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The authors construct a model of the local ketchup market in a Texas city that accounts for household, manufacturer, and retailer decisions. That is, the model develops both demand and supply sides of the market. The authors model the demand side through a latent utility framework that allows for a no-purchase option. Accounting for both sides of the market enables the authors to check for any endogeneity problems on the demand side. They model the supply side through the profit-maximizing decisions of the manufacturers and a multiproduct retailer. Accounting for both the retailer and the manufacturer decisions enables the authors to evaluate the degree of manufacturer competition, retailer–manufacturer interactions, and retailer product-category pricing. Given the model assumptions and the market being studied, the authors find that not accounting for demand endogeneity can create bias in the estimation, the retailer seems to price below the static profit-maximizing prices for two of the three brands, and the inferred marginal wholesale prices are below the equilibrium uniform wholesale prices for two brands. The authors discuss the results with regard to channel bargaining, quantity discounts, and retailer category pricing.

Retailer, Manufacturers, and Individual Consumers: Modeling the Supply Side in the Ketchup Marketplace

In a marketplace of a typical consumer product category, there are several types of players making decisions with different objectives. Manufacturers care about their own profits and make decisions about the products they sell by taking into account the demand conditions, other manufacturers' strategic behavior, and retailer strategies. Similarly, retailers are concerned about retail profits and make decisions about the final prices of the products they carry on the basis of the manufacturers' selling conditions and the demand situation. Finally, individual consumers have their own preferences across the product attributes and, with the conditions set by the retailers and manufacturers, choose whether and which product to buy. The aggregate of potential individual consumers is the demand faced by retailers for each of the products they carry.

When studying the behavior of one type of economic agent, it is important to consider the decisions by other market players, because otherwise, certain behavior may be incorrectly attributed to exogenous factors (e.g., consumer preferences, manufacturer or retailer costs, manufacturer or retailer strategic interaction). It is well known (see, e.g., Morgan 1990) that studying consumer behavior without considering manufacturers' and retailers' decisions may lead to an underestimation of how sensitive consumers are to price. Similarly, modeling manufacturers' decisions without considering retailers' behavior may lead to a failure to consider the retailers' joint-profit-maximizing (category pricing) effect in the analysis and an overestimation of the degree of collusion between manufacturers. In contrast, considering the retailer but forgetting about manufacturers may lead to an overestimation of the way that a retailer responds to demand shocks and wrongly indicate that the retailer is not engaging in category pricing. Finally, not considering individual consumers may lead researchers to consider demands that are inconsistent with utility maximization and fail to account for all possible information about (observed) heterogeneity among consumers.

In this article, we study the decisions of individual consumers,[1] manufacturers, and a retailer in the ketchup mar-

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[1]We use the term "consumer" to refer to households, because we only use observations at the household level.

ketplace in Midland, Tex., between March 1982 and September 1984. The model accounts for both the supply and the demand sides of the market. We derive market demand from a general class of discrete-choice models of consumer behavior. Consumers can choose to buy one of several products or not buy any product at all (the no-purchase option). The utility of a consumer is a function of product characteristics and individual taste parameters. We derive product-level market shares as the aggregate outcome of consumer decisions, assuming that we have a representative panel of consumers. We model the supply side as the profit-maximizing decisions of both the manufacturers and the multiproduct retailer. Manufacturers set wholesale prices, and the retailer takes the wholesale prices as a given and marks them up to set retail prices.

We evaluate the degree of manufacturer competition, the manufacturer–retailer interactions, and the retailer product-category pricing. Are manufacturers competing more or less than Nash competition would predict? Are the retail prices charged consistent with contracts between manufacturers and the retailer that demand a uniform price or allow quantity discounts? Is there any evidence from the retail prices of the relative bargaining power of the manufacturers and retailer? Is the retailer behaving to maximize category profits?

As a summary of the results, we find that some manufacturers seem to set lower marginal wholesale prices than a static Nash competition on uniform prices would predict. This finding is consistent with both pricing dynamic effects and quantity discounts by the manufacturers, in which case the marginal price of the tariff is somewhere between the marginal cost and the Nash uniform price. This result also may be consistent with the retailer's greater bargaining power.

We also find that the retailer seems to price lower than a joint-profit maximization of the products would imply, which may be a result of not considering other complementary products carried by the retailer in the analysis. The retailer may want to lower the price of the products we analyze to encourage consumers to buy other products carried by the retailer. The results seem robust to different specifications of the marginal cost and latent utility.

The strategic interaction among manufacturers that we consider is in the tradition of Bresnahan (1989). Several studies have modeled this strategic interaction while using a well-developed structural demand system. For example, Berry, Levinsohn, and Pakes (1995) study the automobile market; Nevo (2001) examines the ready-to-eat cereal industry; and Besanko, Gupta, and Jain (1998) apply the framework to the yogurt, ketchup, peanut butter, and powdered laundry detergent markets (for a recent survey, see Kadiyali, Sudhir, and Rao 2001). Compared with this type of study, our article adds both the multiproduct retailer's decision making and household-level data to the model. As we argued previously, both these features seem conceptually important in the ketchup market. These two features also may be important in several of the markets that were previously studied. Besanko, Gupta, and Jain (1998) also consider a multiproduct retailer but assume that the retailer's margins and wholesale prices are simultaneously set. This assumption results in higher theoretical retail prices (from the resultant higher wholesale prices); if this assumption does not hold but is used in the empirical analysis, the researcher could infer that the retail prices are too high. In addition to this type of study, we also investigate the degree of manufacturer competitiveness in the market.

Also related to this article, Villas-Boas and Winer (1999) examine the issue of price endogeneity on the demand side of the market using panel data. In comparison with Villas-Boas and Winer, we develop the supply side of the market completely and consider the no-purchase option. We also make several variations to the demand side of the market, such as a flexible form for price and a different set of instruments.

Finally, Kadiyali, Chintagunta, and Vilcassim (2000) study the analgesic market using aggregate data and a non-structural demand side and model the supply side with both manufacturers and a multiproduct retailer. In relation to this study of the analgesic market, we have a fully structural demand side and use a household panel data set. Our approach does not make any assumptions about being able to observe the wholesale prices. Sudhir (2001) also studies competitive pricing in the presence of a strategic retailer with two brands in the yogurt market. Our study and his study were conducted independently and investigate different markets. In addition, we use a household panel data set, which enables us to incorporate the observed heterogeneity among consumers (for a model of disaggregate data with both demand and supply decisions, see also Draganska and Jain 2002). We also develop the model for any number of brands and perform the analysis with more than two brands (see also Villas-Boas and Zhao 1999).[2]

The rest of the article is organized as follows: In the next section, we discuss general issues about the ketchup market in the United States and in Midland, Tex., in particular. Subsequently, we present a general framework of the model, and in the next section, we explain the estimation issues. Next, we present and discuss the empirical results. Finally, we conclude and explore issues for further research.

THE KETCHUP MARKET

Ketchup is the most widely used condiment in the United States, found in 97% of all kitchens, a showing matched only by salt, pepper, and sugar. Currently, 56% of ketchup is consumed with three main foods: hamburgers, hot dogs, and French fries, which remain the most eaten foods for children and adults, according to a survey of national eating trends by NPD Group, a market research firm. Children under the age of 13 consume 50% more ketchup than people in other age groups (Balu 1998).

