equation (6) will therefore be modified to reflect the sum of profits across all stores. Further, the interaction parameters will be the same across stores.
After the store brand is introduced, these equations are:

\[ p^A_{j} s_{j} + \sum_{k=1}^{J+1} r_{k} s_{k} = 0, \quad j = 1, 2, \ldots, J+1. \]

In the above equations, the superscripts \(B\) and \(A\) denote “Before” and “After” store-brand introduction respectively. Hence, we have \(J\) interaction parameters before store-brand introduction and \(J + 1\) interaction parameters after store-brand introduction. In other words, we allow for the nature of manufacturer-retailer interaction to change after store-brand introduction. If the store brand does result in the national-brand manufacturers taking a softer stance towards the retailer, then we would expect the interactions with the manufacturers to be such that the retailer is now able to make larger margins on the national brands than it did previously. This is conditional on the demand parameters pre- and postintroduction. We are able to estimate the \((2 \times J) + 1\) interaction parameters in the empirical analysis without imposing any additional identifying conditions. The main reason for this is that \(r_{j}\) is observed in our data.

**Data**

We use scanner data from a large midwestern supermarket chain (Dominicks Finer Foods) in the estimation. This supermarket chain, with 96 stores around the metropolitan area of Chicago, Illinois, is one of the two largest supermarket chains in this area. Of the 96 stores for which data are available, we used data from 50 stores chosen at random in the estimation in order to ease the computational burden. A number of variables are available for 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,” and store traffic for each store in the chain. These variables are all available on a weekly basis for each store in the chain. In addition, to account for seasonality effects, we include a summer dummy in the estimation. Our analysis pools data across stores without aggregating to the chain level. In this way, we are able to better study the demand for the products analyzed and how the demand varies with the characteristics of the market area to which a store belongs.

A total of 399 weeks of data are available, from 09/14/89 to 05/01/97. Our estimation subsample is chosen around the entry date 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 and after 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 for the market to stabilize to a new equilibrium. Using these criteria, we ended up with 275 weeks of data for each of the 50 stores. Hence, we had 13,750 observations in our estimation sample.

The analysis tests the entry of a new store brand to a subcategory wherein store brands had not existed previously. From a total of 142 available subcategories as defined by IRI, we found six categories for which there existed sufficient data on store-brand entry and enough data before and after the entry of the store brand. Another 62 categories contain the Dominicks store brand. Thus about 10% of the store-brands were introduced within the observation period. Out of the six categories where we found a store-brand entry, the category selected for analysis is oats. No major national brands were introduced to the supermarket shelves over the estimation period. Since there is only one major incumbent national brand in the oatmeal category (Quaker), we are able to abstract from the issue of rivalry among national-brand manufacturers and how this rivalry may be influenced by store-brand entry into a particular market.

We aggregated sales data at the UPC level across both sizes (e.g., 40oz, 12oz) and brand variants (e.g., Quaker Quickcook rolled oats is combined with Quaker regular rolled oats). As noted above, the data contain weekly store traffic figures. We use this to compute the size of the “outside good”, which we define as the market potential figure less the total quantity sold in the category in a given week. The market potential is estimated based on the average quantity purchased by households and aggregated to
the total number of people visiting the stores. The outside good is used to normalize the brand preferences to a common good. If brands are normalized to one of the national brands, without the outside good, then the pricing problem becomes degenerate.

Table 1 reports selected descriptive statistics for the oats category 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 across all stores. Wholesale and retail prices are deflated using the consumer price index (Bureau of Labor Statistics, herein BLS). 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).

In addition to the above variables, we also include information on the market area for each of the 50 stores in our sample. For each store, we used the average values in the market area for each of the following five variables: (a) the average family size, (b) the fraction of the population that is educated, (c) the fraction of the population that is unemployed, (d) the median income, (e) the average driving time to the store. We picked these variables based on the results obtained in previous studies (see, for example, Hoch et al. 1995). The first four variables are demographic characteristics. The fifth variable, driving time, proxies for the level of retail competition and is negatively correlated with it (Hoch et al. 1995). Note that in the estimation, these store characteristics are interacted with the brand preferences as well as the price sensitivity parameter. Consequently, we mean center these variables to ensure that the main effects of the preferences and price sensitivities are easy to interpret.

**Instruments**

Exogenous instruments are required for identification of the population moment conditions for the GMM estimation. 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 current and lagged values of the producer price indices for the product category analyzed as our instruments for retail prices. These data reflect the costs to manufacturers of producing these product categories. We interact these
variables with brand dummies to generate brand-specific instruments. The argument for using these variables is that time varying unobserved attributes in the store are likely to be correlated with in-store activities such as shelf space and shelf location. These activities are likely to be correlated with retail prices, but are less likely to be correlated with the drivers of manufacturer costs. In addition to these variables, we also include all other (assumed to be) exogenous variables as instruments in the estimation.

Results

Descriptive

Table 1 reports descriptive statistics for the oats category. We focus on reporting aggregate sales, market share, wholesale prices, retail prices, and deal statistics. We then describe the changes in the descriptive statistics during the two regimes.

The Dominicks label of store brand was introduced during the month of October 1993, the beginning of the fall season in the Chicago metropolitan area—week 121 (of 275) in the first store it was introduced in our dataset. A graphic inspection of the time series of sales and prices for one specific store (Figure 1) suggests that the entry of the store-brand results in an increased 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 to introduction (in Figure 1a), it appears as if the unit sales have periodic spikes that are more pronounced in nature. This appears to be confirmed in Figure 1(b). The retail and wholesale prices shows large spikes corresponding to the weeks where the sales spikes occur. Notwithstanding the close association between the two price series in Figure 1(b), there does appear to be some weeks in which the retailer is promoting the national brand without a corresponding wholesale price reduction. This of course, raises the issue of other motivations for retail pricing that are not being modeled in this paper.\(^6\) Note that looking at the retail prices in Figure 1 for a particular store, one may (incorrectly) conclude that the variability of prices is much larger after store-brand introduction across all stores in the market. As we shall see below, the variability in retail prices does increase. The amount of variation

\(^6\) See, for example, Pesendorfer (2002) and Chintagunta (2002)
across all stores is, however, smaller than the variation observed in Figure 1.

