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Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data

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In this paper, different models of vertical relationships between manufacturers and retailers in the supermarket industry are compared. Demand estimates are used to compute price-cost margins for retailers and manufacturers under different supply models when wholesale prices are not observed. The purpose is to identify the set of margins compatible with the margins obtained from estimates of cost and to select the model most consistent with the data among non-nested competing models. The models considered are (1) a simple linear pricing model; (2) a vertically integrated model; and (3) a variety of alternative (strategic) supply scenarios that allow for collusion, non-linear pricing, and strategic behaviour with respect to private label products. Using data on yogurt sold in several stores in a large urban area of the U.S. the results imply that wholesale prices are close to marginal cost and that retailers have pricing power in the vertical chain. This is consistent with non-linear pricing by the manufacturers or high bargaining power of the retailers.

1. INTRODUCTION

This paper provides a framework for learning about vertical relationships between manufacturers and retailers when faced with limited data. The conceptual framework developed here provides a basis for determining the stylized vertical contract that best fits the data for a particular market. Wholesale price data are typically unavailable, and retailers' and manufacturers' marginal costs are difficult to measure separately. Given the data limitations faced by researchers now, and for the foreseeable future, examination of the testable implications of different models of vertical contracting, which map from product and cost characteristics to retail price, provides a useful basis for model comparison. The research plan of this paper is as follows: first, I estimate demand and use the estimates to compute price-cost margins for retailers and manufacturers under different supply models without observing wholesale prices. I then compare estimated price-cost margins with the price-cost margins estimated using components of marginal costs to assess the fit of these different vertical models and identify the best among the competing non-nested models. I focus empirically on the yogurt market in a large Midwestern city.

There are many reasons to care about analysing vertical relationships (for a survey of theoretical work, see Katz, 1989). First, vertical relationships determine the vertical profit and the size of total producer surplus to be divided among firms along a distribution chain and are thus of policy relevance for surplus calculations in counterfactuals (see Brenkers and Verboven, 2002; Manuszak, 2003). Second, vertical relationships may promote efficiency in the vertical channel. This efficiency is a result of the departure from a simple uniform pricing scheme that leads to double marginalization. Double marginalization arises when the only contractual instrument used is the wholesale price. As a consequence, the sum of profits for the manufacturer and retailer may be less than the profits had they coordinated in their decisions. Third, vertical relationships may impair competition through their horizontal effects on the upstream manufacturer and downstream retail markets by increasing the possibility of oligopolistic coordination (increasing market power) or by excluding rivals (and hence, diminishing product variety and choices). Finally, the vertical structure in a particular market can significantly affect downstream prices (as in Hastings, 2004) and price dynamics (see, for example, Chevalier, Kashyap and Rossi, 2003) and condition the assessment of merger activities in upstream and downstream markets.

Vertical relationships are especially difficult to examine empirically due to infra-marginal components, transaction costs, and imperfect information issues.[1] The present paper sidesteps these issues by focusing on the case in which relationships try to address the traditional problem of double marginalization. In this context, the paper provides a first step towards the structural estimation of vertical relationships. Limited data availability is another serious problem faced by empirical researchers analysing vertical relationships. I demonstrate how one can draw inferences about vertical relationships, even with these data limitations.

The researcher typically does not have access to the prices retailers pay to manufacturers, but in many industries the researcher *can* get data on retailers' and manufacturers' input prices. Suppose a researcher observes a time series of retail price–quantity pairs, which she believes to be market-equilibrium outcomes of demand and supply conditions. The general identification problem is to infer the consumers' and firms' decision rules from the decisions observable as price–quantity pairs. Without additional information, various combinations of demand and supply models may appear to produce the same price–quantity pairs over time. The econometric problem is, thus, a standard simultaneous-equation model in which a demand and a supply pricing equation, both derived from behavioural assumptions, must be specified and estimated. The demand equation relates quantity purchased to price, product characteristics, and unobserved demand determinants. The supply equation relates prices to a mark-up and to observed and unobserved cost determinants. Villas-Boas and Hellerstein (2006) derive conditions for which data on an industry's retail prices, quantities, and input prices over time are sufficient to identify the vertical model of manufacturers' and retailers' oligopoly-pricing behaviour. Assuming exclusion restrictions such that demand is identified and additive separability in costs across products for the retailer and the manufacturer, non-linearities in the demand model enable researchers to identify the supply-side vertical models. In the Bertrand–Nash pricing model with differentiated products even for linear demand models, as long as single product manufacturers do not work exclusively with single product retailers, Villas-Boas and Hellerstein (2006) show identification of retail and manufacturer models of pricing behaviour.

Several recent papers examine retailer and manufacturer vertical relationships in different industries (see, for example, Bresnahan and Reiss (1985) in the automobile market; Corts (2001) in the U.S. motion picture industry; Mortimer (2002) for video rentals; and Asker (2004) and Hellerstein (2004) for beer). More closely related to this paper, Chintagunta, Bonfrer and Song (2002) estimate the impact of the introduction of a private label by one retailer on the relative market power of the retailer and the manufacturers, and Kadiyali, Chintagunta and Vilcassim (2000) measure the share of profits to retailers and manufacturers. Two key features distinguish this paper from the previous two papers; they use data on wholesale prices reported by the retailer and they use a conduct parameter approach, that measures deviations from Bertrand pricing behaviour, in their analysis. Finally, Villas-Boas and Zhao (2005) evaluate the degree of manufacturer competition and the retailer and manufacturers interactions in the ketchup market in a certain city, and Sudhir (2001) studies competition among manufacturers under alternative assumptions of vertical interactions with one retailer. The current paper innovates in that it

1. There is a growing body of empirical literature on transaction costs and incomplete information, where Sieg (2000) and Mortimer (2002) are two pioneering empirical papers.

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allows for multiple retailers when analysing the vertical interactions between manufacturers and retailers.

The paper is organized as follows. The next section describes the yogurt market and the patterns of the data used to separate the different stylized vertical relationships. The data are described in Section 3 and, in Section 4, I present the plausible economic and econometric models. In Section 5 the method of estimation and inference is presented, and in Section 6 the empirical results and corresponding robustness tests are evaluated. Conclusions and extensions of this research are presented in Section 7, and suggestions are provided as to how the proposed methodology can be adapted to different settings.

2. THE EXPERIMENTAL SETTING—THE YOGURT MARKET

To analyse vertical relationships I focus on the yogurt market in a Midwestern metropolitan area. Yogurt is one of the largest dairy categories in retail, and the "yogurt consumer" is an important consumer type for retailers.[2] Yogurt is produced by a few leading national yogurt manufacturers; Dannon and General Mills together account for almost 62% of the total U.S. yogurt sales. Therefore, it is interesting to confront stylized supply models of upstream price collusion with the data. Private label brands from retail stores are in third place with 15% of the market. One supply model I look at considers the strategic importance that private labels seem to have in the yogurt market. Kraft ranks forth in terms of U.S. sales, and all other manufacturers have individual shares of less than 2% (*Frozen Food Digest*, October 1995, p. 38). One of the most important characteristics of the yogurt market is that yogurt sales are mostly driven by new product introductions (Kadiyali, Vilcassim and Chintagunta, 1999; Draganska and Jain, 2006). Product variety, together with successful advertising to influence consumers' evaluations of different products, can result in positive price-cost margins for the manufacturers. This is reflected in the estimates for the price-cost margins in the non-collusive supply scenarios considered here. At the retail level there is a small number of large retailers (or retail chains) competing directly with each other and who jointly have 75% of total sales to final consumers in the whole metropolitan area. All other retailers not considered had individual shares less than 5% in 1992. Given retail concentration in this market, I shall consider a model of retail collusion.

Given the demand for yogurt, I consider, under different models, how retail prices change as a result of changes in an input price, and I pick which model appears to best describe the data. Correlation between retail and wholesale price variation and input prices is necessary for identification of the demand model. Yogurt exhibits retail price patterns potentially correlated with input price changes. Yogurt has to be consumed within 28 days of production, and so its shelf life is short. In principle, when marginal cost changes significantly, there exists the possibility for manufacturers to adjust wholesale prices accordingly.

3. DATA

Building on a theoretical framework relating to vertical relationships, this analysis is based on a weekly data-set on retail prices, advertising, aggregate market shares, and product characteristics for 43 products produced by five manufacturers. The number of products is equal to 43 for all weeks except for the weeks during which retailer 2 closed due to remodelling and when the number of products in the sample is 25. The price, advertising, and market-share data come from an Information Resources Inc. (IRI) scanner data-set that covers the purchases in three retail

2. "(...) Yogurt is aligned with key consumer trends and (...) is an important product to our retailers (...). Its [*sic*] bigger than you think : The Yogurt category is the 4th largest in the dairy case (...)." *Source*: *Why Yogurt?* General Mills, http://www.pvg.generalmills.com/yogurt_1.html

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TABLE 1

Prices, feature, servings sold, and market shares of products in sample: summary statistics

Description	Mean	Median	S.D.	Max	Min	Brand variation (%)	Week variation (%)
Prices (cents per serving)	49	48	9·2	72	24	68·3	2·4
Advertising (=1 if featured)	0·03	0	0·15	1	0	10·8	5·3
Servings sold (1 serving=6 ounces)	246	132	393·3	9538	1	43·6	4·1
Share of product within market	0·8	0·4	1·3	32	0·03	43·6	4·1
Combined shares of products	34	37	12·7	75	12		
Combined shares by manufacturer (%)							
Dannon	16·8	16·4	7·6	50·0	4·7		
General Mills	8·8	9·0	3·6	31·1	4		
Private label of retailer 2	4·1	3·3	4·2	38·5	0·6		
Kraft	3·4	3·1	1·6	13·6	1·1		
Private label of retailer 3	1·3	1·2	0·5	3·7	0·6		
Combined shares by retailer (%)							
Retailer 1	2·3	2·3	1·0	9·2	1		
Retailer 2	19·8	20·5	9·2	57·6	1·2		
Retailer 3	13·6	13·5	3·4	24·3	6·7		

Source: IRI.

stores in a Midwestern urban area during 104 weeks (see also Bell and Lattin, 1998). Summary statistics for prices, advertising, quantity sold, and shares are presented in Table 1. The combined shares for the products analysed are on average 34%. Quantity sold is defined as servings sold, where one serving corresponds to a six-ounce yogurt cup. Price and servings sold series for the 43 products in the sample listed in Table 2 were obtained by aggregation.[3] Market shares are defined by converting quantity sold to servings sold and then dividing by the total potential servings in the market. The potential market, in terms of servings, is assumed to be half of a serving *per capita* a week. Hence, the potential market in terms of servings is equal to half of the resident population in the two zip code areas.