Heinz is the king of ketchup, claiming 45% of the ketchup market in 1984. Heinz ketchup has more than double the sales and volume of its nearest competitor, Hunts (Balu 1998). It is on four of five restaurant tables, and the company sells 12 billion single-serving packets of ketchup and condiments annually. Hunts is the second major brand,

[2]Chintagunta (2002) studies retail chain decisions, without considering the manufacturers' decisions, in the analgesic market with aggregate data. Villas-Boas (2000) considers competing retailers' and manufacturers' decisions in an extensive study of the yogurt market, also with aggregate data. For theoretical analyses of coordination issues in channels of distribution see, for example, Shugan (1985), Moorthy (1988), Desai (1997), Iyer (1998), and Villas-Boas (1998).

followed by Del Monte. Generic, private-label, regional, and gourmet ketchups have a smaller market share. There is, however, some regional variability in market shares, and for the grocery retailer from Midland, Tex., that we consider in the analysis, the major player is Del Monte, followed by Hunts and Heinz. During the 1980s, 95% of all ketchup sales occurred in grocery stores, 58% in supermarkets alone (www.ketchup.wonderland.org). Heinz's U.S. market share remained stable through the 1980s and 1990s with 43% share in 1998. In 1999, its market share began to grow because of packaging innovations, and it reached 60% in 2002 (H.J. Heinz 1999; *Packaging Digest* 2002).

The ketchup category has little differentiation and is dominated by a few brands. Therefore, the strategic interaction among the different brands is strong. However, it is not clear whether the results obtained for this category extend to categories with more differentiated products and/or less dominance by a few brands.

The data set is from Monday, March 15, 1982, to Sunday, September 2, 1984. This range represents 129 weeks in the data set. Midland is located in west Texas and is home to approximately 100,000 people. Its economy depends on the ups and downs of the oil business, particularly oil prices. Oil prices in the sample were declining but relatively stable at a high level (a big drop in prices occurred from 1985 to 1986).

The panel includes 252 households that shopped at one of the three largest grocery retailers in Midland. The mean household income is $24,121, which is a relatively high income level in the period being analyzed. The members of households in the panel are predominantly white, and the mean household size is 3.2 family members. Furthermore, 93% of the households represent a single-family home. The retailer we consider seemed to have a high degree of market power in the market. Wal-Mart had a modest presence in Midland at the time of the sample; the Midland store opened in 1984 without a grocery component (it became a Supercenter only in 1991). We concentrate on the three largest brands (in 32-ounce packages), which represent 76% of the total ketchup volume in the panel: Del Monte, Hunts, and Heinz. The total number of panel purchases of the three brands is 1265, which means that each household buys, on average, two ketchup bottles per year. The shares of purchases among the three brands in the panel are 52% for Del Monte, 34% for Hunts, and 14% for Heinz. These market shares are different from the national shares because Del Monte has a close connection to Texas, where it has production facilities, and Hunts focuses its attention in the west, whereas Heinz is based on the East Coast in Pennsylvania. In the sample, the average prices per package for Del Monte, Hunts, and Heinz were $.92, $.98, and $1.37, respectively. Table 1 presents the standard deviations of the prices and the means and standard deviations of the unit sales per week in the panel. The standard deviations of the prices are due not only to temporary price cuts but also to changes in the price levels.

THE MODEL: A GENERAL FRAMEWORK

Consider a market in which there are J brands (j = 1, ..., J) that belong to several manufacturers and one retailer. The retailer buys products from manufacturers and sells them to consumers. The researcher is able to observe prices and the choices of a representative panel of consumers, one of which is not to buy any brand.

Demand

The primitives of the model are the product characteristics, consumer preferences, and the equilibrium concept. Consider first the consumer side given the product characteristics. Consumers buy one product from a choice set S with J + 1 alternatives (j = 0, 1, ..., J). We denote I as the number of consumers in the panel and T as the number of weeks for which we observe choices for every consumer. A consumer derives utility from buying one product in that choice set (buying alternative j = 0 means that the consumer made no purchase of the available brands). The consumer buys the product for which the perceived utility is the greatest but will make no purchase if the utility of any brand is less than the utility if he or she makes no purchase. Consumer i's utility for each choice j in week t can be written as $U_{ijt} = x_{ijt}\beta + \psi_{jt} + \nu_{it} + \lambda\varepsilon_{ijt}$, for j = 1, ..., J; if the consumer makes no purchase, $U_{i0t} = \varepsilon_{i0t}$.

The term x_{ijt} is a vector of the product characteristics, which can be individual specific and time varying. In the application that follows, we include the following variables in x_{ijt}: one brand-specific dummy for each brand, a Box-Cox transformation of price $f(p_j) = (p_j^\zeta - 1)/\zeta$ (where $0 < \zeta < 1$), display, feature, household income, family size, a heavy user dummy, and a loyalty-type variable. When ζ approaches 1, the utility becomes linear in price; when ζ approaches 0, the utility becomes linear in the log of price.[3] The income, family size, heavy user dummy (which we define as a household that buys more than three units in the study period), and loyalty-type variables capture some of the taste heterogeneity across consumers and are household specific.[4] We specify the loyalty variable as the number of

[3]Given the probability distribution of errors, the Box-Cox transformation allows the equilibrium margins to be different across products.

[4]Random-effects specifications of heterogeneity, as in the work of Kamakura and Russell (1989) or Chintagunta, Jain, and Vilcassim (1991), could be introduced, but it would not be possible to estimate such a model with the current computational capabilities in a simultaneous and efficient way, as we present subsequently, because the likelihood function becomes a nonseparable, multi-integral probability (Villas-Boas and Winer 1999). Kuksov and Villas-Boas (2001) use a quasi-likelihood approach and Yang, Chen, and Allenby (2003) use a Bayesian approach to deal with this issue. For another specification of the loyalty variable, see Guadagni and Little (1983).

Table 1
SUMMARY STATISTICS: PRICES AND UNIT SALES

	Prices			*Unit Sales*		
	Del Monte	*Hunts*	*Heinz*	*Del Monte*	*Hunts*	*Heinz*
Means	$.92	$.98	$1.37	5.09	3.30	1.41
Standard Deviation	$.08	$.14	$ .07	4.73	3.82	1.30

purchases of a brand by the household and fix it for all time periods. The vector β and scalar λ are parameters to be estimated. The vector β represents the weights in the latent utility given to each element in x_{ijt}. We describe the role of the parameter λ subsequently.

The error terms are ψ_{jt}, ε_{ijt}, and ν_{it} for all possibilities of i, j, and t. We denote ψ_t as the vector of ψ_{jt} for j = 1, ..., J. Any pair of the errors ψ_t, ε_{ijt}, and ν_{it} is assumed with zero covariance for all possibilities of i, j, and t. Moreover, ψ_t is identically distributed across t; ε_{ijt} is identically distributed across i, j, and t; and ν_{it} is identically distributed across i and t.

The vector ψ_t represents market phenomena or brand-specific variables that affect all households and are not observed by the researcher (and therefore are not included in the deterministic part of the choice model) but that marketing managers use in their decisions. These errors are referred to as common demand "shocks" (Villas-Boas and Winer 1999) and involve changes in tastes across all consumers. For example, common demand shocks can represent the difficulty of quantifying aspects of style, prestige, reputation, prior experience, or quantifiable aspects about which the researcher does not have information (Berry, Levinsohn, and Pakes 1995). In consumer packaged goods markets, it can also represent taste changes for brands induced by other marketing-mix variables about which the researcher does not have information, such as in-store effects, advertising, or coupon availability (Besanko, Gupta, and Jain 1998). Seasonal effects could be part of some of these taste changes, though we could not find significant seasonal category effects in the data set. We assume that ψ_t is normally distributed with mean zero and variance–covariance V_ψ. The standard deviation of ψ_{jt} is denoted by $\sigma_{\psi j}$, and the correlation between ψ_{jt} and ψ_{kt} is denoted by $\rho_{\psi_j \psi_k}$.