Returning to the descriptive statistics of the oats data in Table 1, we observe some interesting effects of store-brand introduction. First, we note that post-launch, the total size of the category increases by about 2%. However, sales of Quaker decline 5.3%. More importantly, we find that the volatility in Quaker sales increases dramatically after the store brand is introduced (as mentioned earlier). In particular, the coefficient of variation of Quaker sales goes up from 0.615 to 1.225. From the perspective of the manufacturer, this may not be a desirable outcome, as it could put pressure on the efficiency of store supply. The sales of the store brand also displays a fairly high variability although not as high as that for Quaker.

We find that the retail price of the store brand is much lower than that for Quaker—it is about 80% the price of the national brand. The retail price of Quaker drops about 7% after store-brand introduction. We also find that the variability in Quaker’s retail price goes up somewhat after Dominicks introduces its store brand (coefficient of variation increases from 0.09 to 0.10), although the store brand’s price variability appears to be higher than that for the national brand. The pattern of retail prices seems to support the notion that price sensitivity could have increased with the store-brand’s introduction—to actually make this determination, it will be necessary to estimate the model parameters. Consistent with the drop in retail prices, we also find that wholesale prices decline for Quaker. In absolute terms, the decline is 6.2 cents (on average) compared to a decline in retail prices by about 6 cents. Consequently, the retailer’s markup does not decline even with a decline in retail prices. Prima facie, this seems to indicate that the manufacturer of the national brand is willing to “accommodate” the retailer for the lower margin it makes on Quaker after the store brand is introduced. In percentage terms, the retailer’s margin increases from 20.485% to 22.291%. We also see that 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, is promoted at about half the intensity as before the store-brand entry.

Finally, the last row in Table 1 addresses the “bottom line” question from the retailer’s perspective. Does the store-brand introduction actually raise
the retailer’s total weekly markup (defined as unit sales*(retail price–wholesale price)) in the category? Table 1 tells us the retailer, on average, is indeed better off than what it was prior to launching the store brand. Average weekly margins increase by 3%. However, this increase is accompanied by an increase in the variability of total markups across the two regimes.

Model Estimates
In Table 2, we present the parameter estimates and their standard errors for the demand function. First we discuss the estimates obtained prior to introduction. We then describe the postentry results. Finally, we provide a comparison of the results from the two regimes. The “before” estimates indicate that the only statistically significant parameters (at the 5% level of significance) are those for the mean preference of Quaker, mean price effect, the promotion and seasonality variables, and the Quaker preference—proportion-educated interaction. In addition, we find that the variance parameter for price sensitivity is also statistically significantly different from zero. The negative coefficient for the mean Quaker preference is because the share of this brand relative to that for the outside good is quite small. The price and promotion effects are negative and positive respectively, as one would expect. We also find that the estimate

<table>
<thead>
<tr>
<th>Variable</th>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Standard error</td>
</tr>
<tr>
<td>Store preference</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Store × Family size</td>
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</tr>
<tr>
<td>Store × Fraction educated</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Store × Fraction unemployed</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Store × Median income</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Store × Driving time</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Quaker preference</td>
<td>—3.0386</td>
<td>0.3055</td>
</tr>
<tr>
<td>Quaker × Family size</td>
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<td>0.0074</td>
</tr>
<tr>
<td>Quaker × Fraction educated</td>
<td>0.0378</td>
<td>0.0167</td>
</tr>
<tr>
<td>Quaker × Fraction unemployed</td>
<td>—0.0062</td>
<td>0.0368</td>
</tr>
<tr>
<td>Quaker × Median income</td>
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<td>0.0002</td>
</tr>
<tr>
<td>Quaker × Driving time</td>
<td>0.0007</td>
<td>0.0027</td>
</tr>
<tr>
<td>Price</td>
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<td>0.6502</td>
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<tr>
<td>Price × Family size</td>
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<td>0.0085</td>
</tr>
<tr>
<td>Price × Fraction educated</td>
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<td>0.0306</td>
</tr>
<tr>
<td>Price × Fraction unemployed</td>
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<td>0.0422</td>
</tr>
<tr>
<td>Price × Median income</td>
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<td>0.0003</td>
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<tr>
<td>Price × Driving time</td>
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<td>Seasonality</td>
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<td>0.0141</td>
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<tr>
<td>Heterogeneity effects*</td>
<td>Estimate</td>
<td>Standard error</td>
</tr>
<tr>
<td>Store 1</td>
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</tr>
<tr>
<td>Store 2</td>
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</tr>
<tr>
<td>Quaker 1</td>
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<td>0.3333</td>
</tr>
<tr>
<td>Price</td>
<td>1.1593</td>
<td>0.3512</td>
</tr>
</tbody>
</table>

Notes: Heterogeneity parameters have to be interpreted as follows:
- Store-brand preference variance = (Store 1)² + (Store 2)²
- Quaker-brand preference variance = (Quaker 1)²
- Quaker store preference covariance = Quaker 1 × Store 1
- Price-sensitivity variance = Price²
for λ in Equation (12) is positive. This implies that the summer season has a negative impact on the utility for hot cereal. The significant effect for Quaker preference interaction with the percentage-educated variable implies that neighborhoods with a higher proportion of educated consumers have a higher preference for this cereal. The heterogeneity parameters indicate that there is little variation in the preferences for Quaker among consumers (parameter = 0.221 and standard error 0.333). This could be because of Quaker being the “only show in town,” with consumers having little opportunity to try other hot breakfast cereals. However, consumers do seem to vary in their price sensitivities (parameter estimate = 1.159, standard error = 0.351). This implies that while some consumers are likely to purchase the product at regular price, others might wait for a discount before purchasing.