Dannon ranks first in terms of local market share of its products with an average of 17%. General Mills is second in terms of local market share with 9%. Private labels are third with 4%, and Kraft comes last among the products analysed with 3%. Three retail stores are considered in the data, where store 1 is a smaller store than stores 2 and 3. The last two retail stores belong to two retail chains, while store 1 is unique in the whole metropolitan area. The retail stores in the data are located less than two miles from one another. In fact, retailers 2 and 3 are located across from each other at a street intersection. Some smaller grocery stores are located within the two zip code areas considered, but the closest large retail store is located in a different zip code area. Combined market shares for the 10 products sold by retailer 1 are on average 2%. Store 2 sells 18 products with a combined market share of 20%. Store 3 has average combined shares of its 15 products of approximately 14%.

For the empirical analysis and inference the above IRI data-set is complemented with data on product characteristics and consumer demographics. The product characteristics data were collected by inspection of the label reads and for those products currently unavailable in any supermarket because they were discontinued, from manufacturers' descriptions. A sample from the joint income and age distribution of the two-zip-code resident population was obtained from

3. For a particular retailer, the same "brand/product" sold in different sizes is aggregated as the same product. Also products with the same brand name and with similar product characteristics were aggregated (this aggregates mostly the different fruit yogurts for the same brand. Their price correlation was not significatively different from one). I acknowledge that the variation in the price and quantity data used in estimation may be partially driven by the aggregation method and criteria.

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TABLE 2

Information about the products in sample

Manufacturer	Retailer	Product name	Price Mean	Price S.D.
Dannon	2	Dannon Light Vanilla Yogurt	47·62	3·48
Dannon	3	Dannon Light Vanilla Yogurt	42·06	3·07
Dannon	1	Dannon Lowfat Plain Yogurt	52·56	3·97
Dannon	2	Dannon Lowfat Plain Yogurt	48·19	4·75
Dannon	3	Dannon Lowfat Plain Yogurt	46·90	2·48
Dannon	1	Dannon Light Fruit Yogurt	57·87	5·01
Dannon	2	Dannon Light Fruit Yogurt	54·69	5·09
Dannon	3	Dannon Light Fruit Yogurt	47·08	2·33
Dannon	2	Dannon Nonfat Plain Yogurt	48·69	4·54
Dannon	3	Dannon Nonfat Plain Yogurt	46·56	2·58
Dannon	1	Dannon Classic Flavor Fruit Yogurt	52·50	5·53
Dannon	2	Dannon Classic Flavor Fruit Yogurt	53·68	7·55
Dannon	3	Dannon Classic Flavor Fruit Yogurt	46·96	3·29
Dannon	1	Dannon Classic Flavor Vanilla Yogurt	53·31	3·27
Dannon	2	Dannon Classic Flavor Vanilla Yogurt	48·82	4·68
Dannon	3	Dannon Classic Flavor Vanilla Yogurt	46·38	3·04
Dannon	1	Dannon Fruit on the Bottom Yogurt	51·12	6·48
Dannon	2	Dannon Fruit on the Bottom Yogurt	53·18	6·47
Dannon	3	Dannon Fruit on the Bottom Yogurt	47·31	2·41
Store 2	2	Private Label 2 Lowfat Fruit Yogurt	52·17	7·43
Store 2	2	Private Label 2 Lowfat Plain Yogurt	30·76	2·00
Store 2	2	Private Label 2 Lowfat Vanilla Yogurt	30·13	0·87
Store 2	2	Private Label 2 Nonfat Fruit Yogurt	54·63	7·29
Store 2	2	Private Label 2 Nonfat Plain Yogurt	54·82	7·35
Store 3	3	Private Label 3 Lowfat Fruit Yogurt	35·83	1·01
Store 3	3	Private Label 3 Lowfat Plain Yogurt	30·52	2·07
Kraft	1	Breyer Light Fruit Yogurt	38·94	4·73
Kraft	1	Light N'Lively Nonfat Fruit Yogurt	48·40	4·52
Kraft	2	Light N'Lively Nonfat Fruit Yogurt	46·93	4·71
Kraft	3	Light N'Lively Nonfat Fruit Yogurt	46·44	3·24
Kraft	1	Light N'Lively Lowfat Fruit Yogurt	49·38	4·28
Kraft	2	Light N'Lively Lowfat Fruit Yogurt	46·67	5·04
Kraft	3	Light N'Lively Lowfat Fruit Yogurt	45·23	4·26
General Mills	2	Yoplait Custard Style Lowfat Fruit Yogurt	60·69	5·86
General Mills	3	Yoplait Custard Style Lowfat Fruit Yogurt	57·52	4·77
General Mills	2	Yoplait Custard Style Lowfat Vanilla Yogurt	63·54	6·58
General Mills	3	Yoplait Custard Style Lowfat Vanilla Yogurt	57·06	5·48
General Mills	1	Yoplait Fruit Yogurt	57·69	9·47
General Mills	2	Yoplait Fruit Yogurt	58·67	4·73
General Mills	3	Yoplait Fruit Yogurt	52·62	4·67
General Mills	1	Yoplait Light Fruit Yogurt	52·10	10·65
General Mills	2	Yoplait Light Fruit Yogurt	56·21	5·61
General Mills	3	Yoplait Light Fruit Yogurt	49·15	4·10

Notes: Price in cents per serving. One serving is equivalent to six ounces of yogurt.
Source: IRI.

the 1990 Census. Data on costs, obtained from various sources, are described in Table 3. The first group of cost price series relates more closely to manufacturer costs: price of milk, plastic, and other components of yogurt, wages, and (industrial) energy prices for the state in which the manufacturing plants are located. There is considerable time variation for most of the manufacturer input price data series. These data are supplemented with additional data that enter retail cost: real estate indices and commercial energy prices for the state in which the retailers are located, chain size, as well as the number of employees in the chains and gasoline prices that enter transportation costs.

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TABLE 3

Cost data

Description	Mean	Median	S.D.	Max	Min
Input prices					
Citric acid ($/ounce)	1·9	1·3	0·84	3	1·23
Plastic (cents/ounce)	32·6	33	3·26	3·8	27
Sugar (cents/ounce)	9	8·6	1·14	14·4	8·2
Non-fat grade A milk ($/ounce)	1	1·1	0·08	1·2	0·86
Whey protein ($/ounce)	0·5	0·5	0·09	0·6	0·31
Corn ($/bushel)	2·3	2·3	0·16	2·5	1·98
Strawberry($/hundred weight)	0·8	0·7	0·29	1·4	0·35
Wages and energy and gasoline prices by state/plant location					
Plant for Dannon Yogurts: Minster, OH.					
Wages Ohio (weekly earnings/number of hours a week, $/hour)	11·2	11	0·56	12·6	10·4
Energy prices OH (average revenue by kilowatt industrial)	4·17	4·16	0·08	4·36	4·01
Gasoline prices OH (cents/gallon No. 2 Distilled (2 Dist.))	87·53	86·5	8·26	101·5	72·7
Plant for Breyers, Light N'Lively (Kraft): Moleena, IL; plant for private label of store 3 and location of the three retailers.					
Wages Illinois (weekly earnings/number of hours a week, $/hour)	12·1	12·1	0·3	12·8	11·5
Energy prices IL (average revenue by kilowatt industrial)	5·42	5·31	0·45	6·28	4·69
Gasoline prices IL (cents/gallon No. 2 Dist.)	84·97	84·4	7·37	98·8	72·9
Plant for Yoplait Yogurts: Kalamazoo, MI.					
Wages Michigan (weekly earnings/number of hours a week, $/hour)	12	11·8	0·61	14·4	10·9
Energy prices MI (average revenue by kilowatt industrial)	5·89	5·92	0·14	6·09	5·55
Gasoline prices MI (cents/gallon No. 2 Dist.)	94·04	92·5	8·01	106·4	82
Plant for private label of store 2: Clackamas, OR.					
Wages Oregon (weekly earnings/number of hours a week, $/hour)	12·9	13	0·37	13·8	12·1
Energy prices OR (average revenue by kilowatt industrial)	3·11	3·09	0·18	3·48	2·80
Gasoline prices OR (cents/gallon No. 2 Dist.)	98·24	98·8	7·86	109·1	86·3
Interest rate (Federal funds effective rate, %)	4	3·7	1	6·3	2·9
Interest rate (Commercial Paper three months, %)	4·1	3·9	0·96	6·2	3·1
Retail size					
Number of stores in chain (retailer 2)	86	86	0·5	87	85
Number of employees in chain (retailer 2)	17,407	17,500	0·2	17,597	17,112
Number of stores in chain (retailer 3)	186	184	5·91	198	182
Number of employees in chain (retailer 3)	30,077	30,102	0·21	30,364	29,887
Real estate indices and commercial energy prices IL					
Retail average price ($ per square foot)	111·07	109·22	4·35	121·39	107·74
Retail average rents ($ per square foot)	13·27	13·09	0·32	13·9	13·05
Retail rent cap (%)	8·79	8·8	0·11	8·9	8·5
Energy prices IL (average revenue by kilowatt commercial)	7·95	7·64	0·71	9·13	6·82

Sources: Citric acid (Chemical Week); plastic (Chemical Marketing Reporter); sugar (Coffee, Sugar and Cocoa Exchange); non-fat grade A milk, whey protein (Cheese Market News, U.S. Department of Agriculture); corn, strawberry (National Agriculture Statistics Service, U.S. Department of Agriculture); wages (CPS Annual Earning File—NBER 50); energy (revenue by kilowatt usage, Energy Information Administration, from EIA-826, table 53); gasoline (Petroleum Marketing Monthly, table 18); interest rates (Federal Reserve). Number of employees and chain size (Human Resource Departments); real estate (National Real Estate Index, CB Richard Ellis Survey of Offered Rents).

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4. ANALYTICAL FRAMEWORK

The economic–econometric model appropriate for this study is a standard discrete choice demand formulation (see, for example, McFadden, 1984; Berry, 1994; Berry, Levinsohn and Pakes, 1995; Nevo, 2001) and different alternative models of vertical relationships between manufacturers and retailers. The price-cost margins for the retailers and manufacturers are expressed for each supply model solely as functions of demand substitution patterns. Due to data-set limitations, I do not have wholesale prices or separate data on wholesale and retail costs. This section derives expressions for the total sum of retail and manufacturer price-cost margins as functions of demand substitution patterns for the alternative supply models specified.

4.1. *Demand side*

Assume the consumer chooses in each period[4] t among N_t different products[5] sold by several retailers. Using the typical notation for discrete choice models of demand, the indirect latent utility of consumer i from buying product j during week t is given by

$$U_{ijt} = d_j + d_t + x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt}, \tag{1}$$

where d_j represents product (brand-store) fixed effects capturing time invariant product characteristics, d_t are quarterly dummies capturing quarterly unobserved determinants of demand, x_{jt} are the observed product characteristics, p_{jt} is the price of product j, ξ_{jt} identifies the mean across consumers of unobserved (by the econometrician) changes in product characteristics,[6] and ϵ_{ijt} represents the distribution of consumer preferences about this mean. The random coefficients β_i are unknown consumer taste parameters for the different product characteristics, and the term α_i represents the marginal disutility of price. These taste parameters are allowed to vary across consumers according to

$$[\alpha_i, \beta_i]' = [\alpha, \beta]' + \Gamma D_i + \Upsilon \upsilon_i, \tag{2}$$

where the variable D_i represents observed consumer characteristics such as demographics, while unobserved consumer characteristics are contained in υ_i.[7] The parameters α and β are the mean of the random coefficients described above. The matrix of non-linear demand parameters Γ captures the observed heterogeneity, deviations from the mean in the population of the taste parameters and marginal utility of price due to demographic characteristics D_i. The matrix Υ captures the unobservable heterogeneity due to random shocks υ_i.