The errors ε_{ijt} are assumed to be extreme value distributed with parameter θ. The error ν_{it} is assumed to have the unique distribution derived by Cardell (1997), such that $\nu_{it} + \lambda\varepsilon_{ijt}$ is extreme value distributed with parameter θ. This representation of preferences is the nested logit model, and we adopt it because there is a greater degree of substitutability between any pair of brands than between any brand and the no-purchase option. The error ν_{it} is similar to a common demand shock across brands for consumer i to buy a brand versus not to buy any brand. The parameter λ, which is constrained between 0 and 1, measures the degree to which the no-purchase option and any brand are as substitutable as any pair of brands. If λ approaches 1, any brand is as substitutable for another brand as for the no-purchase option. In this case, we are back in the logit model. If λ approaches 0, any brand is infinitely more substitutable for another brand than for the no-purchase option. The scale of the indirect utility is set by $\sigma^2_{\psi_J} + \pi^2/(6\theta^2) = \pi^2/6$, which enables us to make direct comparisons of the parameters of the latent utility across models. If the common demand shocks are 0, $\sigma_{\psi_J} = 0$, and we obtain $\theta = 1$, the standard nested logit. If we denote $B \equiv \{1, ..., J\}$, the probability of consumer i choosing brand j in week t given that he or she buys one brand is

$$\bar{s}_{ij/Bt} \frac{e^{\theta(x_{ijt}\beta + \psi_{jt})/\lambda}}{D_{iBt}}, \tag{1}$$

where

$$D_{iBt} = \sum_{j \in B} e^{\theta(x_{ijt}\beta + \psi_{jt})/\lambda}. \tag{2}$$

The probability of consumer i choosing one of the group B products in week t (the group share) is $\bar{s}_{iBt} = [D^\lambda_{iBt}/(1 + D^\lambda_{iBt})]$, which makes the probability of consumer i choosing brand j among all possible choices in week t

$$s_{ijt} = \bar{s}_{ij/Bt}\bar{s}_{iBt} = \frac{e^{\theta(x_{ijt}\beta + \psi_{jt})/\lambda}}{D^{1-\lambda}_{iBt}[1 + D^\lambda_{iBt}]}. \tag{3}$$

The probability of consumer i choosing not to buy any brand in week t is given by

$$s_{i0t} = \frac{1}{1 + D^\lambda_{iBt}}. \tag{4}$$

Finally, assuming that we have a representative panel of the market, we construct the share equations for each choice as $s_{jt} = 1/I\ \Sigma_i s_{ijt}$ for j = 0, 1, ..., J. Note that these shares represent shares of the total market (including the no-purchase option).

The model does not allow for the possibility that a consumer purchases multiple units at the same time. In the application, we consider at most the purchase of one unit per time period per consumer (when several units were purchased, they were all of the same brand). Allowing for multiple purchase occasions per time period per consumer would easily solve this problem if we were to assume that ε_{ijt} is independent across i, where i can represent different purchase occasions of the same consumer. For a discussion of the possibility of multiple purchases without this assumption and its implications for the results, see Gupta (1988), Chiang (1991), Chintagunta (1993), Dubé (2004), Guo (2003), and Van Heerde, Gupta, and Wittink (2003). If consumers who purchase more than one unit behave differently in response to the marketing-mix variables, then not incorporating multiunit purchases could affect the results. It is important to measure the impact of this generalization in additional research. The model also does not allow for the impact of inventories on consumer decision making, which may lead to lagged effects, as some of the previously cited articles have discussed. A potential way to introduce these effects is to include the quantity purchased in the past in the latent utility for the no-purchase option. These lagged effects can generate important dynamic implications on the supply side of the market, which can seriously complicate the estimation procedure and is beyond the scope of this article. If the consumption rate is sufficiently high in comparison with the frequency of purchase or if the consumption rate or inventory costs are sufficiently stochastic, we would expect that the inventory effects would be smaller. Therefore, not accounting for these effects would have less impact on the parameter estimates. Finally, the model does not account for the potential interaction between prices and the feature or display variables, which have been shown to be important (e.g., Van Heerde, Leeflang, and Wittink 2001, 2004). Considering these interactions in the context of a model of the supply side of the market can have important implications and should be examined in further research.

This article captures the first-order effects of price, feature, and display. We now turn to our main point: investigating the supply-side interactions in this market given the demand conditions.

Supply

Retailer. On the retail side, we consider a retailer that chooses the prices of the brands in the ketchup category given the wholesale prices. In each week t, given wholesale prices $w_{1t}, \ldots, w_{Jt}$ set by manufacturers and the retailer's (constant) marginal costs $r_{1t}, \ldots, r_{Jt}$, the retailer's problem is to choose the retail prices $p_{1t}, \ldots, p_{Jt}$ to maximize its profit,

$$\pi_t^r = \sum_{j=1}^{J} (p_{jt} - w_{jt} - r_{jt}) s_{jt} M, \tag{5}$$

where M is the total size of the market. The first-order conditions are

$$\frac{\partial \pi_t^r}{\partial p_{jt}^r} = s_{jt} + \sum_{k=1}^{J} (p_{kt} - w_{kt} - r_{kt}) \frac{\partial s_{kt}}{\partial p_{jt}} = 0, \tag{6}$$

for j = 1, ..., J. Note that these conditions imply that when the retailer makes its pricing decision, it takes into account not only the impact that a change in the price of a particular brand has on the demand for that brand but also how that price change affects the demand of all other brands that the retailer sells. Joint-profit maximization of all of its brands means that the retailer acts as a perfect category manager in setting the prices of its brands. Thus, the retailer's margins in week t can be written as follows:

$$\begin{bmatrix} p_{1t} - w_{1t} - r_{1t} \\ p_{2t} - w_{2t} - r_{2t} \\ \vdots \\ p_{Jt} - w_{Jt} - r_{Jt} \end{bmatrix}_{J \times 1} = \begin{bmatrix} \frac{\partial s_{1t}}{\partial p_{1t}} & \frac{\partial s_{2t}}{\partial p_{1t}} & \cdots & \frac{\partial s_{Jt}}{\partial p_{1t}} \\ \frac{\partial s_{1t}}{\partial p_{2t}} & \frac{\partial s_{2t}}{\partial p_{2t}} & \cdots & \frac{\partial s_{Jt}}{\partial p_{2t}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial s_{1t}}{\partial p_{Jt}} & \frac{\partial s_{2t}}{\partial p_{Jt}} & \cdots & \frac{\partial s_{Jt}}{\partial p_{Jt}} \end{bmatrix}_{J \times J}^{-1} \begin{bmatrix} -s_{1t} \\ -s_{2t} \\ \vdots \\ -s_{Jt} \end{bmatrix}_{J \times 1}. \tag{7}$$

To evaluate the retailer's price-setting behavior, we add the parameters $\mu_1, \ldots, \mu_J$ to the $J \times J$ matrix so that the jkth element of the matrix takes the form $(1/\mu_j)(\partial s_{kt}/\partial p_{jt})$. If $\mu_1 = \mu_2 = \ldots \mu_J = 1$, the retailer acts as a perfect category manager in setting the prices of its brands, the full structural model of retailer behavior. If $\mu_j > 1$, the retailer charges a higher price for brand j than is optimal. Testing for $\mu_j > 1$ can also be regarded as a test of the structural model. Alternatively, it can be an ad hoc evaluation of the pricing behavior of the retailer that may capture the impact of the relationship between the retailer and the manufacturers over time on retailer pricing behavior. We denote by μ the vector of μ_j's. Kadiyali, Chintagunta, and Vilcassim (2000) present an alternative way to evaluate the pricing behavior of the retailer and its interaction with manufacturer decisions as "conduct parameters" of the supposed impact of the decision of one player on the decision of another. As Corts (1999) notes, the interpretation that inequality on μ represents the direction of the deviations from the optimal prices depends on the actual deviations being exactly as they are modeled here. This comment also applies to the deviations from manufacturer Nash behavior, which we discuss subsequently. Corts shows, in simulations and a model without retailers, that if the dynamic interaction involves periods of price wars to sustain collusion, these parameters may not capture the degree of deviation with respect to the theoretical pricing model.