Turning to the parameter estimates after the introduction of the store brand, we note the following. First, the statistically significant (i.e., different from zero) parameters in this regime are the following: the mean preferences for Quaker and for the store brand, the mean price effect, and the promotion and seasonality effects. The mean preference for Quaker is significantly greater than the mean preference for the store brand. This is reasonable in as much as Quaker has been a dominant brand in this category for a long period of time. Additionally, we find that some of the interactions between preferences and price sensitivities with the demographic variables are also statistically significantly different from zero. In particular, we find that the preferences for both oats brands are higher in neighborhoods with a higher proportion of unemployed. This could be because oats are perceived to be a low-cost alternative to regular cold cereal and the low-priced store brand “cues” customers to this product category. Similarly, we find these store areas to also be more price sensitive as compared with neighborhoods that have a lower fraction of unemployed people. None of the other interactions is statistically significant.

Table 2 also seems to indicate the presence of heterogeneity in preferences and price sensitivities after the introduction of the store brand. In particular, three of the four heterogeneity parameters in Table 2 are statistically significantly different from zero. To interpret these parameters, we transform them into the covariance matrix of preferences. Doing so, we obtain the following matrix:

\[
\begin{pmatrix}
\text{Store} & \text{Quaker} \\
\text{Store} & 4.114 & -0.709 \\
\text{Quaker} & -0.709 & 0.148
\end{pmatrix}
\]

In the above matrix, the only parameter that is statistically not significantly different from zero is 0.148—the variance for Quaker preferences. The matrix indicates that there is considerable heterogeneity in the preferences for the store brand among consumers in this market. Further, we find very little heterogeneity in Quaker preferences. Finally, the preferences for the two brands appear to be negatively correlated. These findings are all intuitively plausible. Further, they represent good news for Quaker. Not only do consumers, on average prefer Quaker to the store brand, but also there is very little variation in the perception of Quaker among consumers (consistent with the preintroduction situation). For the store brand, there still appears to be some work to be done. While the mean preference level for the brand is quite low relative to Quaker (−7.7390 versus −3.0087 for Quaker with a statistically significant difference at the 5% level), the high variance indicates that there does exist a segment of consumers for whom the store brand is the preferred alternative. Unfortunately, it also implies that a vast majority of consumers will intrinsically still prefer Quaker to the store brand. Postentry, Table 2 also shows that consumers are heterogeneous in their price sensitivities (mean of −3.5461 and variance of 1.4663 × 1.4663 = 2.1500).

**Effects of Store-Brand Introduction**

We now attempt to address one of the motivating questions of this paper. Are consumers’ brand preferences and price sensitivities influenced by the entry of the store brand? First, we formally test to see whether there are market-level differences in the preferences for Quaker as well in the price elasticities across the two regimes. Then, we examine the price-sensitivity differences for individual stores to see whether there are substantive changes in this variable after the introduction of the store brand.
The difference in the mean preference level for Quaker before and after introduction is an increase of 0.2470. The corresponding standard error is 0.4448. Hence, the hypothesis of no change in the preference level of Quaker after store-brand introduction cannot be rejected at the 5% level of significance. Therefore, at the market level, for consumers shopping in Dominick’s stores, the mean preference level of the national brand is not much affected by the retailer’s introduction of the store brand.\footnote{This test assumes that the scale parameter of the logit error in the demand function remains unchanged. Note however, that we cannot separately identify changes in the scale parameter as well as those in the other parameter estimates. Developing a formal test similar to that in Swait and Louviere (1993) to determine changes in the scale parameter is a useful direction for future research.}

For the price parameter, we find that the difference in mean levels is an increase in price sensitivity of 0.8377. The corresponding standard error is 0.8613. This implies that the hypothesis of no change in the level of price sensitivity cannot be rejected at the 5% level of statistical significance. Of course, one could argue that to measure the change in price sensitivities one will have to test whether price elasticities have changed across the two regimes. Accordingly, in Table 3 we provide the estimates for price elasticities in each of the 50 stores along with the market-level mean values.

The mean value of Quaker’s price elasticity prior to introduction is $-2.2839$ and after introduction is $-2.7867$. The difference between the two elasticities is $-0.5028$. The estimated standard error (obtained by simulating from the estimated covariance matrix of parameters) is 0.6631. Hence, the hypothesis of no significant difference in elasticities across regimes cannot be rejected at the 5% level of significance. While the change in price elasticities is not significantly different from the perspective of a statistical test, it nevertheless indicates an increase in price sensitivity in the marketplace. Another way to characterize the change in elasticity is by answering the following thought experiment question. If a monopolist firm is faced with these two elasticity measures, will they have different implications for optimal pricing? Using the simple pricing rule that percentage margin = $-1/\text{elasticity}$, the implied margin computed with the preintroduction elasticity is 44% whereas the implied margin calculated with the postintroduction elasticity is 36%. Assuming identical costs, the substantive difference in margins is not insignificant. Note that this difference in elasticity (and implied margin) is large enough to explain the change in retail prices of Quaker Oats found in Table 1 and described previously.

An obvious question that arises is: What is the reason for the increased price sensitivity in the market? First, recall from Table 1 that the coefficient of variation for retail prices of Quaker increases from 0.09 to 0.10. This increase is not that large. However, the store brand is not only priced lower than Quaker, but also exhibits a greater amount of variability in prices compared to the national brand (coefficient of variation of 0.18). Taken together, these factors seem to be making consumers more price-sensitive. Finally, we carried out statistical tests of the differences in the heterogeneity parameters for Quaker preferences and price sensitivities before and after store-brand introduction. These results indicate no statistically significant change in these effects at the 5% level of significance.