In the econometric model, unobserved random consumer characteristics υ_i are assumed to be normally distributed, and the observed consumer characteristics D_i have an empirical distribution $\hat{F}(D)$ from the demographic data. Additionally, an outside good is included in the model, allowing for the possibility of consumer i not buying one of the N_t marketed goods. Its price is not set in response to the prices of the other N_t products. In the outside good I include yogurt

4. The demand model is static and consumers choose every week among alternatives. Given that yogurt keeps for 28 days and I assume weekly purchase decisions, the consequences of assuming the static demand model in this context are important (as found in Che, Seetharaman and Sudhir, 2003). The substitution patterns from a dynamic model could either be larger or smaller in magnitude than those that ignore dynamics in household brand choices, depending mainly on the estimates of price coefficients. If the price coefficient estimates are smaller in magnitude when accounting for dynamics, the computed price elasticities will also be smaller. I acknowledge that ignoring state dependence is a simplification in this paper and does matter in the test of the supply models as shown in Che *et al.* (2003).

5. The same physical product sold at two different retailers is defined as two different products.

6. In particular, ξ_{jt} includes the (not-seasonal) changes in unobserved product characteristics such as unobserved promotions, changes in shelf display, and changes in unobserved consumer preferences.

7. In this model consumers are choosing a retailer. The correlation of liking certain goods at a certain retail store is in the random coefficient. The i.i.d. extreme value ϵ_{ijt} is introduced to smooth the distribution.

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sold by smaller retail stores, or grocery stores not considered in the analysis, as well as yogurt of small manufacturers sold in the three retail stores studied. The mean utility of the outside good, δ_{0t}, is normalized to be constant over time and equal to 0.[8] The measure M of the market size is assumed to be proportional to the population in the contiguous zip code areas where the stores are located. The observed market share of product j is given by $s_j = q_j/M$, where q_j are the units sold.[9]

I make the usual assumption that consumers purchase one unit of that product among all the possible products available at a certain time t that maximizes their indirect utility.[10] Then the market share of product j during week t is given by the probability that good j is chosen, that is,

$$s_{jt} = \int_{[(D_i,\upsilon_i,\epsilon_{it})|U_{ijt}\geq U_{iht} \quad \forall h=0,\ldots,N_t]} dF(\epsilon)\, dF(\upsilon)\, dF(D). \tag{3}$$

If both D and υ are fixed and consumer heterogeneity enters only through the random shock where ϵ_{ijt} is distributed i.i.d. with an extreme value type I density, then (3) becomes the multinomial logit model. Assuming that ϵ_{ijt} is distributed i.i.d. extreme value and allowing for consumer heterogeneity to affect the taste parameters for the different product characteristics, this corresponds to the full random coefficients model, or mixed logit model.[11]

4.2. *Supply side*

I focus on the case where relationships try to address the traditional problem of double marginalization resulting from the simple linear pricing model. Several plausible stylized vertical relationships are described next, inspired by the potential market structure in the empirical application. In particular, I examine scenarios incorporating the role of non-linear pricing, private labels, and collusion in the design of vertical relationships. In three of the models, either the retailers or the manufacturers are allowed to use non-linear pricing relationships. In several models, the retailers are assumed to behave as if they were vertically integrated with respect to the private labels. In two sets of models, collusion at the manufacturer level, or at the retailer level, is examined. Finally, I consider the model of vertically integrated pricing which maximizes joint profits and, therefore, is the efficient outcome from the retailer's and manufacturer's points of view. The implied price-cost margins correspond to those of a vertically integrated monopolist. In what follows, each supply model is solved as a function of demand side parameters to obtain an expression for both the retailer's and the manufacturer's implied price-cost margins.[12]

4.2.1. Scenario 1: simple linear pricing model. In this model manufacturers set their prices first and retailers follow. The margins that result from this behaviour correspond to the

8. Without making any additional assumptions, it would not be identified. The alternative would be to normalize any one of the N_t goods. The utility of the outside good is allowed to vary over time via ϵ_{i0t}. Alternatively, one could adopt a different normalization per period by introducing a period-specific dummy variable in demand.

9. In this case, q_j are the servings of yogurt sold. One serving corresponds to a cup of six ounces. Accordingly, p_j is the price per serving of product j.

10. The studies that explicitly model multiple-discrete choices (*e.g.* Dubin and McFadden, 1984; Hanemann, 1984; Hausman, Leonard and McFadden, 1995; Hendel, 1999) need individual level data for estimation. Since this paper uses only market-level data, these techniques could not be directly applied here. Failure to account for multiple discreteness has been shown to matter significantly for cross-product substitution patterns and less for aggregate demand predictions, as shown in Dubé (2004) for the soft-drinks industry.

11. This is a very general model. As shown in McFadden and Train (2000), any discrete choice model derived from random utility maximization can be approximated, with any degree of accuracy, to a mixed logit.

12. The (logit and mixed logit) expressions of the price-cost margins in a simplified model with only two retailers, two wholesalers, and two products are available at the journal web-page and also at http://socrates.berkeley.edu/∼villas/homepage.html

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pure double-marginalization price-cost margins with linear pricing in oligopoly markets at the manufacturer and retail level.

Let there be N_r Nash–Bertrand multi-product-oligopolist retailers competing in the retail market and suppose there are N_w Nash–Bertrand multi-product-oligopolist manufacturers competing in the wholesale market. To solve this vertical model, one starts by looking at the retailer's problem. Each retailer r's profit function in week t is given by

$$\pi_{rt} = \sum_{j \epsilon S_{rt}} [p_{jt} - p^w_{jt} - c^r_{jt}] s_{jt}(p), \tag{4}$$

where S_{rt} is the set of products sold by retailer r during week t, p^w_{jt} is the wholesale price he pays for product j, c^r_j is the retailer's marginal cost of product j, and $s_{jt}(p)$ is the share of product j. The first-order conditions, assuming a pure-strategy Nash equilibrium in prices, are

$$s_{jt} + \sum_{m \epsilon S_{rt}} [p_{mt} - p^w_{mt} - c^r_{mt}] \frac{\partial s_{mt}}{\partial p_{jt}} = 0 \quad \forall j \epsilon S_{rt}, \quad \text{for } r = 1, \ldots, N_r, \tag{5}$$

where N_t is the number of products in the market.

Define T_r as the retailer's ownership matrix with the general element $T_r(i, j)$ equal to 1 when both products i and j are sold by the same retailer and 0 otherwise. Let Δ_{rt} be the retailer's response matrix, containing the first derivatives of all the shares with respect to all retail prices, with element $(i, j) = \frac{\partial s_{jt}}{\partial p_{it}}$. Stacking up the first-order conditions given by (5) and rearranging terms, we obtain the following vector expression for the retailers' implied price-cost margins, as a function of only the demand side for each week t,

$$p_t - p^w_t - c^r_t = -(T_r * \Delta_{rt})^{-1} s_t(p), \tag{6}$$

where $T_r * \Delta_{rt}$ is the element by element multiplication of the two matrices. If the equilibrium is unique, equation (6) implicitly defines the retail prices as a function of all the wholesale prices.

Each manufacturer maximizes profit by choosing the wholesale prices p^w, knowing that the retailers behave according to (6). Note that this model allows for different wholesale prices to be chosen for the same "physical product" sold to different retailers.[13] The manufacturer's profit function is given by

$$\pi_{wt} = \sum_{j \epsilon S_{wt}} [p^w_{jt} - c^w_{jt}]\, s_{jt}(p(p^w)), \tag{7}$$

where S_{wt} is the set of products sold by manufacturer w during week t, and c^w_{jt} is the marginal cost of the manufacturer that produces product j. The first-order conditions are, assuming again a pure-strategy Nash equilibrium in the wholesale prices,

$$s_{jt} + \sum_{m \epsilon S_{wt}} [p^w_{mt} - c^w_{mt}] \frac{\partial s_{mt}}{\partial p^w_{jt}} = 0 \quad \forall j \epsilon S_{wt}, \quad \text{for } w = 1, \ldots, N_w. \tag{8}$$

Let T_w be a matrix of ownership for the manufacturers, analogously defined as the matrix T_r above. In particular, element (j, m) of T_w is equal to 1 if the manufacturer sells both products j and m, and is otherwise equal to 0. Let Δ_{wt} be the manufacturer's response matrix, with element $(j, m) = \frac{\partial s_{mt}}{\partial p^w_{jt}}$, containing the derivatives of the market shares of all products with respect to

13. This assumes that manufacturers set a wholesale price for each store. Some retail stores are part of chains (not modelled here), and manufacturers may behave differently towards chain and non-chain stores. Given the existence of these two types of retail stores, a simple robustness check is performed and presented in the results section by weighting the manufacturer profit from selling to a certain retailer by the size of the retail chain.

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all wholesale prices. In other words, this matrix contains the cross-price elasticities of derived demand and the effects of cost pass-through. This matrix becomes very complicated with multiple products and multiple retailers and manufacturers. To obtain Δ_{wt}, first note that $\Delta_{wt} = \Delta'_{pt}\Delta_{rt}$, where Δ_{pt} is a matrix of derivatives of all the retail prices with respect to all the wholesale prices. So all that is needed is to find expressions for, and compute, Δ_{pt}.[14] Dropping time subscripts to simplify notation, to get the expression for Δ_p, let us start by totally differentiating for a given j equation (5) with respect to all prices $(dp_k, k = 1,\dots,N)$ and a wholesale price p^w_f, with variation dp^w_f:

$$\sum_{k=1}^{N} \underbrace{\left[\frac{\partial s_j}{\partial p_k} + \sum_{i=1}^{N}\left(T_r(i,j)\frac{\partial^2 s_i}{\partial p_j \partial p_k}(p_i - p^w_i - c^r_i)\right) + T_r(k,j)\frac{\partial s_k}{\partial p_j}\right]}_{g(j,k)} dp_k - \underbrace{T_r(f,j)\frac{\partial s_f}{\partial p_j}}_{h(j,f)} dp^w_f = 0. \tag{9}$$

Putting all $j = 1,\dots,N$ products together, let G be the matrix with general element $g(j,k)$ and let H_f be the N-dimensional vector with general element $h(j,f)$. Then $G\ dp - H_f\ dp^w_f = 0$. Solving for the derivatives of all prices with respect to the wholesale price f, the f-th column of Δ_p is obtained:

$$\frac{dp}{dp^w_f} = G^{-1}H_f. \tag{10}$$

Stacking all N columns together, $\Delta_p = G^{-1}H$, which has the derivatives of all prices with respect to all wholesale prices.[15] The general element of Δ_p is $(i,j) = \frac{\partial p_j}{\partial p^w_i}$.