Considering no retail competition may not be unreasonable because grocery retailers seem to have great market power.[5] Walters and MacKenzie (1988) and Slade (1995) argue and show evidence that there is limited competition in some categories in the grocery channel. If there is retail competition (and no collusion considerations), the common demand shock ψ_{jt} also represents the prices of the retail competitors, and the distribution assumptions of ψ_{jt} may not be satisfied because they also involve assumptions about the behavior of competitors.

Manufacturers. On the manufacturer side of the market, we assume that each manufacturer chooses its wholesale price to maximize its profit and takes into account the optimal reaction by the retailer for the prices of all brands. Each brand that we consider in the ketchup market is sold by a different manufacturer, and therefore there are J manufacturers. However, the analysis also applies to any manufacturer carrying more than one brand.

Formally, manufacturer j's problem in week t is to choose the price w_{jt} that maximizes its profit,

$$\pi_t^m = (w_{jt} - c_{jt}) s_{jt} M, \tag{8}$$

where c_{jt} is the (constant) marginal cost of manufacturer j in week t. Note that we do not observe either the wholesale prices or the marginal costs, but we may be able to infer the difference between wholesale prices and manufacturer marginal costs from the data on prices and demands given the model parameters, the optimizing behavior of the manufacturers, and an assumed structure of the manufacturers' marginal costs.

The first-order conditions are

$$s_{jt} + (w_{jt} - c_{jt}) \sum_{k=1}^{J} \frac{\partial s_{jt}}{\partial p_{kt}} \frac{\partial p_{kt}}{dw_{jt}} = 0, \text{ for } j = 1, ..., J, \tag{9}$$

where each manufacturer takes into account the impact of its wholesale price on all retail prices. This equation is just an application of the double marginalization literature (e.g.,

[5]For a theoretical analysis of competing behavior in distribution channels and for exclusive dealing, see McGuire and Staelin (1983) and Coughlan and Wernerfelt (1989); for the case of one multiproduct retailer, see Choi (1991); and for competing multiproduct retailers, see Lal and Villas-Boas (1998). Competition may be low between retailers because of high search costs across retailers (for the role of search costs in markets in another setting, see Kuksov 2004a, b). For an empirical application of category pricing, see Tellis and Zufryden (1995).

Lal and Villas-Boas 1998; Moorthy 1988). Manufacturer j's margin can then be written as follows:

$$(10)\qquad w_{jt} - c_{jt} = -\frac{s_{jt}}{\sum_{k=1}^{J} \frac{\partial s_{jt}}{\partial p_{kt}} \frac{\partial p_{kt}}{\partial w_{jt}}}.$$

To calculate the manufacturer's margin, we need to know $\partial p_{kt}/\partial w_{jt}$ for all j and k. Note that these terms measure the extent of passthrough and cross passthrough of changes in the wholesale prices. For estimation of these terms in a reduced-form model, see Besanko, Dubé, and Gupta (2005); for more discussion on these passthrough terms, see Moorthy (2004).[6] We can get $\partial p_{kt}/\partial w_{jt}$ for all j and k by totally differentiating the retailer's first-order conditions with respect to w_{jt} for j = 1, ..., J. For each j, this yields

$$(11)\qquad G_t \begin{bmatrix} \frac{\partial p_{1t}}{\partial w_{jt}} \\ \frac{\partial p_{2t}}{\partial w_{jt}} \\ \vdots \\ \frac{\partial p_{Jt}}{\partial w_{jt}} \end{bmatrix}_{J \times 1} = \begin{bmatrix} \frac{\partial s_{jt}}{\partial p_{1t}} \\ \frac{\partial s_{jt}}{\partial p_{2t}} \\ \vdots \\ \frac{\partial s_{jt}}{\partial p_{Jt}} \end{bmatrix}_{J \times 1},$$

where G_t is a J × J matrix with ikth element

$$(12)\qquad g_{ik}^{t} = \frac{\partial s_{it}}{\partial p_{kt}} + \frac{\partial s_{kt}}{\partial p_{it}} + \sum_{l=1}^{J} (p_{lt} - w_{lt} - r_{lt}) \frac{\partial^2 s_{lt}}{\partial p_{it} \partial p_{kt}},$$

with $p_{lt} - w_{lt} - r_{lt}$ obtained for $\mu_j = 1, \forall j$. Inverting Equation 11, we obtain

$$(13)\qquad \begin{bmatrix} \frac{\partial p_{1t}}{\partial w_{jt}} \\ \frac{\partial p_{2t}}{\partial w_{jt}} \\ \vdots \\ \frac{\partial p_{Jt}}{\partial w_{jt}} \end{bmatrix}_{J \times 1} = G_t^{-1} \begin{bmatrix} \frac{\partial s_{jt}}{\partial p_{1t}} \\ \frac{\partial s_{jt}}{\partial p_{2t}} \\ \vdots \\ \frac{\partial s_{jt}}{\partial p_{Jt}} \end{bmatrix}_{J \times 1}, j = 1, \ldots, J.$$

Thus, manufacturer j's margin in week t can be written as follows:

$$(14)\qquad w_{jt} - c_{jt} = -\frac{s_{jt}}{\left[\frac{\partial s_{jt}}{\partial p_{1t}} \frac{\partial s_{jt}}{\partial p_{2t}} \cdots \frac{\partial s_{jt}}{\partial p_{Jt}}\right] G_t^{-1} \left[\frac{\partial s_{jt}}{\partial p_{1t}} \frac{\partial s_{jt}}{\partial p_{2t}} \cdots \frac{\partial s_{jt}}{\partial p_{Jt}}\right]'}.$$

Finally, we write the retail prices in week t as follows:

$$(15)\qquad \left[p_{jt}\right]_{J \times 1} = \left[c_{jt} + r_{jt}\right]_{J \times 1} - \left[\frac{s_{jt}}{\left[\frac{\partial s_{jt}}{\partial p_{1t}} \frac{\partial s_{jt}}{\partial p_{2t}} \cdots \frac{\partial s_{jt}}{\partial p_{Jt}}\right] G_t^{-1} \left[\frac{\partial s_{jt}}{\partial p_{1t}} \frac{\partial s_{jt}}{\partial p_{2t}} \cdots \frac{\partial s_{jt}}{\partial p_{Jt}}\right]'}\right]_{J \times 1}$$
$$+ \begin{bmatrix} \frac{1}{\mu_1}\frac{\partial s_{1t}}{\partial p_{1t}} & \frac{1}{\mu_1}\frac{\partial s_{2t}}{\partial p_{1t}} & \cdots & \frac{1}{\mu_1}\frac{\partial s_{Jt}}{\partial p_{1t}} \\ \frac{1}{\mu_2}\frac{\partial s_{1t}}{\partial p_{2t}} & \frac{1}{\mu_2}\frac{\partial s_{2t}}{\partial p_{2t}} & \cdots & \frac{1}{\mu_2}\frac{\partial s_{Jt}}{\partial p_{2t}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{\mu_J}\frac{\partial s_{1t}}{\partial p_{Jt}} & \frac{1}{\mu_J}\frac{\partial s_{2t}}{\partial p_{Jt}} & \cdots & \frac{1}{\mu_J}\frac{\partial s_{Jt}}{\partial p_{Jt}} \end{bmatrix}_{J \times J}^{-1} \begin{bmatrix} -s_{1t} \\ -s_{2t} \\ \vdots \\ -s_{Jt} \end{bmatrix}_{J \times 1}.$$