While the change in price elasticities is not significant from a statistical perspective, it does suggest a substantive change in the levels of price elasticities due to store-brand introduction. Accordingly, we compare the store-level price elasticities for Quaker under the two regimes. It appears from this informal look at the elasticities that in 25 of the 50 stores, price elasticities increase in magnitude by over 0.5. In six stores, price elasticities actually decreased by 0.5 or more. In the remaining 19 stores, the change in elasticities was less than 0.5 in magnitude. So, there are some changes in price elasticities (mostly increases) at the individual store level, although these changes seem to be “averaging out” somewhat across stores.

To summarize, in order to address the issue of whether or not store-brand introduction results in a significant change in national-brand preferences and price elasticities, we carried out formal statistical tests and less formal inspection of store-level results. The formal tests indicate that the mean value of Quaker
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Recall that the “vertical Nash” scenario is one in which \( \theta = 0 \). For values of \( \theta \) between 0 and \(-1\), the retailer makes higher markups than those under Nash and for values greater than 0, the retailer’s margins are below those corresponding to vertical Nash. Table 4 reveals that prior to store-brand introduction, the retailer’s markup for the national brand Quaker was, on average, much smaller than that under vertical Nash (\( \theta = 0.7789 \)). However, the situation changes after the store brand is introduced. The value of \( \theta \) drops to 0.2846—closer to the Nash markup. Consequently, it does appear that the national-brand manufacturer is behaving in a more “accommodating”

### Table 3  Price Elasticities for Oats Data by Store

<table>
<thead>
<tr>
<th>Store</th>
<th>Quaker before</th>
<th>Quaker after</th>
<th>Store before</th>
<th>Store after</th>
<th>Quaker before</th>
<th>Quaker after</th>
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</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>-1.9742</td>
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<td>-2.5291</td>
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<td>-2.0261</td>
<td>48</td>
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<td>-2.4417</td>
<td>-1.9787</td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>-2.0716</td>
<td>-3.4971</td>
<td>-2.7245</td>
<td>49</td>
<td>-2.3897</td>
<td>-2.6527</td>
<td>-2.1163</td>
<td></td>
</tr>
</tbody>
</table>

**Mean** 

<table>
<thead>
<tr>
<th>Store before ( \theta_{AS} )</th>
<th>Store after ( \theta_{AS} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.839</td>
<td>-2.7867</td>
</tr>
<tr>
<td>-2.242</td>
<td></td>
</tr>
</tbody>
</table>

*Note. All elasticities are statistically significantly different from zero at the 5% level of significance.*

### Supply-Side Results

In Table 4, we provide the parameter estimates and the standard errors for the interaction parameters. Recall that the “vertical Nash” scenario is one in which \( \theta = 0 \). For values of \( \theta \) between 0 and \(-1\), the retailer makes higher markups than those under Nash and for values greater than 0, the retailer’s margins are below those corresponding to vertical Nash. Table 4 reveals that prior to store-brand introduction, the retailer’s markup for the national brand Quaker was, on average, much smaller than that under vertical Nash (\( \theta = 0.7789 \)). However, the situation changes after the store brand is introduced. The value of \( \theta \) drops to 0.2846—closer to the Nash markup. Consequently, it does appear that the national-brand manufacturer is behaving in a more “accommodating”
manner after the retailer introduces the store brand.\(^8\)

Note that in drawing this conclusion, we have already accounted for changes occurring on the demand side of the equation. Table 4 also indicates that the interaction between the manufacturer of the store-brand and the retailer is such that the retailer is able to make a markup higher than that corresponding to vertical Nash. This seems consistent with our expectations regarding store brands.

One may also be interested in the marginal effects of the interaction parameters on the retailer’s pricing decisions. This is important for two reasons. First, it has a direct bearing on the retailer’s markups from the category. Second, it provides some information to the channel members as to the potential gains and losses from behaving more or less cooperatively towards the other channel members. Note that the Quaker interaction parameter with the retailer exceeds zero both before and after store-brand introduction. As mentioned previously, this scenario corresponds to the retailer making a lower markup than under vertical Nash. So an increase in the value of this parameter results in a lower price to the retailer conditional on the wholesale price remaining fixed. Computing the mean marginal effects of the interaction parameters across observations (\(\frac{\partial p}{\partial \theta_{ij}}\)), we obtain the values 

\[-0.121\text{ (standard error of 0.068)}\] before store-brand entry and

\[-0.182\text{ (standard error of 0.075)}\] after introduction. What this means is that the retail price of Quaker is more sensitive to Quaker–retailer interactions after the retailer introduces the store brand. This finding is consistent with our earlier interpretation of the interaction parameters themselves.

To summarize our results from the supply side analysis of the retailer pricing equations, we find the following. Both before and after store-brand introduction, the Quaker–retailer relationship is such that the retailer’s markup on Quaker is below that implied by vertical Nash behavior. However, postentry, the deviation from vertical Nash is reduced substantially. On the store brand however, the retailer makes a markup greater than that under vertical Nash.

Having discussed the estimation results, we now test whether the data are consistent with one of the possible behaviors for the retailer identified in BVB. Recall the three unique types of retailer behavior in that framework. These scenarios correspond to the retailer making (a) zero margins, (b) vertical Nash margins, and (c) margins corresponding to retail collusion. We can explicitly test for scenarios (a) and (b). Specifically, scenario (a) would be consistent with the \(\theta\) parameters being infinitely large resulting in zero margins. Clearly, the data rejects this situation as all the estimated values are finite and can be seen to be statistically significantly less than 2. Further, the raw data indicate that the retailer’s markup on the national brand is different from zero at the 5% level of significance. Similarly, as discussed above, one can reject scenario (b) as well since the estimated values of \(\theta\) are statistically significantly different from zero.