Collecting terms and solving for the manufacturers' implied price-cost margins yields

$$p^w_t - c^w_t = -(T_w * \Delta_{wt})^{-1}s_t(p). \tag{11}$$

Finally, the sum of the implied price-cost margins for the retailers and the manufacturers is obtained by adding up (6) and (11). For the remaining models, I assume that costs do not vary over the different vertical models.

4.2.2. Scenario 2: the hybrid model. Each retailer behaves as a vertically integrated firm with respect to its own private label products and plays the vertical Nash–Bertrand game in other products (*i.e.* national brands). This scenario's implied price-cost margins relate to portions of price-cost margins from scenario 1 (for a simple model, please refer to the web-page supplement). In particular, the retail margins will be the same as those in scenario 1, given by equation (6). However, the wholesale margins change. When vertically integrating into the upstream market, retailers affect the price-cost margins of national brand manufacturers. By vertically integrating, retailers eliminate wholesale margins of private labelled products, and the final retail price of the private label falls. Demand for the products sold by the manufacturers of national brands decreases and, consequently, the national brand manufacturers must adjust their wholesale prices. At the manufacturer level in this particular market, the wholesale margins for private label products are 0 and thus not optimized over. The implied manufacturers' price-cost margins for the national brands are given by

$$p^w_t - c^r_t - c^w_t = -(T^*_w * \Delta^*_{wt})^{-1}s^*_t(p), \tag{12}$$

14. The possibility of multiple equilibria may be an issue here, in the context of a manufacturer pricing its different products sold at different retailers. Different combinations of products offered at different retailers and different vertical supply models could potentially generate the same observed prices.

15. Matrix G is derived from totally differentiating the first-order conditions of retail profit maximization. The second-order conditions are that G be negative semi-definite, and G is invertible if negative definite, which is the typical case, especially if there is enough product differentiation, and or a large outside good in the market (see also Vives, 1999).

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where excluding the rows and columns that correspond to private label products, T_w^* is the national brand manufacturers' ownership matrix, Δ_{wt}^* is defined like Δ_{wt}, and $s_t^*(p)$ are the shares of the national brands.

4.2.3. Scenario 3: non-linear pricing models. In the classical, non-linear optimal (two-part tariff) pricing model, with one manufacturer and one retailer case, the manufacturer sets wholesale price equal to marginal cost and lets the retailer be the residual claimant. The manufacturer is then able to extract part, or the full "monopoly" (or vertically integrated firm's) surplus, in the form of a fixed fee that the retailer must pay. Two-part tariffs are seen as optimal contracts whenever there is downstream market power in the retail market and fairly general market assumptions hold.[16] It is no longer true that the optimal two-part tariff, in the context of multiple retailers, yields marginal cost pricing by the manufacturers (Schmalensee, 1981; Mathewson and Winter, 1984). However, two-part tariffs are still optimal in the context of multiple manufacturers and a single retailer (Tirole, 1988, p. 180; Shaffer and O'Brien, 1997).

Given the above set-up, two sub-cases are next considered to test the validity of non-linear pricing solutions to the double marginalization problem.[17] I assume first that wholesale price is equal to wholesale costs, and in the second sub-case that the retail mark-up is 0 and retail price is equal to wholesale price plus any remaining retail costs.[18]

Sub-case 3.1. Suppose, in a first scenario, that manufacturers choose to leave retailers as residual claimants, by eliminating the wholesale margin. Therefore, it follows that total vertical profits may also increase compared to the double marginalization scenario. Retailers now maximize their profits given that wholesale prices are equal to marginal costs, since the manufacturers' implied price-cost margins are 0 for all products. The implied price-cost margins for the retailers are given by equation (6) and subject to $p_t^w = c_t^w$. That is,

$$p_t - c_t^r - c_t^w = -(T_r * \Delta_{rt})^{-1} s_t(p). \tag{13}$$

This means that the retailer gets the profits corresponding to the downstream, vertically integrated structure for each of the j products. Manufacturers recover these profits with the fees F.

Sub-case 3.2. Suppose there are zero retail margins and manufacturers make pricing decisions in the equilibrium. There exists an equilibrium where retailers can get all the profits and retail prices are chosen to maximize the profits corresponding to the downstream vertically integrated structure for each of the j products. This is achieved by choosing the retail price-cost margins as zero for all products; the retailers add only retail costs to the wholesale prices, that is, $p_{jt} = p_{jt}^w + c_{jt}^r \ \forall j$. The manufacturers' implied price-cost margins are given by

$$p_t - c_t^r - c_t^w = -(T_w * \Delta_{rt})^{-1} s_t(p). \tag{14}$$

16. Two-part tariff has been shown to be optimal in the simple double marginalization model where retailers follow manufacturers in a price-setting game with certain demand (Tirole, 1988, p. 176), uncertain demand (Rey and Tirole, 1986), or under asymmetric information (Tirole, 1988, p. 177). However, in the presence of uncertainty, two-part tariffs have poor properties in terms of risk sharing.

17. Note that rejection of the sub-case(s) of non-linear pricing does not imply rejection of non-linear pricing.

18. For a more detailed and complete discussion on how these two extreme cases can be derived among other equilibria in non-linear pricing see Rey and Vergé (2004) and a recent paper by Bonnet, Dubois and Simioni (2004), who explicitly and empirically estimate models of retail and manufacturer competition under non-linear pricing for the market of bottled water in France.

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Finally, retailers set franchise fees F to extract the manufacturers' profits. It is worth noting that the implied price-cost margins in equation (14) are different from those implied by equation (13) because the retail ownership T_r differs from the manufacturer ownership T_w. Thus, manufacturers and retailers are maximizing their profits over a different set of products. In Berry *et al.* (1995) and Nevo (2001), the (manufacturer) implied price-cost margins computed are given by expressions similar to (14) and the retailers' decisions are not modelled.

4.2.4. Scenario 4: manufacturer-level collusion model. In scenario 4, manufacturers choose wholesale prices to maximize the sum of manufacturers' profits. Because manufacturers are assumed to be colluding, it is as if one single upstream firm owned the full set of products. Thus, the manufacturers' ownership matrix T_w is a matrix full of ones, henceforth called T_1. Manufacturers' price-cost margins are given by equation (11), subject to $T_w = T_1$. Assuming retailers set their retail prices, given the wholesale prices, the implied price-cost margins of the retailers are given by (6).

4.2.5. Scenario 5: retail level collusion model. Assuming collusion at the retail level corresponds to the assumption $T_r = T_1$. Retail price-cost margins are given by (6) subject to $T_r = T_1$, while manufacturer price-cost margins are given by (11).

4.2.6. Scenario 6: monopolist model. This last scenario examines the question of whether the industry is jointly profit maximizing. Wholesale margins are 0. Furthermore, $T_r = T_w = T_1$. Consequently, the implied price-cost margins of the fully vertically and horizontally integrated structure are given by

$$p_t - c_t^r - c_t^w = -(T_1 * \Delta_{rt})^{-1} s_t(p). \tag{15}$$

5. ESTIMATION AND INFERENCE

With the data sample discussed in Section 3, I estimate demand and use the estimates to compute price-cost margins for retailers and manufacturers under different supply models. Because wholesale prices are unobservable, I compare estimated price-cost margins with the price-cost margins estimated using components of marginal costs to assess the fit of these different vertical models and select the non-nested models that are most compatible with the data. Besides the technical simplicity, a two-step procedure also provides an elegant way to compare different supply models without having to re-estimate the demand system (see also Goldberg and Verboven, 2001; Brenkers and Verboven, 2002). The estimation of a firm's (implied) price-cost margins, without observing actual costs, follows Bresnahan (1989).

5.1. *Demand estimation*

When estimating demand, the goal is to derive parameter estimates that produce product market shares close to the observed ones. This procedure is non-linear in the demand parameters, and prices enter as endogenous variables. The key step is to construct a demand side equation that is linear in the parameters associated with the endogenous variables so that instrumental variables estimation, generalized method of moments (GMM), can be directly applied. This follows from

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equating the estimated product market shares[19] to the observed shares and solving for the mean utility across all consumers, defined as

$$\delta_{jt}(\Gamma, \Upsilon) = d_j + x_{jt}\beta - \alpha p_{jt} + \xi_{jt}. \tag{17}$$

For the logit model, the mean utility δ_{jt} can be recovered analytically, following Berry's (1994) inversion technique, by $\log(s_{jt}) - \log(s_{0t}) = \delta_{jt}$. However, in the full model, solving for the mean utility has to be done numerically (see Berry *et al.*, 1995). Finally, once this inversion has been made, one obtains equation (17) which is linear in the parameter associated with price. Let θ be the demand side parameters to be estimated, where in the logit case $\theta = \theta_L = (\alpha, \beta, d)$ and, in the full model, $\theta = (\theta_L, \Gamma, \Upsilon)$, where Γ and Υ are the non-linear parameters. For the logit case, θ_L is obtained directly from estimating (17) by feasible two-stage least squares (2SLS).[20] In the full random coefficients model, θ is obtained by feasible Method of Simulated Moments following Nevo's (2000) estimation algorithm, where equation (17) enters in one of the steps.[21] I start by using a simplex search and then a gradient method (providing an analytical gradient) with different starting values of the non-linear parameters to find a minimum of the simulated GMM objective function.

5.2. *Instruments and identification of demand*

The remainder of the paper relies heavily on having consistently estimated demand parameters or, alternatively, demand substitution patterns. What is the exogenous variation that identifies these substitution patterns? There are basically two sources of identification in the data. One source is the relative price variation over time. In this paper, the experiment asks consumers to choose between different products over time, where a product is perceived as a bundle of attributes (among which are prices). Since prices are not randomly assigned, I use manufacturer and retail level input price changes over time that are significant and exogenous to unobserved changes in product characteristics to instrument for prices. These cost instruments separate cross-brand variation in prices, as well as cross-store/brand variation in prices due to exogenous factors from endogenous variation in prices from unobserved product characteristics changes. Using retail level input price data, the same argument applies to the identification of elasticities for the same product sold at different retailers. The fact that consumer choice sets changed due to renovation in one store provides an additional and fortunate source of identification.