In the empirical specification, we assume that the marginal cost for each brand j incurred by its manufacturer and the retailer, $c_j + r_j$, is a brand-specific linear function of observable cost shifters z_t, so $c_{jt} + r_{jt} = z_t\gamma_j + \eta_{jt}$, where γ_j is a vector of cost parameters, η_{jt} is a random shock that we assume is normally distributed with zero mean, and the vector η_t (of all η_{jt} in week t) has variance V_η. The term η_{jt} can capture variations in the marginal costs that are not included in Z_t, and it may also include inventory-level effects for the retailer. The standard deviation of η_{jt} is denoted by σ_{η_j}, and the correlation between η_{jt} and η_{kt} is denoted by $\rho_{\eta_j\eta_k}$. We also denote the covariance between η_t and ψ_t as $V_{\eta\psi}$. The correlation between η_{jt} and ψ_{kt} is denoted by $\rho_{\eta_j\psi_k}$.

Thus, we perform the analysis without observing the wholesale prices. Using the retailer reports of the wholesale prices could help in the analysis, but they should not be taken at face value because they may be based on accounting practices and may not fully reflect the economic marginal costs to the retailer. This is particularly important in the case in which there are implicit nonlinear incentives and deals vary from one week to the next. The economic marginal costs to the retailer, namely, the relevant wholesale prices, reflect not only the formal wholesale prices but also trade promotions, the marginal effects of different types of allowances, "street money," and/or items that are classified as "over and above" or "spiffs" (sales promotion incentive fund; Lewis 2001). Typically, manufacturers do not choose formal wholesale prices every week for the coming week, but some other types of allowances can change from week to week. If trade promotions and wholesale prices have an effect only on the marginal price paid by the retailer, they can be lumped into one variable. Note, however, that manufacturers choose both formal wholesale prices and trade promotions, and these two choices may have different impacts on the retailer's behavior. It may be interesting to create a model that incorporates this distinction if such a model could be developed from primitive assumptions and have important substantive implications. If wholesale prices and trade deals have different implications on the behavior of retailers, not modeling them separately suggests a shortcoming of the model.

We obtained some anecdotal evidence about these effects through interviews with brand managers in consumer prod-

[6]Besanko, Dubé, and Gupta (2005) find that passthrough varies substantially across products and categories; that own-brand passthrough rates are, on average, quite large; and that cross-brand passthrough is significant (either positive or negative).

ucts sold in supermarkets.[7] An important message from those interviews was that economic marginal wholesale prices change substantially from week to week. Furthermore, we received no indication that these managers believed that the formal wholesale prices significantly affected the choice of economic marginal wholesale prices that they deemed to be desirable in each week. Finally, these economic marginal wholesale prices seem to be chosen on the basis of the market conditions in each week in terms of both costs and demand. Additional research should investigate these effects further and check the general validity of this anecdotal evidence. Note that the wholesale prices we mentioned previously are the marginal wholesale prices considered by the retailer. These prices are the only part of any contract between the retailer and the manufacturers that can be recovered with only retail prices and demand information.

We can write the retail pricing equations that will be estimated in the model as follows:

$$\text{(16)} \qquad \left[p_{jt}\right]_{J\times 1} = \left[z_t\gamma_j\right]_{J\times 1} - \left[\xi_j \frac{s_{jt}}{\left[\frac{\partial s_{jt}}{\partial p_{1t}}\ \frac{\partial s_{jt}}{\partial p_{2t}} \cdots \frac{\partial s_{jt}}{\partial p_{Jt}}\right] G_t^{-1} \left[\frac{\partial s_{jt}}{\partial p_{1t}}\ \frac{\partial s_{jt}}{\partial p_{2t}} \cdots \frac{\partial s_{jt}}{\partial p_{Jt}}\right]'}\right]_{J\times 1}$$

$$+ \begin{bmatrix} \frac{1}{\mu_1}\frac{\partial s_{1t}}{\partial p_{1t}} & \frac{1}{\mu_1}\frac{\partial s_{2t}}{\partial p_{1t}} & \cdots & \frac{1}{\mu_1}\frac{\partial s_{Jt}}{\partial p_{1t}} \\ \frac{1}{\mu_2}\frac{\partial s_{1t}}{\partial p_{2t}} & \frac{1}{\mu_2}\frac{\partial s_{2t}}{\partial p_{2t}} & \cdots & \frac{1}{\mu_2}\frac{\partial s_{Jt}}{\partial p_{2t}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{\mu_J}\frac{\partial s_{1t}}{\partial p_{Jt}} & \frac{1}{\mu_J}\frac{\partial s_{2t}}{\partial p_{Jt}} & \cdots & \frac{1}{\mu_J}\frac{\partial s_{Jt}}{\partial p_{Jt}} \end{bmatrix}_{J\times J}^{-1} \begin{bmatrix} -s_{1t} \\ -s_{2t} \\ \vdots \\ -s_{Jt} \end{bmatrix}_{J\times 1} + \left[\eta_{jt}\right]_{J\times 1},$$

where the parameters ξ_j test the price-setting behavior of the manufacturers. If $\xi_j = 1, \forall j$, the manufacturers are acting as Nash price setters. This case can represent a structural model of the manufacturers' behavior. If $\xi_j > 1$, manufacturer j sets its price higher than the Nash price. Alternatively, testing for $\xi_j = 1$ can be a test of the structural model. We denote ξ as the vector of all ξ_j. Equation 16 is obtained in a straightforward way from the equilibrium behavior of the manufacturers and retailer (presented independently in Sudhir [2001] for the two-product case). The first and second derivatives of the market shares can be analytically obtained from the demand structure and are available on request from the authors (the second derivatives are necessary to obtain the passthrough terms in Equation 13).

With the nonlinearities of the demand function, we can identify the retail and manufacturer margin effects. We can illustrate the identification method as follows: Suppose that we have consistent estimates of the latent utility parameters and know the common shocks ψ (e.g., in a two-step estimation procedure). Then, Equation 16 is a regression equation of prices on cost shifters and on known (given the first stage) manufacturer and retailer margins. More technically, given the assumption of the distribution of η (and considering the scalar case), we know that $p - \xi m_m(p) - \mu m_r(p) - z\gamma$—where the functions $m_m(p)$ and $m_r(p)$ are, respectively, the manufacturer and retailer margins presented in Equation 15—is normally distributed with mean zero. If we know the parameters of the latent utility and ψ, then the functions $m_m(p)$ and $m_r(p)$ are known exactly. Moreover, we can easily verify that $m''_m(p) \neq 0$, $m''_r(p) \neq 0$, and $m'_m(p) \neq m'_r(p)$, so the regularity conditions for a maximum likelihood procedure of η are satisfied. A maximum likelihood estimation would yield consistent estimates for ξ, μ, and γ.