This brings up the issue of collusion at the retail level (Scenario (c)). Note that if such collusion existed, the retailer must be making markups higher than those under vertical Nash discussed above. To the contrary, for the national brand, Quaker we find that the retailer’s markups are lower than those under vertical Nash (although increasing from the first regime to the second). This would not seem to be consistent with retailer collusion and so we scenario (c) does not appear to be very plausible.\(^9\) An approach such as that proposed here is sufficiently flexible that it allows for markups that span the range from 0 to those under collusion.

As noted in the introduction, the one aspect of channel interactions that we do not account for has to do with fixed payments made by manufacturers to the retailer. In the case of the oats data, fixed payments from Quaker to Dominicks could certainly exist. So the question is: Would our supply-side conclusions change in the presence of such payments? In other words, if side payments did exist, could

\(^8\)The retailer’s margins being lower than vertical Nash could also indicate the effects of retail competition. Note however, that we have attempted to account for this in our model via the driving time variable. Further, it does not explain the change in the interaction parameter with the introduction of the store brand.

\(^9\) It is possible however, that there is some combination of aggressive manufacturer behavior and retailer collusion that results in the retailer’s net markups being lower than those under vertical Nash.
the manufacturer in reality be behaving more aggressively towards the retailer after the store-brand introduction? Our results described above indicate that Quaker behaves in a more “accommodating” fashion towards Dominicks after the latter launches its own brand. This result would be reversed if Quaker used to make fixed payments prior to introduction, but now withholds a part of or the entire payment to the retailer. If this (unobserved) reduction exceeds the gains to the retailer from the accommodating behavior, then the result would change. In the absence of manufacturer-to-retailer payments prior to introduction, a reversal of the result would also happen if the retailer launches the store brand and starts making fixed payments to Quaker. While both these scenarios are indeed possible, they do not appear to be intuitively very plausible. However, in the absence of real data on fixed payments, we cannot definitely ascertain the impact of such payments on the nature of manufacturer-retailer interactions.

Robustness Checks
In this section, we test the sensitivity of our results to a variety of assumptions in order to verify the robustness of our results to those assumptions. The first is whether the supply-side results are specific to store-brand introduction. The second issue pertains to our (implicit) assumption of a zero markup on the outside good for the retailer’s profit-maximizing problem. The third issue is whether or not the interaction parameters change over time, and the fourth issue pertains to the nature of the estimation procedure, i.e., are the results influenced by the choice of the two-step method (whose results we have provided) or the simultaneous approach in which the demand as well as interaction parameters are estimated simultaneously.¹⁰ We address each of these issues in turn.

(i) Do the Changes in the Interaction Parameters Truly Correspond to the Introduction of the Store Brand? To answer this question, we divide the preentry time horizon into two (approximately) equal time periods. We then estimate the demand- and supply-side parameters for each of these two time periods. Given that no introduction has taken place, we should not observe differences in the estimated value of θ_{BQ,Q} for time periods B1 and B2. Table 5 provides the estimates of this parameter for the two time periods

Table 5  Parameter Estimates Obtained by Splitting the Pre–Introduction Data into Two Periods

<table>
<thead>
<tr>
<th></th>
<th>Quaker before 1 θ_{BQ,Q}</th>
<th>Quaker before 2 θ_{BQ,Q}</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.6293</td>
<td>0.7933</td>
</tr>
<tr>
<td></td>
<td>(0.2110)</td>
<td>(0.2377)</td>
</tr>
</tbody>
</table>

Table 5 reveals that the B1 parameter estimate is 0.63 whereas the estimate for B2 is 0.79. First, we note that the difference is not statistically significant at the 5% level of significance. Further, the magnitude of the parameter in B2 is higher than that for B1. Hence, the results are not consistent with a steady decline in the interaction parameter over time independent of the store-brand introduction. Taken together, the findings in Table 5 indicate that our supply-side results can be attributed to the introduction of the store brand.

(ii) Assumption of a Zero Markup on the Outside Good for the Retailer’s Profit-Maximizing Problem. Recall the retailer’s category profit-maximizing equation given by the expression in (6). We could alternatively, write Equation (6) as follows (see Sudhir 2001):

\[
\max_{r_{jt}} \pi_r = M_t \left( r_0 s_{0t} + \sum_{j=1}^{j+1} r_{jt} s_{jt} \right).
\]

In the above expression, \( r_0 \) is the fixed (time invariant) markup on the share of the outside good. And Equation (6) sets \( r_0 = 0 \). The idea behind setting this markup level to zero is that the retailer does not account for the cross-category effects of pricing within a particular product category. In other words, the retailer’s pricing within a category is independent of its effects on other categories. Allowing \( r_0 \) to be different from zero in an empirical context and then testing whether this parameter is significantly different from zero is one possible way of testing whether the retailer focuses on single categories while setting prices. Accordingly, we estimated the supply-side parameters along with estimating \( r_0 \). Note that

¹⁰ We thank a reviewer for raising these issues.
since we observe retail as well as wholesale prices for brands within a category, the parameter $r_0$ is econometrically identified. We found that the estimated values of this parameter (before and after store-brand introduction) were close to zero in magnitude as well as equal to zero in statistical significance in both regimes. Hence, we conclude that the retailer is focusing on intracategory effects while setting the prices for oats.