Instrumental variables in the estimation of demand are required because when retailers consider all product characteristics when setting retail prices, not only the ones are observed. That is, retailers consider both observed characteristics, x_{jt}, and unobserved characteristics, ξ_{jt}. Retailers also account for any changes in their products' characteristics and valuations. A product fixed

19. For the random coefficient model the product market share in equation (3) is approximated by the logit smoothed, accept–reject simulator given by

$$s_{jt} = \frac{1}{R}\sum_{i=1}^{R} \frac{e^{\delta_{jt} + [x_{jt}, p_{jt}](\Gamma\ D_i + \Upsilon\ \upsilon_i)}}{1 + \sum_{k=1}^{N_t} e^{\delta_{kt} + [x_{kt}, p_{kt}](\Gamma\ D_i + \Upsilon\ \upsilon_i)}}, \tag{16}$$

where R are the random draws from the distribution of υ and D. This simulator is continuously differentiable in the data and in the parameters to be estimated, so gradient-based methods are applied to estimate Γ and Υ.

20. This is optimal in the presence of homoscedastic errors. The 2SLS estimators are unbiased, consistent, and asymptotically normally distributed, even in the presence of heteroscedasticity and autocorrelation. However, one needs to obtain an appropriate Newey and West (1987) estimate of the 2SLS estimators' variance covariance matrix.

21. The aim is to concentrate the simulated "GMM" (SGMM) objective function, so that it will only be a function of the non-linear parameters. By expressing the optimal vector of linear parameters as a function of the non-linear parameters, and then substituting back into the SGMM objective function, it can be optimized with respect to the non-linear parameters alone.

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effect is included to capture observed and unobserved product characteristics/valuations that are constant over time. Quarterly dummies capture quarterly unobserved determinants of demand. The econometric error that remains in ξ_{jt} will therefore only include the (not-seasonal) changes in unobserved product characteristics, such as unobserved promotions and changes in shelf display and/or changes in unobserved consumer preferences. This implies that the prices in (17) are correlated with changes in unobserved product characteristics affecting demand. Hence, to obtain a precise estimate of the price coefficients, instruments are used. I use, as instruments for prices, direct components of marginal cost, namely, manufacturer input prices, interacted with product-specific fixed effects. The price decision takes into account exogenous cost-side variables, such as input prices. It is reasonable to assume that the prices of inputs are uncorrelated with changes in unobserved product characteristics, ξ_{jt}. For example, changes in shelf display are most likely not correlated with manufacturer input prices such as the prices of plastic, milk, and sugar. The intuition for interacting input prices with product dummies is to allow each input to enter the production function of each product differently: some yogurts are more sugary, fruit yogurts use more fruit, and so on. Since the exact content is not observed, it is estimated this way. Using these instruments for prices is a new approach and, given the good first-stage fit, it appears to generate robust results.[22] Thus, these cost data multiplied by product fixed effects are instruments for endogenous retail prices. To examine the effects of the two alternative instrumental variables specifications, two sets of instruments are considered when estimating demand. In the first specification, I interact 43 product dummies (where product is defined as brand store) with the input prices, allowing marginal cost of a given yogurt brand sold at two different retailers to vary. In the alternative specification, I assume that the manufacturer marginal cost of the same brand sold at two different retailers is the same. This results in 21 brand dummies interacted with the manufacturer-input prices. There exists one additional reason why these instruments (input prices multiplied by product fixed effects) are valid. The residual in the demand equation contains only the part that is not explained by "store-brand" level fixed effects. Had I not included brand dummies in the demand estimation, the instruments would have been correlated with constant unobserved product characteristics. I have included seasonal dummies to control for unobserved seasonal variation in consumer preferences. Their inclusion implies that some of the seasonal input prices are less problematic as instruments. Retail level input prices (retail size measured by the number of stores and number of employees in the chain, real estate indices on retail average price per square foot, and retail average rent per square foot) are also used as instruments. It is reasonable to assume that the changes in unobserved product characteristics ξ_{jt}, such as changes in shelf display, are most likely not correlated with retail input prices, such as the rental price of square foot and the price of electricity.

5.3. *Inference*

After having estimated the demand model as a first step, I investigate the validity of the supply models as a second step. I follow two approaches: one more formal, non-nested hypothesis testing approach and another more informal specification testing procedure.

5.3.1. Informal model specification check. The idea is to estimate, given demand estimates θ, a supply equation that is derived from the firms' profit maximizing decisions and is

22. One problem remains with the above instrumentation method: I cannot control for the case when manufacturer input prices vary and manufacturers may change the set of products proposed for sale to retailers (and input prices would be correlated with changes in unobserved product characteristics). I acknowledge the assumption that T_r and T_w are exogenous as a limitation. The instrumentation approach is used in subsequent papers with a good first stage (*e.g.* in Chintagunta *et al.*, 2002; Draganska and Mazzeo, 2003; Hellerstein, 2004).

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given by

$$p = f(C\gamma) + \text{SIPCM}_r(\theta)\lambda_r + \text{SIPCM}_w(\theta)\lambda_w + u^s, \tag{18}$$

where C is a matrix of cost-side variables such as input prices, γ is a vector of coefficients associated with cost-side variables, $\text{SIPCM}_r(\theta)$ and $\text{SIPCM}_w(\theta)$ are the retail and manufacturer price-cost margins, respectively, implied by the different scenarios, and λ_r and λ_w are parameters associated with the implied margins. Alternative cost specifications are estimated. First, it is assumed that $f(C\gamma) = C\gamma$, then that $f(C\gamma) = \ln(C\gamma)$, and finally that $f(C\gamma) = e^{C\gamma}$. For each model, the specification test evaluates the null hypothesis that all the coefficients in λ_r and λ_w are not significantly different from 1. I also consider an even more informal and intuitive check for the supply models, which examines whether implied marginal costs are negative for some models.

5.3.2. Formal ranking of supply models. This paper follows a menu approach (as in Bresnahan, 1987; Gasmi, Laffont and Vuong, 1992). I present different models of vertical relationships, and the objective is to determine the model that fits the data best. Because most of the models cannot be nested in another proposed model, pairwise, non-nested testing procedures proposed by Smith (1992) are applied here. The basic idea builds on the previously described informal testing procedure; if a certain model is true, then all parameters associated with the price-cost margins variables in equation (18) are not different from 1. I now subtract the implied price margins from the retail price and recover marginal costs for the vertical supply model in question. Let y be the difference in retail price and price-cost margins. Then, for each pairwise comparison, there are two competing regression models, M_g and M_h defined, respectively, as M_g: $y_g = f(c\beta) + u_g$ and M_h: $y_h = f(c\gamma) + u_h$. In the model, c is a matrix of input prices, and β and γ are parameters to be estimated by GMM. To compare each pair of models, the Cox-type statistic is constructed by examining the difference of the estimated GMM criterion functions for model M_h and for the alternative model M_g. Normalized, standardized, and compared to a standard normal critical value, a large positive statistic in this one-sided goodness-of-fit test leads to the rejection of the null model M_h against M_g. The intuition behind the non-nested pairwise comparisons is to see how the price-cost margins of alternative models explain the residual (unobserved determinants of price) of the null model. This residual is obtained by subtracting the computed price-cost margins and estimated marginal costs from retail prices under the null model being considered.

6. EMPIRICAL RESULTS

6.1. *Demand estimation*

I use the logit model for demand as a basis for comparing and choosing between different instrumental variable specifications, illustrating the need to instrument for prices when estimating demand, and accessing the sensitivity of the demand estimates with respect to the market size definition. Understanding the drawback of having poor substitution patterns (see McFadden, 1984; Nevo, 2000), I then estimate a random coefficients discrete choice model of demand for differentiated products.

6.1.1. First stage. In the first instrumental variable (IV) specification, prices are instrumented by manufacturer input prices multiplied by 43 product dummy variables and retail level input prices. In the second IV specification, prices are instrumented by retail level input prices and by manufacturer input prices interacted with 21 product dummies. This second specification

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corresponds to assuming that manufacturer marginal cost for the same product sold at different retailers is equal. Choosing between the two different instrumental variables specifications, I test and cannot reject the assumption that the coefficients associated with the same input for the same "physical" product are equal to each other, as in specification 2. The "First Stage" part of Table 4 reveals that the first stage R-squared and F-statistic of the IV specifications are high, and the F-test for zero coefficients associated with manufacturer instruments is rejected. The F-test for testing that the coefficients associated with retail level additional instruments are 0 is also rejected at any significance level. This suggests that manufacturer instruments, and also the additional retail level instruments, are valid. In general, estimates of first-stage coefficients have the expected positive sign and are significant (*e.g.* for plastic, sugar, and milk). Coefficients for the wages in U.S. states in which plants of the different products are located are significant as are retail level instruments' coefficients. Considering the use of instrument for prices, the Hausman test for exogeneity suggests that there is a gain from using instrumental variables vs. OLS when estimating demand.

6.1.2. Logit demand. Table 4 presents the results from regressing the mean utility δ_j, which for the logit case is given by $\ln(s_{jt}) - \ln(s_{0t})$, on prices and quarterly and product dummy variables in equation (17). The second column displays the estimate of ordinary least squares for the mean price coefficient α, and columns 3 and 4 contain estimates of α for the two different instrumental variables (IV) specifications, using manufacturer and retail level input prices as instruments for the prices. The last columns 5–7 of Table 4 present results when advertising is included as an additional R.H.S. variable. The coefficient of advertising is not significant and the effects from including advertising on the price and product characteristic coefficients are insignificant, both statistically and economically. To access the sensitivity of the demand estimates with respect to the definition of market size, please refer to the bottom of Table 4. As the servings *per capita* increase, the estimate of the mean marginal utility of price decreases for all specifications.

6.1.3. Random coefficients demand. Results from estimating equation (17) are presented in columns 3–7 of Table 5. Consumer heterogeneity is investigated by allowing the coefficients on price, store dummy variables, and product characteristics to vary across consumers as a function of their income, age, and other unobserved consumer characteristics, following McFadden and Train (2000). All the demographic variables that interact with prices and product characteristics are expressed as deviations from the mean. GMM estimates of the random coefficient specification, which allows log of income and the age to influence the price coefficient, are presented in column 3. Column 4 allows for the log of income to affect the price coefficient non-linearly by including a quadratic term. Columns 5–7 present estimates for additional demand specifications as robustness checks. Interpreting the estimates in columns 3 and 4, the mean price coefficients are different from the logit estimate for the mean of the marginal disutility of price. Age and income do not significantly affect the mean price sensitivity. However, unobservable characteristics in the population seem to affect it significantly. The last line of Table 5 presents the percentage of estimated individual price coefficients that have the wrong and positive sign. For the specification in column 3, this happens but very rarely (less than 0·2%). The results presented in column 4 reduced the percentage of positive predicted coefficients $\alpha_i = \alpha + \Gamma D_i + \Upsilon v_i$ to 0. In this case, as in Nevo (2001), the zero percentage of estimated positive α's is due mainly to the inclusion of the interaction of price with income and income squared. The coefficients associated with the store dummies are interpreted relative to the smaller store. Unobservable characteristics in the population do not seem to explain why people choose stores two and three over store one.