MODEL ESTIMATION

To estimate the model, we can write the likelihood function as the product of the likelihood of purchases and observed prices, conditional on the common demand shocks ψ_{jt} and the marginal likelihood of those common demand shocks. Conditional on observing the common shocks ψ_t, we can obtain the error term in the marginal costs, $\eta_t(p_t, \psi_t)$, and set up the joint likelihood of the household demands and prices being observed. Denoting the density of p_t given ψ_t as $h(\cdot)$ and the marginal density of ψ_t as $\phi(\cdot)$, we can write the likelihood function as follows:

$$\text{(17)} \qquad \prod_{t=1}^{T}\int\prod_{i=1}^{I}\text{Prob}\left(j_{it}/\psi_t\right)h\left(p_t/\psi_t\right)\phi(\psi_t)d\psi_t,$$

where j_{it} denotes the choice by consumer i in week t. Note that $\text{Prob}(j_{it}) = s_{ij't}$, with $j' = j_{it}$, as defined in Equations 3 and 4. Given the assumed normality of η_t and ψ_t, $\phi(\cdot)$ is a normal density; $h(\cdot)$ is the normal density of η_t given ψ_t times the Jacobian of η_t with respect to p_t, $|[\partial\eta_t(p_t, \psi_t)]/\partial p_t|$. We must multiply the density of η given ψ with the Jacobian of η_t with respect to p_t because we observe p_t, not η_t (e.g., Amemiya 1985).[8] This estimation method yields consistent estimators under the assumption that there is a one-to-one correspondence between η_t and p_t, given ψ_t. If the products are sufficiently differentiated (lower parameters in absolute value on the latent utility), this one-to-one correspondence is guaranteed because we are close to the case in which products are independent in demand.

The parameters to be estimated are as follows: (1) a vector $\boldsymbol{\beta}$ of response coefficients of the product and individual characteristics of x_{ijt} (brand-specific dummies, feature, display activity, Box-Cox transformation of price, household income, family size, dummy for heavy users, and individual loyalty); (2) the parameter of the Box-Cox transformation of price; (3) J vectors of the cost shifters' parameters γ_j; (4) the nest parameter $\boldsymbol{\lambda}$; (5) the variance–covariance matrix $(J \times J)$ of η_t; (6) the variance–covariance matrix $(J \times J)$ of ψ_t; (7) the covariance matrix $(J \times J)$ between η_t and ψ_t; (8) J parameters $(\xi_1, \ldots, \xi_J)$ to test the manufacturers' pricing behavior; and (9) J parameters $(\mu_1, \ldots, \mu_J)$ to test the retailer's pricing behavior.

[7]We interviewed managers of a large supermarket chain in Spain and Portugal: Continente. We also talked extensively with David Soberman, a professor at INSEAD, with regard to his experience with trade practices in the Canadian confectionery and beer industries.

[8]Note that because of the possible nonlinearity of the relationship between p_t and η_t, the Jacobian may not be a constant in this case.

Testing for price endogeneity tests for $V_{\eta\psi} = 0$ if $\xi_j = \mu_j = 0$, $\forall j$ (under different distribution and functional form assumptions than those in the structural model of the supply side). Testing for the retailer's price-setting behavior tests $\mu_j = 1$, $\forall j$. If $\mu_j = 1$, $\forall j$, the retailer acts as a perfect category manager in setting prices. Note that in this test, the retailer must have market power. Testing for the manufacturers' price-setting behavior tests for $\xi_j = 1$, $\forall j$. The model is estimated by the simulated maximum likelihood estimator (Gourieroux and Monfort 1993), where the integral over ψ_t is simulated.

The cost shifters used in the analysis are the prices of different types of tomatoes, obtained from the United States Department of Agriculture; wage rates for Texas, obtained from current population surveys (the government monthly household survey of employment and labor markets); and gas prices, obtained from the United States Department of Energy. The R^2 of the linear regression of the brand prices on the different prices of tomatoes, wage rates, and gas prices was .35. An important assumption in the following discussion is that the cost shifters are independent of the common demand shocks ψ_t. We believe that this assumption is reasonable because it is difficult to find a direct connection between the prices of tomatoes, wage rates, and gas prices and the demand function for ketchup.

EMPIRICAL RESULTS AND DISCUSSION

Endogeneity of Prices

An important issue in the analysis is whether there are common demand shocks and whether endogeneity exists in the brand prices. To test for these effects, we compare a standard choice model (Guadagni and Little 1983) with a model in which we allow for common demand shocks and possible correlations between the common demand shocks and brand prices. This test is similar to that in Villas-Boas and Winer (1999) and has the advantage of allowing for more general specifications of the brand pricing equilibrium behavior (though not the specification presented here). This approach is known as a limited information approach because we do not use any information about how prices are set. The only information we use is that the cost shifters are independent of the common demand shocks. However, this limited information model has a different specification (different distribution and functional form assumptions) than does the complete model, and we can make comparisons with the estimates for the complete model only if this different set of distribution assumptions has a small impact on the results.

In terms of the parameters of the model, this test involves comparing the model with $\mu = \xi = V_\psi = V_{\eta\psi} = 0$ with the model with only $\mu = \xi = 0$. The former is the standard choice model without common demand shocks under the assumption that prices are independent of any demand errors. The latter allows for common demand shocks and possible correlations between prices and demand errors but eliminates any information about possible equilibrium margins in retail pricing.

We present the results in Table 2. A grid search between 0 and 1 on the Box-Cox price transformation parameter ζ shows that $\zeta = .1$ maximizes the likelihood functions for both models, as is the case for the models we consider next. This value indicates that the way that price enters the latent utility is close to the logarithm function. In addition, for both models, the estimate of the nested logit parameter λ was at the corner at 1. Thus, the model reduces to the logit, and there is no greater substitutability among the ketchup brands than between a ketchup brand and the no-purchase option, which also may refer to ketchup brands we did not include in our analysis. In the other models, we also obtain the same result for λ. This result is robust across different specifications of the latent utility and may have occurred because we do not consider other ketchup products or other retail outlets.

The results show that V_ψ and $V_{\eta\psi}$ are statistically different from zero, which indicates that price endogeneity is important. Consistent with the work of Villas-Boas and Winer (1999), we find that accounting for price endogeneity can increase the evaluation of price sensitivity significantly. In this case, the point estimate goes from –2.33 to –5.26, which indicates that the price elasticities more than double. In other words, not accounting for price endogeneity may significantly underestimate demand price sensitivity. Similarly, the other parameters in β, for the most part, are overestimated in absolute value.

As we noted previously, this model does not fully account for unobserved heterogeneity, as studied in the literature, without accounting for price endogeneity (e.g., Chintagunta, Jain, and Vilcassim 1991; Kamakura and Russell 1989). Therefore, we could question whether this difference in parameter estimates could reflect unobserved heterogeneity, not really price endogeneity. To gain additional information and given that both explanations cannot be included in the model with this estimation method because of constraints on the current computational capabilities, we run a model without accounting for price endo-

Table 2

LIMITED INFORMATION APPROACH ($\mu = \xi = 0$)

		$V_\psi = V_{\eta\psi} = 0$
Del Monte	–5.81	–9.40
	(.19)	(.18)
Hunts	–5.94	–8.96
	(.20)	(.16)
Heinz	–4.38	–6.67
	(.19)	(.18)
Price	–5.26	–2.33
	(.19)	(.04)
Display	.07	1.25
	(.04)	(.07)
Feature	.07	–.53
	(.04)	(.04)
Income	.007	.99
	(.019)	(.07)
Family size	.002	.18
	(.025)	(.02)
Heavy user	.06	.02
	(.09)	(.02)
Loyalty	.06	2.94
	(.12)	(.09)
LLK	–4872.39	–6940.06

Notes: LLK is the value of the log likelihood without the fixed terms. Standard errors are in parentheses. The Loyalty variable is the number of purchases of a brand by a household and is fixed throughout the estimation periods. $\lambda = 1$, and $\zeta = .1$. V_ψ, V_η, $V_{\eta\psi}$, and the parameters for the cost shifters are not reported but are available on request from the authors.

geneity, but including unobserved consumer heterogeneity, interacting with the marketing-mix variables and being normally distributed.[9] We present the parameter estimates of this model in Table 3. Because the utility is being scaled differently in this model and the models in Table 2, we cannot compare the sensitivity to price across models by simply comparing the parameters values across Tables 2 and 3. In Table 4, we present the comparison between demand–price elasticities for the two models. The results of Table 4 suggest that accounting for endogeneity alone increases the absolute value of the size of the demand elasticities with respect to price, which is not the case for this data set when we account solely for unobserved heterogeneity. In any case, the results for the unobserved heterogeneity model may indicate that there is unobserved heterogeneity, and not accounting for it may create biased results.[10] Another important potential issue in the estimation is that the model does not distinguish between regular price changes and temporary discounts (Van Heerde, Leeflang, and Wittink 2004), though price sensitivity to temporary discounts typically is different.[11] If this distinction is important, the potential effects of not accounting for heterogeneity could be more significant.