(iii) Is the Nature of Manufacturer–Retailer Interactions Time Invariant? There is some evidence in the literature that the nature of interactions among competing players does change over time (see for example, Slade 1992). Hence, it is reasonable to expect that interactions among channel members are also dynamic in nature. In our model formulation, we find that the nature of interactions do change with store-brand entry. Previous researchers (Kadiyali et al. 2000, for example) have allowed interactions to vary each time period based on past values of shares and prices. Their motivation in doing so was to help in the identification of the interaction parameters—not so much as to estimate time-varying interactions. To understand time-varying behavior, it is necessary to have clear theories as to what factors influence these interactions (see, for example, Rotemberg and Saloner 1996). If such theories existed, one could make the interaction parameters a function of the factors driving time-varying behavior to study whether these theories are valid in a particular empirical context (Sudhir et al. 2001 provide an illustration of such an approach).

For our empirical application, we did investigate the effect of “last week in the quarter” on the nature of channel member interactions. In particular, we wanted to test whether the manufacturer behaved in a more accommodating fashion towards the retailer during the last week of the quarter, which is when the manufacturer’s sales representatives have to meet quotas for that quarter. We made $\theta$ a function of an intercept (to estimate the mean value) and a dummy variable that took the value 1 only during the last week in the quarter. However, we did not find any statistically significant effects for this variable. Future research will have to consider alternative reasons why the nature of channel interactions varies systematically over time.

(iv) Two-Step Versus Joint Estimation. We assessed the sensitivity of our results to the joint estimation method by using that method for parameter estimation and then carrying out a Hausman (1978) test to see whether these estimates for the demand model are significantly different from those obtained via two-step estimation. We failed to reject the hypothesis of a significant difference in the estimates at the 5% level of significance.

(v) Are Results Generalizable Across Product Categories? To assess whether we obtain similar results from other product categories, we carried out the analysis described above for a second category—frozen pasta. The data source once again is the Dominicks Finer Foods dataset. We used information from 35 stores in the chain for which continuous data were available. The time period for which we have “clean” data in this category is from November 1994 over an 86-week horizon. The store brand was introduced after 49 weeks. This gives us postentry information for 37 weeks. Table 6 indicates that before the introduction of the store brand, Rosetto is the largest name brand, followed by Floresta, Mrs. Belgos, and Italia. After the introduction of the Dominicks brand however, we see the sales of the Floresta brand increases dramatically. We also see an increase in the sales of the Rosetto brand although not to the same extent as that for Floresta. For both these brands, we find that the retail price did not decline with store-brand entry. So the main explanation for the sales increase is the introduction of new pasta varieties by these brands. At the same time, we find that Mrs. Belgos and Italia are relatively unaffected by store-brand entry. Interestingly, Table 6 reveals that while the retail price of the store brand is lower than the prices for the name brands, the wholesale prices are not much lower. In fact, the wholesale price to the retailer is higher than the corresponding prices for some of the name brands. Effectively then, the retailer is making a smaller margin on the store brand in this product category (26% as compared to 38% on average across name brands after entry). The Dominicks brand however, does enjoy the highest level of promotional activity in this product category.
Table 6  Descriptive Statistics for the Frozen Pasta Data

<table>
<thead>
<tr>
<th></th>
<th>Sales</th>
<th>Retail price $/10 oz.</th>
<th>Wholesale price $/10 oz.</th>
<th>Margin %</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mrs. Belgos</td>
<td>Before</td>
<td>211</td>
<td>1.468</td>
<td>0.927</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(134)</td>
<td>(0.059)</td>
<td>(0.038)</td>
<td>(0.2)</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>171</td>
<td>1.415</td>
<td>0.908</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(119)</td>
<td>(0.117)</td>
<td>(0.062)</td>
<td>(3)</td>
</tr>
<tr>
<td>Floresta</td>
<td>Before</td>
<td>284</td>
<td>1.245</td>
<td>0.568</td>
<td>52</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(324)</td>
<td>(0.222)</td>
<td>(0.122)</td>
<td>(15)</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>917</td>
<td>1.269</td>
<td>0.779</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2009)</td>
<td>(0.316)</td>
<td>(0.165)</td>
<td>(14)</td>
</tr>
<tr>
<td>Italia</td>
<td>Before</td>
<td>190</td>
<td>1.093</td>
<td>0.643</td>
<td>41</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(161)</td>
<td>(0.066)</td>
<td>(0.096)</td>
<td>(9)</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>187</td>
<td>1.074</td>
<td>0.637</td>
<td>41</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(141)</td>
<td>(0.066)</td>
<td>(0.053)</td>
<td>(5)</td>
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<td>Rosseto</td>
<td>Before</td>
<td>725</td>
<td>1.052</td>
<td>0.683</td>
<td>35</td>
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<tr>
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<td>(415)</td>
<td>(0.043)</td>
<td>(0.029)</td>
<td>(3)</td>
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<tr>
<td></td>
<td>After</td>
<td>896</td>
<td>1.087</td>
<td>0.667</td>
<td>39</td>
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<tr>
<td></td>
<td></td>
<td>(697)</td>
<td>(0.070)</td>
<td>(0.057)</td>
<td>(4)</td>
</tr>
<tr>
<td>Dominicks</td>
<td>Before</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>521</td>
<td>1.012</td>
<td>0.731</td>
<td>26</td>
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<tr>
<td></td>
<td></td>
<td>(972)</td>
<td>(0.131)</td>
<td>(0.011)</td>
<td>(15)</td>
</tr>
</tbody>
</table>

Notes. Sales figures are in units per week and per store. Standard Deviations in parentheses.

Before turning to the empirical results, recall from Equations (3) and (4) that the estimation of the demand parameters requires us to estimate the parameters of the joint distribution of the preferences and price-sensitivity parameters $\Sigma$, before and after store-brand introduction. The one simplification we make in the estimation is that while we allow the brand preferences to be correlated with one another, we assume that the price sensitivity is not correlated with brand preferences. The parameter estimates and their standard errors are presented in Table 7.