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TABLE 4

Results from logit demand

	No advertising			With advertising		
Variable	OLS	IV1	IV2	OLS	IV1	IV2
Price	−5·06	−5·53	−5·93	−5·10	−5·57	−5·73
	(0·32)	(0·45)	(0·47)	(0·34)	(0·44)	(0·49)
Feature				0·33	0·32	0·27
				(0·20)	(0·22)	(0·22)
Measures of fit						
R^2	0·73			0·73		
Price exogeneity test		5·17	6·38		4·16	4·64
95% critical value		(3·84)	(3·84)		(3·84)	(3·84)
First stage price						
R^2		0·85	0·82		0·87	0·83
F-statistic (p-value)		12·95(0·00)	16·24(0·00)		14·49(0·00)	17·98(0·00)
F : cost coefficients = 0		2·52(0·00)	2·65(0·00)		2·61(0·00)	2·69(0·00)
F : manufacturing cost coefficient = 0		1·60(0·00)	1·36(0·00)		1·59(0·00)	1·40(0·00)
F : retail cost coefficient = 0		1·60(0·00)	2·24(0·00)		1·73(0·00)	2·26(0·00)
Serving-capita-week		Estimated price coefficient sensitivity to market definition				
0·25		−6·36	−6·29		−6·18	−6·05
		(0·54)	(0·57)		(0·58)	(0·61)
0·75		−5·46	−5·86		−5·13	−5·66
		(0·46)	(0·47)		(0·49)	(0·50)
1		−5·43	−5·82		−5·10	−5·62
		(0·45)	(0·47)		(0·48)	(0·49)

Dependent variable in all columns is $\ln(s_{jt}) - \ln(s_{0t})$. Market definition: Half a serving *per capita* per week on the top part of the table. Sensitivity to market definition on the bottom part. Regressions include brand dummy variables and quarterly dummies. 4310 observations. Newey–West heteroscedasticity- and autocorrelation-consistent standard errors are in parentheses. Instrumental variables (IV1) for prices in this column are all input prices multiplied by 43 product dummy variables, assuming that marginal cost differs for the same product sold at different retailers (*Specification* 1). Instrumental variables (IV2) for prices in this column have two sets: (i) manufacturer input prices multiplied by 21 product dummy variables, assuming that manufacturer marginal cost for the same product sold at different retailers is constant; (ii) retail input prices interacted with product dummy variables (*Specification* 2). OLS, ordinary least squares; IV, instrumental variables.

Source: My calculations.

In fact, the positive and significant coefficient associated to the interaction between the store two dummy and age of the population suggests that older people significantly prefer store two over store one. One other possibility is that older people live closer to store two than store one since this model does not control for store distance. The preferences for larger store two decreases and for store three rises with an increase in income. Perhaps this is due to the location of a higher income population around store one. For the average consumer, calories have a negative marginal utility, and calcium content has a positive marginal utility. The estimates for the interactions of demographics with the constant term (that captures consumers' valuation for the outside option) suggest that unobserved characteristics in the population explain significantly and positively how likely or unlikely a consumer is to buy other yogurt not included in the sample.

6.2. *Elasticities*

For the estimated logit model own and cross elasticities, see columns 2 and 3 of Table 6. The elasticities vary by brand, where the mean of the distribution of own price elasticities is −5·91 with a standard deviation of 0·02. Cross-price elasticities are, on average, 0·019 with a standard deviation of 0·02. One limitation of the logit demand specification is the implied cross-price

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TABLE 5

Results from random coefficient model of demand

	Variable	GMM Est. (S.E.)	$GMM-Inc^2$ Est. (S.E.)	NLLS Est. (S.E.)	$\upsilon_i = 0$ Est. (S.E.)	$GMM-Inc^2$ Est. (S.E.)
Mean	Constant	−8·25(4·71)	−7·97(4·81)	−5·92(2·52)	−5·73(5·12)	−8·11(4·83)
	Price	−0·79(0·25)	−0·39(0·25)	−1·02(0·24)	−4·33(0·25)	0·64(0·21)
	Advertising					0·37(0·20)
	Store 2	−0·35(0·04)	2·08(0·04)	−0·12(0·03)	3·12(0·03)	2·33(0·03)
	Store 3	−1·02(0·04)	1·11(0·04)	−0·66(0·03)	2·29(0·03)	0·84(0·03)
	Calories	0·06(0·01)	−0·26(0·01)	−0·26(0·00)	−0·27(0·00)	−0·19(0·01)
	Calcium	2·06(0·13)	3·54(0·13)	3·77(0·12)	4·33(0·13)	2·84(0·13)
S.D.	Constant	0·25(0·08)	0·25(0·08)	0·1(0·05)		0·25(0·08)
	Price	0·92(0·18)	0·92(0·18)	0·57(0·13)		0·92(0·18)
	Store 2	0·07(0·13)	0·06(0·14)	0·03(0·07)		0·05(0·14)
	Store 3	0·15(0·15)	0·15(0·15)	0·12(0·05)		0·15(0·15)
	Calories	0·00(0·00)	0·00(0·00)	0·00(0·00)		0·00(0·00)
	Calcium	0·28(0·11)	0·28(0·11)	0·19(0·05)		0·28(0·10)
Interact with income	Constant	0·01(0·53)	−0·01(0·56)	−0·18(0·31)	0·00(0·59)	−0·00(0·55)
	Price	1·40(0·84)	0·87(0·65)	−0·17(0·51)	0·84(0·65)	0·86(0·65)
	Store 2	−1·56(0·40)	−1·36(0·48)	−0·11(0·09)	−1·37(0·52)	−1·36(0·48)
	Store 3	−0·43(0·31)	1·43(0·50)	0·14(0·10)	−0·67(0·53)	−0·39(0·48)
	Calories	0·00(0·00)	0·00(0·00)	0·00(0·00)	0·00(0·00)	0·00(0·00)
	Calcium	0·42(0·16)	0·33(0·16)	0·08(0·07)	0·31(0·14)	0·32(0·16)
$Inter.\ Inc.^2$	Price		−0·61(0·14)	0·05(0·05)	0·16(0·10)	0·08(0·11)
Interact with age	Constant	0·52(1·40)	0·57(1·41)	0·22(0·72)	0·16(1·54)	0·56(1·40)
	Price	−2·55(2·11)	−2·68(2·11)	−1·68(1·18)	−1·61(2·38)	−2·68(2·12)
	Store 2	1·04(0·55)	1·11(0·55)	0·56(0·23)	0·87(0·56)	1·11(0·54)
	Store 3	0·55(0·59)	0·55(0·56)	0·51(0·21)	0·50(0·58)	0·55(0·57)
	Calories	0·00(0·00)	0·00(0·00)	0·00(0·00)	0·00(0·00)	0·00(0·00)
	Calcium	0·25(0·41)	0·25(0·42)	0·42(0·18)	0·07(0·45)	0·25(0·41)
First stage						
R^2		0·82	0·82		0·82	0·83
F-statistic		16·24	16·24		16·24	17·98
GMM/NLLS		1063·8	1063·0	2020·9	1115·8	1058·2
R^2 min.dist		0·75	0·79	0·87	0·83	0·87
Price coef > 0		0·2%	0%	0%	0%	0·3%

Notes: Estimates (Est.) and Newey–West heteroscedasticity- and autocorrelation-consistent simulation corrected standard errors are in parentheses (S.E.) for different specifications in each column. Column 3 presents the generalized method of moments (GMM) estimates, column 4 the GMM estimates, but including an interaction of price coefficient with income squared (Inter. Inc.^{2}), column 5 has the non-linear least squares (NLLS: not instrumenting for price) for the same specification and column 6 presents the GMM estimates with $\upsilon_i = 0$. Column 7 is the same specification as column 4 but includes advertising. The R^2 min.dist reports the R^2 from the Generalized Least Squares regression of estimated product fixed effects on product characteristics.

Source: My calculations.

elasticity pattern. That is, products with similar market shares and prices have similar cross-price elasticities.

In the full model, the elasticities-related limitations described above disappear. On the one hand, own price elasticities are no longer uniquely driven by functional form specifications. In particular, the marginal utility of price α will now vary by product, in the sense that it is obtained as the average of all the price sensitivities α_{ij} for all the consumers i of that particular product j. On the other hand, cross-price substitution patterns are richer. The mean of own price elasticities is now $-5{\cdot}64$ with a standard deviation of 0·03. For all products, the standard deviation

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TABLE 6

Mean estimated own and cross-price elasticities

	Logit demand		Random coefficients demand				
	Own price	Cross-price	Own price	Cross-price		Same store	
Summary statistics	Elasticity	Elasticity	Elasticity	Mean	S.D.	Yes	No
Kraft	−5·918	0·014	−5·702	0·018	0·020	0·032	0·011
Dannon	−5·908	0·024	−5·489	0·031	0·041	0·043	0·019
PL 2	−5·911	0·020	−6·738	0·031	0·038	0·030	0·013
PL 3	−5·912	0·019	−5·568	0·021	0·018	0·021	0·017
Yoplait	−5·908	0·024	−5·657	0·032	0·036	0·046	0·011
Store 1	−5·926	0·006	−4·669	0·006	0·003	0·008	0·006
Store 2	−5·904	0·027	−6·663	0·043	0·046	0·062	0·026
Store 3	−5·906	0·025	−5·265	0·027	0·025	0·033	0·020
Average all	−5·910	0·021	−5·640	0·019	0·037	0·039	0·015

Notes: Own and cross elasticities of logit demand specification, own, mean, and standard deviations of the cross-price elasticities under a random coefficients demand specification. Last two columns present mean cross-price elasticities for products in the same store (yes column) and across different stores (no column).

is fairly large relative to the mean, and the logit restrictions seem less reasonable. Mean cross-price elasticities vary significantly by product, ranging, on average, from 0·001 to 0·134. Due to the large dimension of the matrix of cross-price elasticities, detailed information on estimated cross-price elasticities for the 43 products in the sample is not presented. However, overall, the results seem reasonable and intuitive: products seem to be less sensitive to changes in prices of products in other stores than changes in prices in the same store. This is true when breaking up by manufacturer (top of the table), or across manufacturer and breaking up by store (bottom of the table).

6.3. *Estimated price-cost margins*

Summary statistics for the price-cost margin estimates with a random coefficient demand model are provided in Table 7. In each line are the price-cost margins for the different models. For the models that estimate both retail and wholesale margins, total vertical margin is reported. When retailers determine prices (scenario 3, case 1), the median price-cost margins estimated are slightly higher than the price-cost margins that result when manufacturers set prices (scenario 3, case 2). For the random coefficient specification, only for the non-linear pricing models 3.1 and 3.2 all estimated mark-ups are significantly smaller than 100%. For all other models there are some products, during some weeks, that exhibit estimated price-cost margins greater than 100%, which implies negative marginal cost estimates. For the logit specifications, the simple linear pricing model (model 1), the hybrid model (model 2), and the collusion models (models 4 and 5), also exhibit mark-ups greater than 100%. Whether this problem is going to be statistically significant is addressed next.