[9]We thank an anonymous reviewer for this suggestion.

[10]For discussions of heterogeneity and endogeneity, see Kuksov and Villas-Boas (2001) and Chintagunta, Dubé, and Goh (2003). For a Bayesian approach to endogeneity in brand choice models, see Yang, Chen, and Allenby (2003).

[11]For a descriptive analysis of price variation through time and across stores, see Zhao (2006). In our data set, regular price changes accounted for approximately three-quarters of the total price variation.

Table 3

CONSUMER UNOBSERVED HETEROGENEITY MODEL

	Mean	*Standard Deviation*
Del Monte	–8.95	.003
	(.23)	(.35)
Hunts	–8.54	.04
	(.26)	(.68)
Heinz	–6.60	.08
	(.23)	(.14)
Price	–2.41	.81
	(.10)	(.11)
Display	.99	.45
	(.11)	(.05)
Feature	–.55	.02
	(.07)	(.29)
Income	.02	
	(.02)	
Family size	.07	
	(.03)	
Heavy user	.02	
	(.11)	
Loyalty	2.90	
	(.21)	
LLK	–6861.45	

Notes: No price endogeneity, $V_\psi = V_{\eta\psi} = 0$. LLK is the value of the log likelihood without the fixed terms. Standard errors are in parentheses. The Loyalty variable is the number of purchases of a brand by a household and is fixed throughout the estimation periods. $\lambda = 1$, and $\zeta = .1$.

Table 4

DEMAND–PRICE ELASTICITIES

	Endogeneity	*Heterogeneity*
Del Monte–Del Monte	–5.01	–1.60
	(.01)	(.06)
Del Monte–Hunts	.04	.01
	(.00)	(.00)
Del Monte–Heinz	.02	.00
	(.00)	(.00)
Hunts–Hunts	–5.05	–1.53
	(.01)	(.06)
Hunts–Del Monte	.05	.02
	(.00)	(.00)
Hunts–Heinz	.02	.01
	(.02)	(.00)
Heinz–Heinz	–5.17	–1.40
	(.01)	(.06)
Heinz–Del Monte	.05	.02
	(.00)	(.00)
Heinz–Hunts	.03	.01
	(.00)	(.00)

Notes: The endogeneity column represents an estimation that accounts for endogeneity but not for unobserved heterogeneity. The heterogeneity represents an estimation that accounts for unobserved heterogeneity but not for endogeneity. The notation "brand i–brand j" represents the elasticity of the demand of brand i with respect to the price of brand j. Standard errors are in parentheses.

Restricted Model

As we stated previously, assuming that the manufacturers earn all their revenue from the wholesale prices and that they behave according to Nash yields $\xi_j = 1$, $\forall j$. Similarly, assuming that the impact of the retail prices on retail profit is captured in the demands for the brands in the analysis and that the retailer maximizes (static) profits yields $\mu_j = 1$, $\forall j$. Estimating the model with both these constraints provides the complete information model, in which we use the assumed information on the supply side.

We present the results in Table 5. Note that the estimate of the price coefficient is approximately the same as the estimate with the limited information approach (left column in Table 2). To test whether the data are consistent with the specified supply-side behavior, we must consider the complete model.

Complete Model

We present the results of the complete model in Table 5. An aspect of note is that the estimates of the parameters in the latent utility β are similar to the estimates in the limited information approach (Table 2), particularly for the price coefficient parameter. This finding may indicate that use of the supply-side information, with the introduction of the parameters μ and ξ, does not create bias in the demand parameter estimates (under the assumption that different distribution assumptions across models do not have much impact).

The tests on the conduct parameters μ_j and ξ_j reject the null hypothesis that all parameters are equal to one. In particular, we find that the μ for Del Monte and Heinz are statistically less than one, whereas the μ for Hunts is not statistically different from one. Similarly, the ξ for Del Monte and Heinz are statistically less than one, whereas that for Hunts is not statistically different from one. These results

Table 5

FULL INFORMATION APPROACH

	Complete Model	$\mu_j = \xi_j = 1, \forall j$
Del Monte	–5.66	–5.65
	(.30)	(.57)
Hunts	–5.79	–5.78
	(.30)	(.59)
Heinz	–4.30	–4.29
	(.26)	(.46)
Price	–5.13	–5.16
	(.27)	(.53)
Display	.07	.05
	(.07)	(.07)
Feature	.06	.08
	(.05)	(.04)
Income	.01	.002
	(.02)	(.02)
Family size	–.004	–.003
	(.03)	(.03)
Heavy user	.03	.03
	(.09)	(.08)
Loyalty	.03	.02
	(.14)	(.14)
μ_1	.82	1.00
	(.06)	
μ_2	.91	1.00
	(.06)	
μ_3	.72	1.00
	(.06)	
ξ_1	.87	1.00
	(.06)	
ξ_2	.97	1.00
	(.06)	
ξ_3	.64	1.00
	(.05)	
LLK	–3988.42	–5053.28

Notes: LLK is the value of the log likelihood without the fixed terms. Standard errors are in parentheses. The Loyalty variable is the number of purchases of a brand by a household and is fixed throughout the estimation periods. $\lambda = 1$, and $\zeta = .1$. V_ψ, V_η, $V_{\eta\psi}$, and the parameters for the cost shifters are not reported but are available on request from the authors.

Table 6

RETAILER AND MANUFACTURER MARGINS

	Del Monte	*Hunts*	*Heinz*
Restricted Model			
Retailer margins	.18	.19	.26
	(.02)	(.02)	(.03)
Manufacturer margins	.13	.15	.28
	(.01)	(.01)	(.03)
Complete Model			
Retailer margins	.15	.17	.18
	(.02)	(.02)	(.02)
Manufacturer margins	.15	.16	.27
	(.010)	(.009)	(.019)

Notes: The retailer and manufacturer margins are evaluated at the mean market shares and prices. All values are in dollars. Standard deviations of the estimates are in parentheses.

indicate that the supply-side model is misspecified for Del Monte and Heinz and, taking into account the remarks in Corts (1999), a deviation in the same direction for both the manufacturers and the retailer. Misspecification of demand or costs also could generate estimates of μ_j and ξ_j different from one. Under the assumption that demand is well specified, the manufacturers of Del Monte and Heinz seem to price lower than the Nash-specified behavior, and the retailer seems to price the Del Monte and Heinz products lower than a profit-maximizing retailer should. Although statistically significant, the differences in the point estimates do not seem too large. Consider, for example, Table 6, in which we present the estimates for the manufacturer and retailer margins for both the restricted and the complete models at the mean market shares and prices. The restricted model case supplies the margins predicted by theory, whereas the complete model case represents the estimated margins. In terms of margins at the mean prices and markets shares, the only statistical difference between the restricted and the complete models is the retailer margin on Heinz; the estimated retailer margin for Heinz is lower than that obtained in the restricted model. This result is consistent with the idea that Heinz might have more bargaining power than the other manufacturers with respect to the retailer.