Note from Table 7 that we have not reported the interaction effects between the preferences and prices with the demographic variables (these are the same variables included in the case of the oats category). This is done in the interests of space and the complete results are available from the authors. In terms of the intrinsic preferences of the name brands, we find that the corresponding mean preference levels for all the name brands increase with the introduction of the Dominicks store brand. Further, Floresta and Rosseto have higher mean intrinsic preference levels and lower variability in preferences than the store brand. Additionally, we find that the mean price effect increases in magnitude from $-3.080$ to $-3.868$ with the Dominicks introduction. However, we need to compute elasticities to determine whether or not price sensitivity has increased with the new brand.

One of the features of the pasta data, unlike those for oats, is that we estimate the covariance matrix of brand preferences both before and after introduction. Looking at these matrices will give us some indication as to how substitution patterns may have changed across brands due to the retailer’s launch of its own brand. Accordingly, in Table 8, we provide these two matrices.

Table 8 indicates that the preferences for the store brand are virtually uncorrelated with those for Floresta and Rosseto. From Table 6, we see that these are the two name brands whose sales increase after the introduction of the store brand. By contrast, we find that the preferences for Mrs. Belgos and Italia are negatively correlated with those for the Dominicks brand. Along with their low preference correlations...
find that the own elasticity of all four name brands is greater than the own price elasticities. More importantly, we find that the high own elasticity brands are Mrs. Belgos and Italia—this could explain the relative insensitivity of the sales of Mrs. Belgos and Italia to the store-brand launch.

We now address the issue of whether or not price elasticities change with the introduction of the store brand. For this, we present in Table 9 the mean price elasticities change with the introduction of the store brand. However, substantively, the effects are similar to those found for oats, i.e., that the magnitude of the elasticity does increase.

Table 7  Parameter Estimates for Pasta Data—Demand Functions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Before (Mean)</th>
<th>After (Mean)</th>
<th>Variable</th>
<th>Before (Mean)</th>
<th>After (Mean)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mrs. Belgos</td>
<td>−3.995</td>
<td>−2.936</td>
<td>Rosetto</td>
<td>−1.080</td>
<td>0.149</td>
</tr>
<tr>
<td>σ (Mrs. Belgos)</td>
<td>(0.439)</td>
<td>(0.426)</td>
<td>σ (Rosetto)</td>
<td>(0.288)</td>
<td>(0.291)</td>
</tr>
<tr>
<td>Floresta</td>
<td>−1.883</td>
<td>−0.373</td>
<td>Dominicks</td>
<td>−</td>
<td>−1.348</td>
</tr>
<tr>
<td>σ (Floresta)</td>
<td>(0.333)</td>
<td>(0.317)</td>
<td>σ (Dominicks)</td>
<td>(0.245)</td>
<td></td>
</tr>
<tr>
<td>Italia</td>
<td>−3.123</td>
<td>−2.533</td>
<td>Price</td>
<td>−3.080</td>
<td>−3.868</td>
</tr>
<tr>
<td>σ (Italia)</td>
<td>(0.968)</td>
<td>(1.078)</td>
<td>σ (Price)</td>
<td>(0.440)</td>
<td>(0.396)</td>
</tr>
<tr>
<td>Summer</td>
<td>0.029</td>
<td>−0.026</td>
<td>Promotion</td>
<td>0.165</td>
<td>0.187</td>
</tr>
</tbody>
</table>

Notes. Standard errors in parentheses. σ(·) refers to the standard deviation of the heterogeneity distribution.

with the other name brands—Floresta and Rosetto—this could explain the relative insensitivity of the sales of Mrs. Belgos and Italia to the store-brand launch.

For the Italia brand, the difference is significant at the 10% level. Therefore, unlike the case of the oats category, here we find an increase in the own price elasticities of the name brands that is statistically significant. Introduction of the lower-priced store brand does appear to have played a role in raising elasticities. However, substantively, the effects are similar to those for oats, i.e., that the magnitude of the elasticity does increase.

Table 8  Covariance Matrix of Brand Preferences for Frozen Pasta

<table>
<thead>
<tr>
<th></th>
<th>Mrs. Belgos</th>
<th>Floresta</th>
<th>Italia</th>
<th>Rosetto</th>
<th>Dominicks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mrs. Belgos</td>
<td>6.723</td>
<td>−1.083</td>
<td>−0.880</td>
<td>−0.087</td>
<td>−0.500</td>
</tr>
<tr>
<td>Floresta</td>
<td>−1.083</td>
<td>0.652</td>
<td>0.167</td>
<td>0.035</td>
<td>0.040</td>
</tr>
<tr>
<td>Italia</td>
<td>−0.880</td>
<td>0.167</td>
<td>1.527</td>
<td>−0.173</td>
<td>−0.438</td>
</tr>
<tr>
<td>Rosetto</td>
<td>−0.087</td>
<td>0.035</td>
<td>−0.173</td>
<td>0.031</td>
<td>0.011</td>
</tr>
<tr>
<td>Dominicks</td>
<td>−0.500</td>
<td>0.040</td>
<td>−0.438</td>
<td>−0.011</td>
<td>0.328</td>
</tr>
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</table>
Next, we discuss the results from the supply side. In Table 10, we provide the estimates for the interaction parameters along with their standard errors. Again, recall that values between 0 and −1 imply that the retailer is making higher than Nash markups, whereas values greater than zero imply lower than Nash markups. A value of 0 corresponds to the Nash levels. It is clear from Table 10 that the retailer was making higher than Nash markups on all the four name brands prior to store-brand entry. Further, in the case of three of these manufacturers, the interaction parameters become larger in magnitude postentry. This implies that Mrs. Belgos, Italia, and Rosetto are behaving in a more accommodating fashion towards the retailer after the store brand is introduced. The finding is consistent with the descriptive statistics data in Table 6 in which we find that, while the average retail prices for these brands decline somewhat (consistent with the increase in price sensitivity), the wholesale prices decline even more. An interesting point to note here is that we observe this behavior of manufacturers even though the retailer has no real cost advantage vis-à-vis the store brand (in Table 6, the average wholesale price of the store brand is $0.731, which is higher than the corresponding prices for Italia and Rosetto). However, the results are quite different for the Floresta brand. Here we find that the manufacturer behaves in a less accommodating fashion after the Dominicks brand launch. Although retail prices increase, wholesale prices increase even more. Despite this, sales of this brand increase. The main reason for this is the added value from new varieties offered by the manufacturer of Floresta.