6.4. *Model comparison*

6.4.1. Informal specification check. The next step is to subtract estimated price-cost margins from observed retail prices to recover the total marginal costs implied by each vertical supply model. Summary statistics of recovered marginal costs for all supply models are presented

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TABLE 7

Percentage price-cost margins (PCM) by scenario

Wholesale, retail, and total PCM	Median	S.D.	Min	Max
Given random coefficient demand				
Model 1: Simple linear pricing: T-PCM	43·8	25·4	25·5	136·5
Model 2: Hybrid model: T-PCM	41·6	28·6	15·8	136·7
Model 3.1: Zero wholesale margin: R-PCM	21·1	9·0	12·5	50·0
Model 3.2: Zero retail margin: W-PCM	20·6	4·7	12·8	45·8
Model 4: Wholesale collusion: T-PCM	72·8	22·4	38·8	253·0
Model 5: Retail collusion: T-PCM	69·9	25·8	23·4	263·2
Model 6: Monopolist: T-PCM	40·6	11·5	21·8	103·7

PCM $= (p-c)/p$ where p is price and c is marginal cost. S.D., standard deviation; W, wholesale; R, retail; T, total.

Source: My calculations.

TABLE 8

Sample statistics of recovered costs and informal testing

	Recovered retail and wholesale costs				
	Mean	S.D.	Min	Max	Percentage <0
Model 1: Simple linear pricing	0·2730	0·1552	−0·1532	0·5364	1·35
Model 2: Hybrid model	0·2757	0·1681	−0·1541	0·5364	1·45
Model 3.1: Zero wholesale margin	0·3796	0·0907	0·1201	0·6298	0
Model 3.2: Zero retail margin	0·3815	0·0895	0·1302	0·6279	0
Model 4: Wholesale collusion	0·1352	0·1114	−0·4590	0·4409	13·12
Model 5: Retail collusion	0·1530	0·1329	−0·4895	0·5053	12·6
Model 6: Monopolist	0·2953	0·0951	−0·0089	0·5628	0·08

Notes: Recovered costs = $p -$ epcm where p is retail price and epcm are the estimated margins. Last column has the percentage of cases with recovered estimated costs being negative.

Source: My calculations.

in Table 8. As the informal test for the estimated models, note that only the two non-linear pricing models (models 3) and the efficient pricing model (model 6) imply less than 0·1% negative recovered costs. Model 3.2 has slightly higher cost estimates than model 3.1. This is an interesting fact that reinforces the identification strategy among these two non-linear pricing sub-cases, namely, that the difference in recovered marginal costs estimates and price-cost mark-up estimates can be attributed to different ownership structures.[23] Results of informal validity testing for each supply model are the result from estimating a regression of prices on price-cost margins and costs, and testing for the hypothesis that the coefficients associated with the price-cost margins are equal to one. The null hypotheses imply that, given the assumptions for demand, the price-cost margins estimated under the scenario in question are consistent with the price-cost margins obtained from supply-side estimates.[24] The price-cost margins implied by the model with vertically integrated private labels and the retail and collusion models seem the least consistent with the data for random coefficients and logit specifications. In terms of rejection of individual firm parameters, the

23. See Villas-Boas and Hellerstein (2006) for the role of multi-product manufacturers and retailers without exclusive dealerships, identification of manufacturer and retail price mark-up behaviour, and the role of differentiated products and demand non-linearities for identification of retail and manufacturer pricing behaviour.

24. The purpose and interpretation of the supply parameters λ are different from the conduct parameter models where, for some values of the estimate of the cost price, inferences (subject to Corts, 1999 cautions) are drawn about market power in a certain industry.

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other models' ranking varies from random coefficients and logit specifications. Looking at more efficient contracting solutions, with just one margin, between manufacturers and retailers, the test for unit coefficient is less rejected. The efficient pricing model is also rejected about 40% of the time. As a preliminary conclusion, there seems to be mixed informal evidence on the contracting solution followed, but the least likely is the double marginalization model with integrated private labels (hybrid model) and models involving both retail and manufacturer non-zero margins, which are on average rejected over 70% of the time along the testing above for several demand specifications.

Finally, Table 9 presents the estimates of projecting the estimate of total recovered retailer and manufacturer marginal costs on retail and manufacturer input prices and retail and manufacturer dummies. In particular, Table 9 presents the parameter estimates for the simple uniform pricing model with vertically integrated private labels (model 2), and for the zero wholesale and Nash–Bertrand retail pricing model (sub-case 3.1). A linear cost specification and a non-linear cost specification are estimated, and the goodness of fit of each specification is assessed for a product chosen at random, due to space limitations. First, the $R^2 = 0{\cdot}50$ is fairly high. Overall, the parameters are reasonable, the coefficient on wage is significant and positive. The coefficients on retail level transportation input prices and retail wages also look reasonable for some states; in general, increases in gasoline price and wages are associated with an increase in marginal costs.

6.4.2. Ranking of supply models. Formally ranking the models, Table 10 presents the p-values for the test statistics for pairwise comparisons of all models. In each row is the (null) model being tested, and in each column is the alternative being used to test it. If the alternative model is performing well, then the null model is rejected by a large and significant test statistic. In an element (i, j) of this table the p-value is reported for the null model in row i being true when confronted with the specified alternative model in column j. In the bottom of Table 10 I present the same non-nested comparisons for a supply specification discussed below in the additional robustness checks. From the pairwise comparisons, I conclude that the models assuming zero wholesale margin, in which retailers have pricing decisions, provide the most reasonable fit given the other specified alternatives. 3.1 outperforms other models at 5% significance since the p-values in the elements of the column labelled 3.1 are less than 5%: this happens for the simple linear pricing model (model 1) and for the retail pricing model (model 3.2). In addition, the model escapes rejection against all alternatives confronted for this supply-side specification, since all the elements in the row corresponding to model 3.1 have p-values larger than 5%. For the logit specification model 3.1 escapes rejection from any alternative specified here. The two margin models are rejected by other models, such as the linear pricing model (model 1), the hybrid model (model 2), and the retail collusion model (model 5). Rejection of the collusion models may be explained by the difficulties associated with both price coordination in the vertically non-integrated case and penalties to sustain collusion (see, for example, Nocke and White, 2003). From the top of the table of non-nested comparisons, I may conclude that models 3.1 and 6 both reject other models and are in turn not rejected by any other specified alternative models. They have in common that wholesale margins are zero but differ in the retail pricing behaviour being Bertrand–Nash or Collusive.

This result is consistent with several scenarios that include non-linear pricing by manufacturers via quantity discounts, or two-part tariff contracts. In the optimal non-linear pricing contract, the manufacturer sets the marginal wholesale price close to the manufacturer's marginal cost and leaves retailers as residual claimants, such that the retailers have the correct incentives when setting the retail prices (especially with non-contractible retail efforts as in Rey and Vergé (2004)). The manufacturer extracts revenue from retailers via a fixed fee or by selling the non-marginal

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TABLE 9

Estimated cost parameters

	For model 2			For model 3.1		
Dependent variable	Obs	R^2	F	Obs	R^2	F
Price-estimated margins	104	0·482	3·43	104	0·546	4·43
	Coefficients	S.E.	t	Coefficients	S.E.	t
Citric acid	−0·003	0·035	−0·090	0·002	0·023	0·090
Plastic	0·018	0·008	0·960	0·012	0·005	1·190
Sugar	−0·004	0·008	−0·470	0·001	0·005	0·100
Milk	−0·485	0·246	−1·970	−0·330	0·158	−2·090
Strawberry	−0·005	0·094	−0·060	0·005	0·060	0·080
Wages IL	0·045	0·040	1·120	0·034	0·026	1·330
Wages MI	0·044	0·027	1·620	0·031	0·017	1·770
Interest rate	−0·019	0·054	−0·350	−0·008	0·035	−0·240
Retail square-foot-price IL	0·015	0·017	0·890	0·011	0·011	1·050
Retail rental IL	0·053	0·239	0·220	0·016	0·153	0·100
Gasoline IL	−0·006	0·008	−0·770	−0·005	0·005	−1·060
Gasoline OH	0·005	0·003	1·570	0·002	0·002	1·230
Electricity (industrial) IL	0·056	0·107	0·520	0·007	0·068	0·110
Electricity (industrial) MI	0·005	0·138	0·030	0·030	0·089	0·340
Electricity (industrial) OR	−0·161	0·184	−0·880	−0·138	0·118	−1·160
Electricity (industrial) OH	−0·389	0·214	−1·820	−0·305	0·137	−2·220
Expon (price-estimated margins)	104	0·512	3·86	104	0·562	4·72
Citric acid	−0·001	0·030	−0·030	0·003	0·026	0·130
Plastic	0·012	0·007	0·970	0·010	0·006	1·580
Sugar	−0·003	0·007	−0·370	0·001	0·006	0·140
Milk	−0·372	0·211	−1·760	−0·346	0·184	−1·880
Strawberry	−0·001	0·080	−0·010	0·008	0·070	0·120
Wages IL	0·042	0·034	1·240	0·043	0·030	1·440
Wages MI	0·038	0·023	1·640	0·036	0·020	1·780
Interest rate	−0·014	0·047	−0·300	−0·009	0·041	−0·230
Retail square-foot-price IL	0·013	0·014	0·890	0·013	0·013	1·030
Retail rental IL	0·040	0·205	0·200	0·018	0·179	0·100
Gasoline IL	−0·004	0·007	−0·620	−0·006	0·006	−0·950
Gasoline OH	0·004	0·003	1·580	0·003	0·002	1·250
Electricity (industrial) IL	0·043	0·091	0·470	0·007	0·080	0·090
Electricity (industrial) MI	−0·006	0·118	−0·050	0·024	0·103	0·230
Electricity (industrial) OR	−0·160	0·158	−1·010	−0·175	0·138	−1·270
Electricity (industrial) OH	−0·341	0·183	−1·860	−0·361	0·160	−2·260

Notes: This table presents a sample of the estimated cost parameters. Given the size of the full matrix of coefficients from regressing seemingly unrelated regressions for the different supply models and for alternative cost specifications, I present the results for one of the products' regressions for model 2 (single uniform pricing and vertically integrated private label) in columns 2–4, model 3.1 (preferred model), columns 5–7. On the top, for linear cost specification, on the bottom, for logarithmic cost specification. Obs are the number of observations.

Source: My calculations.

units at higher wholesale prices.[25] The existence of quantity discounts is common practice in this industry. Anecdotal evidence suggests that retail supermarkets do not often pay fixed fees to their manufacturers and, if they do, these fees are not close to the retail profits. Instead, there seem to be substantial fees paid by the manufacturers to the retailers (the so-called slotting allowances). The non-existent, or small fixed fees, could be explained by the fact that there are multiple manufacturers in this market with whom the retailers can bargain more aggressively for a lower fixed

25. One of the retail stores (the one that is not a chain) confirmed anecdotally that the manufacturers present them with step-wise quantity discounting for some of their shipments. That is, the first units are shipped at a certain price and additional units are shipped at lower prices.