We also performed the analysis without using all the input prices or a different structure of the latent utility as a robustness check, and the main ideas regarding the μ and ξ parameters are not affected. We estimated the parameters over samples (different time periods) of the data set, with the possibility of repetition, and found that the parameters for retailer and manufacturer behavior remained relatively stable for different samples (see Table 7). This finding is related to the prediction sum of squares split sample technique (e.g., Quan 1988). Finally, we tested for the normality of η with a Kolmogorov-Smirnov test and found that the null hypothesis that η is normally distributed is not rejected. We now discuss the possible sources of these misspecifications that may be consistent with the observed deviations in μ and ξ.

Manufacturers. Under the assumption that the demand structure is well specified, the manufacturer conduct parameters, ξ, for Del Monte and Heinz being less than one could be regarded as consistent with contracts between the manufacturers and the retailer involving quantity discounts. It is well known (e.g., Tirole 1988) that optimal contracting between a manufacturer and a retailer with market power may involve quantity discounts. For the retailer to have the right incentives in terms of its prices, the marginal wholesale price paid by the retailer to the manufacturer should be lower than the wholesale price that results from uniform price contracts. The manufacturer receives most of its revenues from the prices of the nonmarginal units. The inframarginal prices that a manufacturer can extract from a retailer are then connected to the extent to which the manufacturer contributes to the retailer profit. The results of ξ for Del Monte and Heinz may demonstrate a way that manufacturers and the retailer coordinate in the channel. Note, however, that the effects are not too large; the ξ for Del Monte and Heinz are relatively close to one, and the ξ for Hunts is not statistically different from one.

Anecdotal evidence suggests that the payments of these inframarginal prices from the manufacturers to the retailer are not significantly different from marginal prices, or even go in the other direction (slotting allowances), in the grocery market (e.g., Sullivan 1992). This evidence could be consistent with the findings in Table 5 if carrying a manufacturer's product contributes minimally to the retailer's profit and given the small impact on margins (Table 6) (O'Brien and Shaffer 1997).

Table 7
STANDARD DEVIATION OF PARAMETER ESTIMATES FROM SAMPLES OF DATA SET (BOOTSTRAP)

	Parameter Estimate	*Standard Deviation*
Del Monte	–5.66	.06
Hunts	–5.79	.07
Heinz	–4.30	.04
Price	–5.13	.11
Display	.07	.01
Feature	.06	.01
Income	.01	.00
Family size	–.004	.01
Heavy user	.03	.01
Loyalty	.03	.04
σ_{ψ_1}	.33	.04
σ_{ψ_2}	.07	.17
σ_{ψ_3}	.38	.10
σ_{η_1}	.80	.13
σ_{η_2}	.63	.17
σ_{η_3}	.75	.10
$\rho_{\eta_1\psi_1}$	–.46	.12
$\rho_{\eta_1\psi_2}$	–.40	.18
$\rho_{\eta_1\psi_3}$	–.51	.19
$\rho_{\eta_2\psi_1}$	–.82	.07
$\rho_{\eta_2\psi_2}$	–.84	.22
$\rho_{\eta_2\psi_3}$	–.54	.17
$\rho_{\eta_3\psi_1}$	–.28	.17
$\rho_{\eta_3\psi_2}$	–.18	.10
$\rho_{\eta_3\psi_3}$	–.51	.20
μ_1	.82	.07
μ_2	.91	.02
μ_3	.72	.07
ξ_1	.87	.18
ξ_2	.97	.13
ξ_3	.64	.09

Alternatively, this lack of high inframarginal payments could be a result of the nonspecifiability of the product exchange (Iyer and Villas-Boas 2003), because retailers are not willing to pay high inframarginal payments when they cannot be guaranteed lower prices on the marginal units. If the product exchange is not specifiable in a contract, a retailer would not be willing to make payments upfront, because the manufacturer could renegotiate for higher wholesale prices in the future. The results for ξ lower than one then may be evidence of bargaining power on the retailer side (for alternative methods to measure bargaining power, see Frazier 1983; Messinger and Narasimhan 1995).

The results also may be consistent with dynamic effects in demand. The model was specified as if demand and profits in every period were independent of previous periods. If there is, for example, state dependence such that greater current demand causes demand in the future to be higher, manufacturers may be willing to price lower than the myopic case would imply to gain from greater demand in the future. Note, however, that this effect should not be important in a relatively stable product category, such as ketchup.

Another feature of this market that could have potential effects on the results is if the selling conditions offered by the manufacturers are common across different retailers in a region or nationally. If this is the case and the average consumer outside Midland is more price sensitive than the average consumer in Midland, the manufacturers would set their wholesale prices lower than if they were choosing their wholesale prices for the store in Midland alone. This difference could explain the two ξ_j that are less than one. However, manufacturers may be able to tailor their selling conditions to specific retailers with various mechanisms that affect the marginal wholesale price.

Retailer. Under the assumption that the demand structure is well specified, the retailer conduct parameters, μ_j, suggest that the retailer is pricing Del Monte and Heinz lower than profit maximizing would indicate. The effect seems to be greater for Heinz. The estimates of μ_j may be consistent with a scenario in which manufacturers work with the retailer to coordinate the distribution channel. Alternatively, these estimates could be consistent with the retailer carrying other products that are complements to ketchup. If the retailer lowers the prices of ketchup, it may increase the demand for other products, which provides greater profits for the retailer (a loss-leader–type of behavior). This effect was not included in the analysis (for demand analyses across categories, see Lal and Matutes 1994; Manchanda, Ansari, and Gupta 1999; Rao and Syam 2001; Wedel and Zhang 2004), which means that we should observe lower prices than the prices specified in Equation 15. Note that this observation is consistent with Heinz, which may be the most visible brand, pricing the most below the optimal price. The lower prices for Heinz could also indicate that Heinz has greater bargaining power with respect to the retailer and is able to push the retailer to squeeze its margins.

CONCLUDING REMARKS

We construct a structural model that includes manufacturers, one multiproduct retailer, and individual consumers to test for the degree of manufacturers' competition, category pricing of a retailer, and price endogeneity on the demand side. The results show that in the ketchup market in Midland, Tex., there is some degree of competition between manufacturers (two of the inferred marginal wholesale prices are slightly lower than the Nash prices), and the retailer sets prices for two of the three brands lower than the prices that would maximize category profits. The results seem robust to different specifications of the marginal cost and latent utility and are consistent with some form of quantity discounts, retailer bargaining power, and/or the retailer carrying complementary products. However, given the small differences in the double marginalization theoretical model, the results also could appear to be supporting that model.

Potential issues for further research include the study of competition between retailers, the interactions between manufacturers and retailers, effects across product categories, and the dynamic effects on demand. Developing an analysis of manufacturer–retailer interactions could involve formal consideration of bargaining and/or quantity discounts. Another important issue not considered here is that in these markets, the retailer may keep inventory and occasionally forward buy (Lal, Little, and Villas-Boas 1996).[12] We only model the pricing strategic behavior of the retailer,

[12]The results hold with inventory even if both retailers and manufacturers are myopic.

but the retailer also makes display and feature decisions. Modeling such decisions also seems important and may be computationally possible with aggregate store data. Examining other markets also may lead to notable insights. Finally, the demand side of the model could be enriched to account for several effects on consumer decision making, such as consumer heterogeneity. Not accounting for a richer demand model could generate biased results; in particular, endogeneity could be overstated if heterogeneity is not fully accounted for.

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