To summarize the results from the pasta category, we find that these results are to a large extent consistent with those from the oats category. Specifically, the price elasticities go up in magnitude (although in the pasta case the differences are statistically significant). Further, the manufacturers behave in a more accommodating fashion after store-brand entry. The one exception to this is Floresta where the results can be attributed to the manufacturer’s ability to enhance

<table>
<thead>
<tr>
<th>Table 9 Mean Price Elasticity Estimates for Frozen Pasta Data</th>
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<tr>
<td>Mrs. Belgos</td>
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<tr>
<td>Mrs. Belgos Before</td>
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<td>After</td>
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<tr>
<td>Floresta Before</td>
</tr>
<tr>
<td>After</td>
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<tr>
<td>Italia Before</td>
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<td>After</td>
</tr>
<tr>
<td>Rosetto Before</td>
</tr>
<tr>
<td>After</td>
</tr>
<tr>
<td>Dominicks Before</td>
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<td>After</td>
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</tbody>
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*Note: Effect of row price on column sales*

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<tr>
<th>Table 10 Parameter Estimates (Standard Errors) for Pasta Data—Pricing Equations</th>
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<tr>
<td>Brand</td>
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<tr>
<td>Mrs. Belgos</td>
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<tr>
<td>After</td>
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<tr>
<td>Floresta</td>
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<td>After</td>
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<tr>
<td>Italia</td>
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<tr>
<td>After</td>
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<tr>
<td>Rosetto</td>
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</table>
the value of its products to the end consumers. We see this as evidence, albeit limited, of the generalizability of our results across product categories.

Conclusions
In this paper, we conduct 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 is on investigating the impact of store-brand entry on the preferences for the national brands in the category and on the price sensitivities of consumers.

On the supply side, the study has attempted to measure the nature of manufacturer-retailer interactions before and after the introduction of a store brand.

An important issue pertaining to the supply-side analysis is the potential implication for managers. This is an important point to address, especially in the light of the burgeoning literature on supply-side analyses and the fact that correcting for the endogeneity bias does not really require estimation of the supply side (recall the discussion on the two-step method above). There are two reasons for being interested in the supply side. First, able to describe the nature of manufacturer-retailer interactions is of interest to both researchers as well as policy makers (e.g., the FTC has been looking into the issue of shifting channel power to the retailer as well as certain practices by retailers that may be preventing the access of smaller manufacturers to their consumers). The second, and managerially relevant, reason is that while manufacturers may be aware of their individual relationships with the retailer, they do not know the nature of interactions between other manufacturers and the retailer(s). To understand these relationships, they need to study the supply side of the equation. A legitimate question is, of course, that the manufacturer does not have access to wholesale prices of the other manufacturers. In such a situation, the manufacturer can estimate the (average) wholesale prices for the other manufacturers by using the supply-side equations and treating those wholesale prices as unknown parameters (as in BVB). Estimating the wholesale prices and interaction parameters for the other manufacturers, gives the focal manufacturer a better understanding of the nature of channel relationships.

There are of course, several caveats to our analysis. First, while we have tried to focus our attention on a product category (oats) in which the store-brand entry was the dominant event, there could have been other systematic factors affecting our before-and-after estimates. Accordingly, we conducted a check of robustness to address this issue. Second, having data from a single retailer could affect our conclusions on various levels. We assume that the retailer is a multiproduct monopolist. However, we did attempt to proxy for the level of retail competition in each store area by including the driving time variable in the analysis.

Our analysis of the supply side as described above includes only the analysis of the retailer’s problem and not of the manufacturer’s problem. In other words, we investigate the nature of the retailer-manufacturer interaction in how this would influence the pricing behavior of the retailer. This is in contrast with recent studies such as those by BVB, Kadiyali et al. (2000), and Sudhir (2001). There are several reasons for focusing only on the retailer’s markup. As we observe the retailer’s actual markup, and we are able to predict the markup conditional on the demand specification, the deviation between the two can be ascribed to the nature of interactions quite unambiguously. Further, it is unclear whether manufacturer-retailer interactions occur on a weekly basis or if manufacturer decision making is over longer horizons. Future research needs to examine manufacturer-related issues as doing so will shed light on the important issue of whether channel “power” has shifted from the national brand manufacturer to the retailer due to store-brand introduction (Messinger and Narasimhan 1995).

Finally, the biggest limitation in a complete empirical analysis of manufacturer-retailer channel interactions is the lack of data on fixed payments made in the channel. To the extent that these data are unavailable, investigating the nature of interactions and obtaining implications for channel power will be necessarily incomplete.

In summary, this study provides evidence of both demand and supply effects of store-brand entry. In the oats category, we find that national-brand preferences
do not change, but consumers become more price sensitive after the launch of the store-brand. Further, after the retailer introduces the store-brand, the national-brand manufacturer behaves in a more “accommodating” fashion towards the retailer in terms of the latter’s pricing decisions.

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