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TABLE 10

p-Values for pairwise non-nested comparisons

	Alternative models						
H_0 model	1	2	3·1	3·2	4	5	6
1: Simple linear pricing	–	0·50	0·00	0·50	0·24	0·00	0·50
2: Hybrid	0·00	–	0·50	0·50	0·12	0·00	0·50
3.1: Zero wholesale margin	0·41	0·29	–	0·05	0·50	0·39	0·07
3.2: Zero retail margin	0·39	0·40	0·05	–	0·50	0·39	0·17
4: Wholesale collusion	0·49	0·48	0·50	0·50	–	0·48	0·50
5: Retail collusion	0·00	0·00	0·50	0·50	0·22	–	0·50
6: Monopolist	0·34	0·35	0·17	0·31	0·48	0·34	–
Chain size weighted							
1: Simple linear pricing	–	0·08	0·01	0·06	0·08	0·00	0·00
2: Hybrid	0·17	–	0·15	0·22	0·00	0·06	0·14
3.1: Zero wholesale margin	0·08	0·15	–	0·11	0·15	0·12	0·00
3.2: Zero retail margin	0·01	0·07	0·00	–	0·09	0·01	0·00
4: Wholesale collusion	0·00	0·05	0·04	0·09	–	0·00	0·02
5: Retail collusion	0·00	0·02	0·03	0·11	0·02	–	0·00
6: Monopolist	0·10	0·20	0·00	0·15	0·20	0·14	–

Notes: *p*-Values reported from non-nested, Cox-type (Smith, 1992) test statistics of the null model in a row being true against the specified alternative model in a column. Bottom part is a robustness check. It has the same format as above, but the non-nested comparisons are based on estimates for the case when the portion of the manufacturer's profit due to each retailer is weighted by the retailer's chain size.

Source: My calculations.

fee by threatening to buy from another manufacturer. This result is also consistent with the high bargaining power of retailers that are able to force wholesale prices down to marginal cost. In fact, in the last few decades, retailers may have acquired greater bargaining power relative to manufacturers (*Progressive Grocer*, April 1992), suggesting a possible departure from the simple linear pricing model in the industry. Industry participants and researchers have pointed out that private labels now compete directly with national brands (Narasimhan and Wilcox, 1998), and provide a new bargaining tool for retailers when negotiating with manufacturers.[26] Another reason is the increase in concentration at the retail level; retailers have market power with which they can bargain more aggressively with manufacturers.[27] One indication of retailer market power is the increase in competition for shelf space, implying that manufacturers have to pay retailers slotting allowances (*e.g.* Shaffer, 1991; Chu, 1992) to get their products displayed. Ultimately, however, without information on fixed fees, the above theoretical and anecdotal predictions cannot be tested, and one cannot formally identify which interpretation of the results applies.

The results have implications for pricing decision-makers in a particular industry. In the related literature (*e.g.* Berry *et al.*, 1995; Nevo, 2001), traditionally, the retailers' pricing decisions have been assumed away. For the market I study, this model is outperformed by the alternative model where retailers have pricing decisions. Estimating the price-cost margins under the assumption that manufacturers are setting the prices and retailers are neutral pass-through intermediaries, when in fact retailers are deciding prices, could lead to bias and affect the conclusions when accessing market power or merger activities in a certain industry. Indeed, the bias is expected to be more serious when retailers sell more sets of products and the sets of products that

26. Retailers are able to sell private label products at a potentially lower wholesale price. Furthermore, the products carry their store-brand and are displayed next to the national brands. At a 1995 convention, Douglas Ivester, then-president and CEO of Coca Cola, called private labels "*parasites*" and said they were responsible for "*eroding category profits*".

27. For example, see *New York Times*, 13 November 1998, p. C1.

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manufacturers sell do not coincide. Since retailers may not be neutral pass-through intermediaries, when analysing price dynamics in the economy as a whole, retail behaviour and retail market conditions should also be considered in addition to manufacturer behaviour.

6.5. *Additional robustness checks*

In terms of robustness of the demand assumptions for the logit demand specification, the ranking of the two best models is invariant. Additional demand specifications departing from the base models of specifications in columns 3 and 4 are presented in columns 5–7 of Table 5. Column 5 presents the NLLS estimates of the full model (without instrumenting for price). The demand coefficients change considerably. Column 6 presents the estimates from the specification that sets the unobserved shocks υ_i to 0 for all the product characteristics. Comparing columns 4 and 6, the estimates are in general unchanged. This suggests that unobservable heterogeneity may not be important for the results of interest, but heterogeneity might still be important for some aspect of demand. Column 7 is equal to 4, but adds advertising. The coefficient for advertising is statistically insignificant and, comparing column 4 with column 7, there is not a significant effect on the estimates. Finally, the ranking of the supply models is robust to small variations in weekly *per capita* consumption assumption and the introduction of demand seasonality. I further considered alternative scenarios, modelling retailers to be vertically integrated with respect to their private labels and estimating in that context retail collusion, as well as wholesale collusion models.

The price-cost margins estimated for all specifications described above assume that manufacturers set a wholesale price for each store. Some stores are part of chains, and it may be that manufacturers behave differently towards these stores (stores 2 and 3) than towards the non-chain store (store 1). As a robustness test, I estimate the profit maximization of the manufacturers by weighting the profit portion from selling to a certain retailer k by the size of store k's retail chain (measured by the numbers of employees in the chain and by the number of stores in the chain).[28] The non-nested model comparisons and estimated price-cost margins and recovered costs are very similar when weighted by stores or employees. Noting that chain size did somewhat affect the magnitude of price-cost margin and cost estimates, the weighting did not significantly change the conclusions from model comparisons relative to the unweighted specification. Looking at the bottom of Table 10, on the one hand model 3.1 is rejecting significantly all models except the hybrid model, with reported p-values less that 5% significance, but on the other hand model 3.1 is not rejected by any of the specified alternatives, except the monopolist model 6 (note, however, that model 3.1 also rejects model 6 at 5% significance level). The insight from this alternative supply model specification could be interpreted as providing evidence that wholesale margins are 0 and that retail pricing may lie between Bertrand–Nash (as in model 3.1) and collusive retail pricing (model 6).

7. CONCLUSIONS AND EXTENSIONS

This paper presents a method to analyse vertical relationships. Alternative models of competing manufacturers' and retailers' decision-making are used to determine whether contracting in the supermarket industry follows the double marginalization pricing model or whether more efficient contracting solutions are in place. This paper extends the literature in analysing vertical relationships as it considers multiple retailers and does not require observed data on wholesale prices. Given demand estimates, the approach is to compute price-cost margins for retailers and manufacturers implied by alternative vertical contracting models and to contrast these with price-cost

28. I thank an anonymous referee for this suggestion.

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margins obtained from direct estimates of cost. With the more efficient relationships I considered, the double marginalization externality imposed by retailers disappears. Consequently, the sum of retailers' and manufacturers' profits may increase.[29]

For the market I study, the results rule out double marginalization. In particular, they suggest that, on the margin, manufacturers are pricing at marginal cost and that retail prices are the unconstrained profit maximizing prices. Why should we care about the efficiency gain from solving the vertical coordination problem associated with double marginalization? For the market studied here, the magnitude of the deadweight loss associated with the simple linear pricing model compared with the most compatible model of no wholesale mark-ups and Nash–Bertrand retail pricing is roughly \$12,600 a week, which represents 2% of the sum of the three retailers' revenues. Assuming that retailers behave collusively and there are no wholesale margins results in a simulated change in welfare amounting to \$12,400 a week. Extrapolating to a U.S., yearly basis (given that national yogurt-retail revenues are about \$2 billion), then the deadweight loss is approximately \$46 million, a considerably large number.

An extension of this paper is to consider models of vertical relationships under the presence of non-linear pricing, following the modelling approach proposed by Rey and Vergé (2004) and first implemented empirically by Bonnet *et al.* (2004) who explicitly and empirically estimate models of retail and manufacturer competition under non-linear pricing for the market of bottled water in France. The idea there is to let retailers and manufacturers play the following "market break-down" game: (1) manufacturers simultaneously propose non-linear contracts, specifying a franchise fee F_j and a wholesale price p_j^w to each j retailer (and, if retail price maintenance is allowed, a retail price p_j); (2) then retailers accept or reject the contracts offered, which are public information; (3) if all contracts are accepted, then retailers simultaneously choose retail prices. Otherwise, if one of the contracts is rejected, no product is sold and firms earn zero profits. The estimates under this non-linear pricing model, when confronted with the alternative models specified in this paper, do not change the non-nested comparisons for the yogurt market analysed here.

Building on these results, future research will consider the fact that looking at just one category may be restrictive since manufacturers, retailers, and consumers make their pricing and purchase decisions in the context of multiple categories.[30] Given that consumers purchase a basket of goods during a shopping trip, a multiple category demand may be a more realistic framework to consider. In terms of pricing decisions, the fact that a manufacturer may sell products in different product categories affects not only its pricing strategy, but may also improve its bargaining flexibility with the retailers. In addition, retailers use strategic category pricing to drive consumers into the store and increase sales.[31]

Finally, to motivate future empirical research on vertical relationships, I identify two questions for which the methodology proposed in this paper can be applied. First, given the estimates of demand and a model of pre- and post-vertical merger supply behaviour, one can predict whether a potential vertical merger affects horizontal competition in the upstream and downstream markets involved.[32] The second relates to pass-through effects of foreign trade policy. Given the estimates of demand in a certain country for a particular good from a vertical trading supply model across different countries, one can analyse the effect of a tariff increase or exchange

29. In certain cases, profits may decrease and the manufacturers may not choose the vertically integrated solution, for example, as in McGuire and Staelin (1983) and Coughlan and Wernerfelt (1989).

30. For the retailers analysed, yogurt sales represent on average only 2% of total retail sales in contrast to the two largest dollar sales categories: soft drinks 17% and cereal 12%.

31. In terms of the econometrics, it would be useful to consider semi-parametric estimation and inference procedures that are possibly more robust for the problem at hand. In this context, information theoretic formulations appear to offer interesting possibilities (Judge, Mittelhammer and Miller, 2004).

32. See Manuszak (2003) for an analysis on how upstream (horizontal) mergers affect market power in the retail gasoline markets.

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rate depreciation on domestic or foreign margins. Trade policy-makers are particularly interested in whether foreign margins or domestic margins absorb most of the effects of a particular trade policy. That, in turn, is determined by the vertical relationships between domestic and foreign upstream or downstream firms.[33]

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33. See also Hellerstein (2004) and Hellerstein and Villas-Boas (2006). For example, if import prices do not rise as much as the dollar depreciation (*i.e.* the pass-through effect is less than one), then foreign profit margins are being diminished (see, for example, Feenstra, 1989).

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